THE APPLICATION OF THE ARTIFICIAL NEURAL NETWORK MODEL FOR RIVER WATER QUALITY CLASSIFICATION WITH EMPHASIS ON THE IMPACT OF LAND USE ACTIVITIES: A CASE STUDY FROM SEVERAL CATCHMENTS IN MALAYSIA

by

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Thesis submitted to the University of Nottingham for the degree of Doctor of Philosophy

Sponsored by
the Malaysian Public Service Department

March 2007

ABSTRACT

Several methods of river water quality assessment techniques have been introduced. Among the most commonly used are the water quality index system and classification scheme. These two systems are designed to simplify the huge amount of water quality data down to its simplest form, while retaining the essential meaning of the information. They offer the means for measuring the effectiveness of pollution abatement strategies by comparing the status of water quality both temporally and spatially. In this way, it is useful for management purposes, especially in determining priorities for resource allocation and planning of new development areas.

The water quality index system and the classification schemes currently available, however have some limitations in their structural design. They often exhibit inherent loss of information, are complex and may involve subjective judgement in their interpretation. However, because of the critical issues on water pollution and the scarcity of water resources, these systems are being applied despite of these limitations. The current situation is that, different countries are applying different models of water quality assessment system. Based on the limitations of the existing assessment systems, it is appropriate to explore other approaches that can be more flexible, robust to noisy data, and adaptable to new form of environmental data, in order to provide direct and prompt results for classifying of river water quality. One avenue for research is that based on Artificial Neural Network (ANN).

Artificial Neural Network comprises of several techniques. One of this technique that is widely being used is the Back-Error Propagation (BEP). BEP of ANN was used in this research in conjunction with the Interim National Water Quality Standard (INWQS) data for Malaysia. The findings of the study shows that the classification results based on the evaluation of the water quality variables were good when compared with the results obtained from other water quality classification models, which include; the Department of Environmnet Water Quality Index (DOE-WQI), the Harkins'-WQI, Mahalanobis Distance Classifier, Maximum Likelihood Distance Classifier and the Decision Tree Classifier. The accuracy for

BEP of ANN was found to be 86.9% and correlated well with all of these five models. The highest correlation was, with the Mahalanobis Distance Classifier and the DOE-WQI. The analysis on sensitivity shows that the BEP of ANN was sensitive to Dissolved Oxygen, a condition similar to the DOE-WQI model.

Comparisons were made with two types of BEP of ANN architecture, a simple network with less number of hidden nodes and a relatively complex network with more hidden nodes. It can be concluded from the analysis that a small and simple network performed well with large samples and with test data that are widely distributed than the complex network with more hidden nodes.

Using the same model, different approaches were used in evaluating the classification of water quality were applied, such as the used of the land use variables and hydrological features (LUVHF) to replace the water quality data. Using these variables, the performance of the BEP of ANN in classification of water quality was low (24% and 31%). However, its performance can be improved, if more samples with wider range of LUVHF were used.

Throughout this study, the BEP of ANN model has shown some remarkable achievements. In view of these, several knowledge contributions have been made. The first contribution is the flexibility of the system approach and operationally simple to perform. Secondly, it provides a practical approach in classification of river water quality, such that through a single network computation of a sample, the results are presented promptly as the probability value and the class grade value. The third contribution is that the water quality can also be classified based on the land use variables and hydrological features, without dependence on water quality data. This approach is suitable for remote areas, where accessibility is relatively difficult.

ACKNOWLEDGEMENTS

In completing this course of study, so much effort, patience and determination has been gone through. This thesis would not be successfully accomplished without the support of many individuals. As such, I would like to express my sincere gratitude and heartfelt thanks to my supervisors, Professor Roy Haines-Young and Dr. Peter Downs. Through their suggestions, criticisms and guidance throughout the period of study, I finally managed to produce this piece of research finding in its current form.

My gratitude is also specifically extended to my employer who sponsor this study, The Public Service Department of Malaysia, for giving me the opportunity, providing the scholarship and other financial assistance to enable me and my family to be here in Nottingham. In view of this, I am also indebted to the Hon. Dato' Hajjah Rosnani Ibarahim, Director General of the Department of Environment, Malaysia, who continously encouraged and supported my study through several statutory and legal clarifications of the existing Malaysian Water Quality Management Programme, which I crucially needed. My gratitude also goes to the other DOE officers, which include; Pauziah Hanum Abd. Ghani, Dr, Zulkifli Abd. Rahman, Yusof Ibrahim, Jefry, Mohd. Hidzir and Zakaria Ismail, for continuously providing me with the water quality data, maps, additional information and so forth.

I would also like to convey my gratitude to the Hon. Dato' Dr. Islahuddin Hj Baba, Deputy Secretary-General, Mininstry of Science, Technology and the Environment, Malaysia, and Professor Muhammad Awang, Deputy Vice Chancellor, University Putra Malaysia and the Hon. Dato' Haji Othman Muhammad, Chief Executive Officer of KESEDAR, Kelantan for their continuous support and encouragement since the beginning of this study.

I would also like to acknowledge Dr. Abdul Kadir, Director of Map Production, and Marzuki Mohd. Kassim, Director of CAMS, Department of Mapping and Survey; Major Sutimin Fahsar, Division of Military Mapping; Associate Professor Dr. Mohd Kamil Yusoff, Department of Environment, University of Putra Malaysia; Saari Omar, Ministry of Land and Cooperative Development; Jamariah, Department of

Town Planning, Federal Territory; Azhar and Alui Bahari of the Meteorology Service Department; Sahibi Mokhtar, Ministry of Agriculture; Yazan Zainol of the Department of Town Planning for the State of Selangor and Negeri Sembilan, Zainal Malik from the Office of Town and Country Planning, Seremban; Awang Mat Ali, State Economic Development Corporation of Negeri Sembilan, Shahrin Hitam of Malaysian Industrial Development Authority for their valuable encouragement and information.

I am highly indebted to all the staff and members of the School of Geography, University of Nottingham, particularly Dr. Duraid Omar, Rosemary Hoole, John Love, Ian Conway, Elaine Watts, Chris Lewis and Amanda Rowley for their assistance and cooperation. Thanks are also due to all my research colleagues, especially Dr. Carlos Vieira, Dr. Jasmee Jaafar, Dr. Taskin Kavzoglu, Dr. Norkhair Ibrahim, Dr. Sanusi Ahmed, Dr. Mohammed Al-Amri, Dr. Najib Marzuki, Dr. M. Premalatha, Dr. Mahesh Pal, Dr. Zakaria Hadi (University of Leicester), Dr. Nurul Salmi, Dr. Muhammad Al-Haj, Zamane Abd. Rahman, Dr. Ranita Ratnayake, Dr. Heriberto Gomez, Dr. Rosalba Gomez, Dr. Nabegh G. Aswad, Dr. Mokhtar Elatrash and Dr. Major Carlos Fernando de Abreu.

Lastly, my deepest gratitude is to my wife, Khadijah Mohamed, daughters Nur Zahidah, and Nabilah and son Muhammad Zakwan for their patience, continuous support and encouragement throughout my course of study.

To others not mention, thanks and TERIMA KASIH.

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CHAPTER ONE

INTRODUCTION: AIMS AND BACKGROUND

1.1 PURPOSE OF THE STUDY

The management of water quality is a major factor affecting modern societies (Singh, 1995; Robinson et al., 2000). The demand for water is ever growing with an increase in population and human lifestyle, whereas the total volume remains constant (Gray, 1999). In both developed and developing countries, land cover change has often resulted in the marked deterioration of water quality over time. Such changes can impact negatively on the continued use of those water resources for future human use, public health, and the ecological integrity of fresh water and coastal ecosystems (Walling and Webb, 1994; Williams et al., 2000). As a result, societies need both to monitor changes in water quality and use these data effectively in planning for future developments.

This study examines some of the issues surrounding the problem of monitoring water quality, with particular reference to Malaysia. It will be shown that the concept is a complex one, and monitoring approaches are usually based on the development of some kind of water quality index. In Malaysia the Department of the Environment uses two main systems, based on the DOE-WQI mathematical and the Harkins'-WQI non-parametric statistical models. **The aim of this study is to examine the limitations of these indices and explore alternative approaches to the classification of water quality using novel methods based on the concept of 'Artificial Neural Networks' (ANN).**

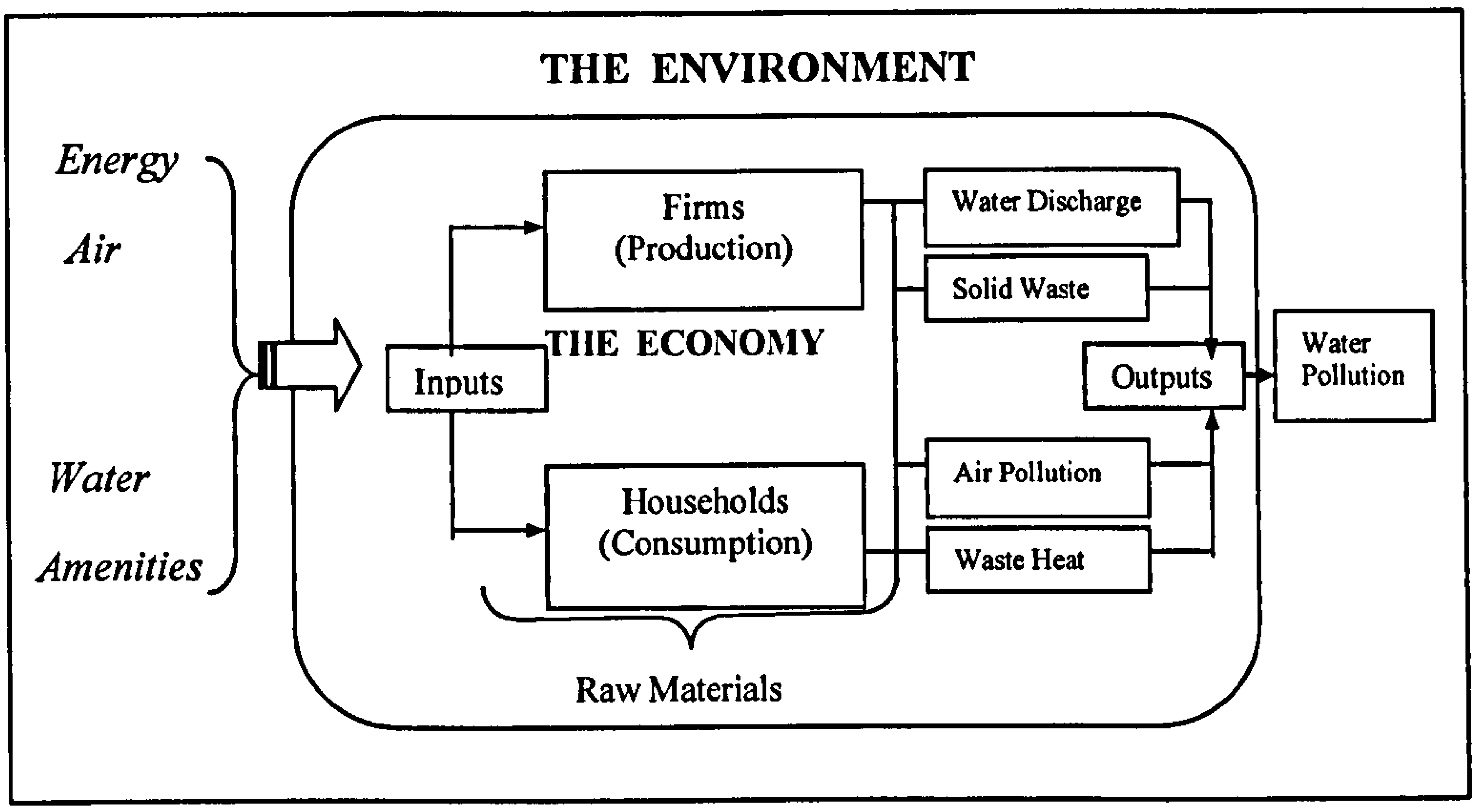
Although the focus of the work is Malaysia, the problems and issues examined are sufficiently general to have relevance elsewhere, in situations when environmental managers need to make a rapid assessment of water quality. The new techniques will be explored in details to whether it provides an improved method of classifying water quality compared to traditional approaches. The techniques should be more flexible than existing approaches and can be implemented more easily and quickly.

1.2 BACKGROUND TO THE STUDY

1.2.1 Defining Water Quality

History suggests that mis-management of river water can be catastrophic to human civilisation as shown by incidents of cholera through out the world (Viesman and Hammer, 1998). As a result of the impacts on human health, most countries have set-up systems for water quality management to ensure the safety of supply for domestic consumption and the health of the aquatic ecosystem. In view of the current rate of increase of the world's population, the demand for fresh water supply is increasing tremendously (McGhee, 1991; Celia and White, 1994). More efficient ways of managing water resources need to be found. In some areas where the situation is critical, recycling of used water predominates (McGhee, 1991; James and Eden, 1992). Where the inbalance of populations and land use activity outweigh the volume of water available, environmental control becomes a critical factor, particularly with the interaction between land and water management (Begon, 1996; Jimenez et al., 1998).

The impacts of land use activities have profound effect on the receiving water body, especially on its quality and the character of aquatic ecosystems. As illustrated in Box 1.1, usually natural resources are the main input in economic activities, and they are being heavily exploited and utilised for human consumption (Tietenberg, 1996). Wastes liberated from these activities are either recycled through effective management practices or otherwise may be dumped directly or indirectly into the existing river systems. Generally, it is extremely difficult to find any river systems that have not been altered in some way and negatively affected by the people (Hynes, 1970; Meybeck et al., 1989). In some countries, river systems have been treated as pollution sinks to an extent that some are so seriously polluted that rehabilitation may be impossible (Meybeck et al., 1989). Evidence of water supply contamination by toxic and hazardous materials has become common and the concern about broad-water-related environmental issues has heightened (Alloway and Ayres, 1993; Dojlido and Best, 1993). In developing countries, examples of human activities that render devastating impact on the receiving water body are the uncontrolled land use for urbanisation, deforestation, industrialisation and agriculture activities (Jamaluddin, 1991). These activities discharge suspended solids, toxic and hazardous substances, noxious liquids from solid waste deposits, organic and inorganic substances, fertilisers and pesticides. Spiro and Stigliani (1996) summarised some of the effects on water quality from the major uses on water as in Table 1.1. It shows that domestic, commercial and industrial activities reduce the concentration of dissolved oxygen, which is a vital component for sustaining aquatic species.



Box 1.1 The economic system and the environment
(Source: Modified from Tietenberg, 1996)

Water use	Effects on water quality
Domestic/Commercial	Decreases in dissolved oxygen
Industrial/Mining	Decreases in dissolved oxygen; increased chemical oxygen demands; pollutes water with toxic heavy metals and organics; causes acid mine drainage
Thermoelectric	Increases water temperature (thermal pollution)
Irrigation/Agriculture/Livestock	Causes salinization of surface and groundwaters; decreases dissolved oxygen (near feedlots); increased chemical oxygen demands from organics and inorganic applications; causes eutrophication.

Table 1.1 Effects on water quality from water use
(Source: Modified from Spiro and Stigliani, 1996).

Surface fresh water exists as an aqueous solution of inorganic and organic substances at varying concentrations (Dojlido and Best, 1993). The quality of this aqueous solution is difficult to define, because it depends not only on the level of pollutants in the water but also on its intended use (Chapman, 1992; Dojlido and Best, 1993).

According to Chapman (1992), WHO (1993), WRI (1995), Abel (1996) and Giller et al. (1998), water pollution is defined as the introduction by human activities either directly or indirectly, of substances or energy which result in such deleterious effects as harmful to biological resources; hazards to human health; hindrance to instream aquatic activities; impairment of water quality with respect to domestic supply and the reduction of amenities.

However, the definition of water quality can best be explained in terms of water's characteristics where different authors have characterised it into several major components. Walling and Webb (1994) characterised it into three separate components, namely: physical, chemical and biological; Meybeck et al. (1989) also characterised it into three different components: hydrological, physico-chemical and biological; and Dojlido and Best (1993) characterised it into two separate components; physico-chemical and biological components. Due to its scientific complexity with the large choice of variables, most of the water experts have characterised it into two major components, the physico-chemical and biological components, leaving hydrological as separate component.

The physico-chemical components in natural river systems include those elements that are determined largely by the climatic, geomorphological and geological processes within the catchment and the underlying aquifer (Newsome, 1994; Wilby, 1993; Singh, 1995). These components accumulate from the wastewater discharge and other land use activity as described in Table 1.1. Examples of these components include: dissolved solids, conductivity, temperature, turbidity, acidity, alkalinity, biological oxygen demand, chemical oxygen demand and suspended sediments. The biological components are the aquatic flora and fauna and their distribution is governed by a variety of environmental conditions. Some of the examples of these biological components include: species of algae, bacteria, fishes, molluscs, invertebrates, macrophytes and other biological organisms.

In water quality management, water quality standards for running and drinking waters are set-up to ensure the health safety for public water consumption taking into consideration on the survival and the health factors of aquatic species (Thanh and Tam, 1990). The standards are quantified and enforcement is based on various criteria and objectives, normally the highest beneficial uses of water are selected (DOE, Malaysia, 1986). At certain point in time and space, when the status of water quality frequently remains at undesired situation, standards are reviewed in order to revive the critically low quality state to a higher quality state. Water pollution control strategy will be amended to include more stringent standards and increases the enforcement activity. This possibly will only take place when the water-related legislation is first amended. Along with these amendments, other measures have to give due considerations particularly in planning strategy that will emphasise on land use factors such as urbanisation, agriculture, industrialisation and population concentration. Once, everything is in order, with consistent monitoring and enforcement activity, pollution levels can be reduced (Viessman et al., 1998).

1.2.2 The Measurement of Water Quality

In water resources management, water quality monitoring is a fundamental step that should be taken. Although it may cover many aspects, basically the objectives of monitoring programmes concern the preliminary assessment of water quality for the identification of concentration and trends; identification of the mass flow; standards compliance and classifications; and early warning and detection of pollution (Thanh, and Biswas, 1990; DOE, Malaysia, 1995; Tebbutt, 1998).

Monitoring activity starts with measurement of water samples at specific stations. The sampling frequency is one of the critical factors in the assessment of water quality. If the sampling frequency is too low, it will cause difficulty in data analysis that may possibly produce erroneous interpretation. If the frequency is too high, costs will increase without necessarily resulting in better information (WHO, 1987; Chapman, 1992). Optimising monitoring programs to resolve these problems should aim to reduce excess costs incurred in monitoring activities (GEMS, 1992; Tietenberg, 1996). The specific water quality variables monitored depends on the objectives of management and the different type of water users. Thus, a standard list of water quality variables cannot be prescribed for all river basins at national scales since some of these variables may not be required for different water bodies (GEMS, 1992). The specific choice of variables can also be limited due to the available financial resources, skilled manpower or laboratory equipment.

As issues of water pollution become critical, more countries are implementing water quality monitoring programme to control and reduce its impact to a minimum level. Huge volumes of water quality data are being collected, covering a wide range of variables. This makes interpretation more complicated (Ott, 1978; Newman, 1988). While the changes of individual variables are easy to understand, it becomes increasingly difficult to interpret water quality when it involves a wide range of other variables. These variables may have greater impacts when they exist in large volume or at higher concentration (Dojlido and Best, 1993). Although less impact may occur at lower concentration, they can be more toxic when interacting with one or more other variables. In such situations, the selection of variables to represent the state of water quality is crucial. Generally, once the significant variables are selected, they are measured so as to fit into mathematical or statistical formula. This formula was designed to produce a single numerical value, or index value, calculated from the observed water quality data set. Therefore, an index is a means to reduce a large quantity of data down to its simplest form that is capable of retaining the essential meaning in describing the status of water quality (SDD, 1976; Ott, 1978; WRI, 1995).

Besides the wide use of water quality index systems, water quality classification schemes are another simple approach being applied by some countries (SDD, 1976; Newman, 1988). These classification schemes have been designed to simplify a mass of data into water quality classes that can be readily compared and used to demonstrate compliance with the requirements of water quality directives or water quality criteria and standards (Newman, 1988). Based on these criteria and standards, individual variables can be classified. When more than one variable are involved, the index values obtained from mathematical or statistical formula can be transformed into classes. In this way, some index systems can also be used to demonstrate compliance with the requirements of water quality directives or water quality criteria and standards (DOE, 1986; House, 1986). Thus, both of these approaches, the index system and classification scheme offer the means for measuring the pollution abatement progress by comparing the status of water quality at different times and in different geographical regions. In this way, it is useful for management purposes especially in determining priorities for resource allocation and planning of new development areas.

In relation to planning and river basin management, water quality classification can act as one input in strategic environmental assessment (Bean and Rovers, 1998). For example, different classes, or index values signify different impacts on aquatic species and on intended uses of water. If the detail of the assessment results in relation to these impacts have already been examined and documented earlier in the water quality assessment process, the same impacts need not be addressed again. Thus, it can reduce the number of project EIAs that are required (DOE, 1994). In addition to this, water quality classes may facilitate site selection. For example, a water body of relatively high-class value may contain an abundance of different aquatic species. This water body may specifically designate for conservation purposes or for a site of special scientific interest. Since different segments of a water body may exhibit different classes, the whole length of the river system can be utilised effectively, based on the intended water uses. In this case, the water quality and its supply relate both to social and economic aspects particularly on the impact of cost factor. Therefore, the index systems and classification schemes may act as an important means in achieving the environmental, social and economic goals (Bishop, 1972; Bhargava, 1983; Burrows and House, 1989).

Water quality assessment based on index and classes incur some limitations. In most of the systems developed, there exists inherent and unavoidable loss of information during aggregation process. This loss does not change the overall result, where both of the index and class grading values still retain the exact meaning or interpretation of water quality status (Horton, 1965; Ott, 1978; House, 1986; Newman, 1988). However, in some assessment systems, results are only acquired through a lengthy computational operation. In addition, the use of statistical approaches, especially those that based on ranking procedures, involves highly complicated calculations that need computers with powerful processing capabilities (Landwehr and Deininger, 1976). These approaches will be resolved with the recent advancement in computer technology.

The application of water quality index system and classification scheme may not only be confined to the determination of water quality, but it can also provide an important input for the beneficial uses of water, as well as in checking the compliance on water quality criteria and standards. In countries with diverse climatic conditions, and the existence of several geographical regions, the index and classification systems that are based on water quality criteria and standards may have limited applicability (Dee et al., 1973; Tebbutt, 1998). This is due to the fact that in different geographical regions, the concentrations of variables that exist under natural conditions are different. These natural concentration values may exceed the values in water quality criteria and standards from other geographical regions. This is one reason why different water quality standards have been adopted in different geographical regions. Therefore, index and classification systems should not be applied over large or environmentally diverse areas without careful consideration of assumptions. The difficulty of applying a uniform index and classification system nation-wide may also arise due to the existence of various water controlling authorities with different water-related legislative requirements. Consequently, their span of control of water bodies varies considerably. If, however, a uniform or standardised index is introduced, it is difficult to avoid 'customising' among water authorities, where the water quality results can be modified at their ease. Thus, application of a uniform index can be problematic (Ott, 1978).

Some water quality index systems are too rigid to allow the addition of new variables. These pose critical issues in water resource management especially in areas of rapid urbanisation and industrialisation, where new types of pollutants not monitored before being discharges into their river system. At some point in time and space, the index and classification values calculated from the rigid system may not represent its true values, leading to an erroneous interpretation. One way to overcome this rigid system, especially when incorporating large number of variables, is to venture into a new technique of assessment that provides a more flexible aggregation function. The new techniques should be easy to understand, simple, capable of providing prompt results and applicable to geographical regions that differ in their legislative water quality criteria and standards.

1.2.3 The Malaysian Approach

In developing countries, particularly those in hot and arid climatic environments, issues of water quality are regarded as an equally important and critical as its quantity (Sham Sani, 1981; Lim and Valencia, 1990; Thanh and Tam, 1990). In traditional approaches, water management is treated separately from other environmental management issues, such as land management practices. The land management practices cover broad range of land use activity, which comprises urbanisation, industrialisation, agriculture and forestry (Newson, 1994; Viessman and Hammer, 1998; Gray, 1999). However, as issues for water management are becoming more complicated to resolve, water management needs to be integrated with land management practices (Abu Bakar, 1992). The inter-dependency between land and water management practices requires the co-ordination on water resources planning and management with land use planning and regulations (Newson, 1994; Viessman and Hammer, 1998). This situation is being experienced in the context of water management and water pollution in Malaysia, as well as other developing countries.

In Malaysia, the extensive programmes of water resources management started in 1985, with the development of water quality criteria and standards (DOE, Malaysia, 1986). This programme aimed at developing an advanced water quality management approach for the protection of the nation's water resources in the long term. An effective way is to classify rivers or river segments into five water quality classes (I, II, III, IV and V) that relates to water quality objectives or standards required for the protection of the identified beneficial uses of the water sources. These objectives and standards for various physical, chemical and microbial parameters of the ambient river water were formulated through the review of international and local literature for the protection of beneficial uses after taking into consideration of the baseline levels, technological and socio-economic factors. The beneficial uses of water include; domestic water supply, fisheries and aquatic life propagation, livestock drinking, recreation and agricultural use. Thus, the DOE has adopted the Interim National Water Quality Standards (INWQS) that allows them to focus on checking any potential deterioration of the rivers, while putting more effort for the rehabilitation and upgrading of the existing river water quality (DOE, 1986). With the adoption of INWQS, running waters are assessed at an identified point along the river system. The assessed waters are classified and the highest sustainable beneficial uses are identified. The outcomes of this programme will assist the government in planning and decision making for the zoning purposes such as housing, industry, agriculture projects in-line with the suitability and availability of local water supply.

The other approach in water quality assessment is through forecasting. However, forecasting model provides a characterisation of what is expected in the present, conditional upon the past, from which it infer what to expect in the future, conditional upon the present and past (Diebold, 2001). Taking into consideration of this characteristic, forecasting approaches may seems to be inappropriate and difficult to link and formulate the forecasted results in relation to the objectives and standards required for the protection of the identified beneficial uses of the water sources. However, the outcomes of the forecasted results may also assist the government in planning and decision making for short term basis. Thus, classification approaches are preferred and adopted as compare to forecasting approaches.

Studies by the Malaysian Department of Environment have shown that the major sources of water pollution in Malaysia came from the discharges of large amount of effluents from palm-oil mills and rubber factories (DOE, 1986, 1992, 1994). This is due to the fact that, since the 1970s, Malaysia has become one of the world's largest producer and exporter of raw natural rubber and palm oil. The next major contributing sources are from land clearance, deforestation, livestock farming and domestic waste. Other major sources of pollution come from agro-based and manufacturing industries, tin-ore mining and small-medium size industries which produce fish products, textiles or involve metal finishing and fabrication. Based on the main polluting sources, the DOE water quality experts have designed a water quality index based on a mathematical formula comprises of six significant water quality variables, which include; ammoniacal nitrogen (AN), biological oxygen demand (BOD), chemical oxygen demand (COD), dissolved oxygen (DO), pH (alkalinity/Acidity) and suspended solid (SS) (Lohani and Norhayati, 1982). Another method of classification being applied is based on non-parametric statistical approach originally developed by Harkins (1974).

Generally, the enforcement of water pollution control by the DOE is based on the effluent discharge standards stipulated in the regulations under the Malaysian Environmental Quality Act, 1974 (EQA, 1974). Effluent discharges are monitored or measured at the outlet of the discharge point. However, in the context of the local environment, this is no longer adequate for the protection of the ambient water resources in regions with rapid industrialisation and high socio-economic growth. The pollutant loads being discharged into the watercourses have increased beyond the assimilative capacity of the receiving body. Despite the fact that the industries may generally be in compliance with the effluent discharge standards, continuing degradation in water quality is being experienced in these watercourses (DOE, 1990). As a result, the DOE decided that an effective and practical means for the protection of water resources under such circumstances is to control the discharge of effluents based on the water quality objectives or standards required for the protection of the identified beneficial uses of the water sources.

The complexity of applying these standards as a direct application in water quality management and programmes makes it very difficult to use them, especially for a developing country like Malaysia. Therefore, based on the existing criteria developed and the need of the beneficial uses in water quality management, the DOE has recommended Interim National Water Quality Standards (INWQS), as a transitory reference for the establishment of a more practical system of quality standards that can be used. Five-banded classes of INWQS were recommended for water quality classification to sustain the designated uses of water body. The design of this five-banded class system was based on international and local water quality standards, such as the WHO standards for drinking water supply. Using an ascending quality class order, the most sensitive use has been adopted in protecting a particular water body that was designated to more than one-use criteria. Therefore, a segment of river can be assigned to various beneficial uses according to the highest known existing uses. Any review and improvements to be made on the corresponding criteria and standards should consider the geographical regions and the site-specific effects. These criteria and standards can readily be complied and achieved, and at the same time it can be reviewed for further enhancement in the future (Thanh and Tam, 1990).

The needs to review the existing criteria and standards may also linked to the rigorous development activities in line with the strategy of the Government that has shifted from concentrating on producing raw natural resources to the manufacture of processed goods (Government of Malaysia, 1991, 1991a; 1997). To boost the economy, high priorities were set on these manufacturing and other highly value-added sectors such as industrial, agriculture, forestry and construction. These activities can lead to indiscriminate discharges of pollutants that seriously deteriorate the environment, particularly water and air (DOE, 1995). These situations forced the Government to tighten their control by introducing the stringent legislative measures especially on manufacturing, chemical production, agriculture and construction activities.

In compliance to the stringent legislative measures imposed by the Government's, most of these sectors have step-up their own programme in managing, controlling and reducing the harmful effect of their discharges into the environment. Substantial funding was allocated for environmental control especially for installing high technology equipment specifically in controlling and reducing effluent discharges. As illustrated in Table 1.2, the projected cost of environmental control in all sectors has increased from 1991 to 1999 (ADB, 1994). These costs include those of internalising environmental externalities in the production process; expenditures on pollution treatment for an acceptable level of environmental quality; and the cost of equipment for controlling pollution. The figures show that the projected cost of environmental control was highest for the chemical industry. The types and magnitude of water pollutant discharges from this industry have also increased greatly. Although this chemical industry or other chemically related industry has complied with the Environmental Quality Act (1974) Regulations, due to its increasing in numbers as well as the increase in output productions, pollutant discharges into water body has accumulated. This accumulation not only rendered great impact on the sensitive and delicate freshwater aquatic species but also may increase the cost for treatment for public water supply.

The complaints and the pressure from the public have forced the Government to review the existing regulations of the EQA, 1974. Regulation such as the Environmental Quality (Sewage and Industrial Effluents) Regulations 1979 was amended and gazetted in 1979 to tighten the control of the effluents discharges from industries. In addition to this, the Environmental Impact Assessment (EIA) was introduced and made mandatory for the respective project development. Enforcement activities were increased and those found violating these regulations were prosecuted. Table 1.3 shows the statistics for the offences prosecuted from 1988 to 1995; the highest numbers of offences were those under water-related regulations. In addition to these legislative measures, there is the continuous clean river campaigns set up by both the Federal and States Governments to enhance public awareness on the importance of river systems as the main source of public water supply.

Sector	1991	1993	1995	1997	1999
1. Agriculture./Fisheries/Forestry	19	21	23	25	27
2. Mining	67	83	101	114	141
3. Food Production	74	87	101	116	146
4. Textiles	11	12	17	18	22
5. Wood Production	35	43	55	59	75
6. Chemical Production	176	215(22)	266(24)	301(13)	399(33)
7. Rubber Production	48	60	75	84	106
8. Non-Metal Production	27	36	44	50	58
9. Metal Production	75	99	123	139	168
10. Machine Transportation	14	15	16	18	21
11. Electronics	44	58	73	82	99
12. Utilities	26	31	38	43	52
13. Construction	143	163	217	248	289
14. Transport/Communications	85	103	128	145	178
15. Financial	19	23	26	30	36
16. Trade Service	114	139	158	181	218
Total	**975**	**1,118**	**1,460**	**1,651**	**2,035**
% of National GDP	**1.19**	**1.25**	**1.33**	**1.33**	**1.45**

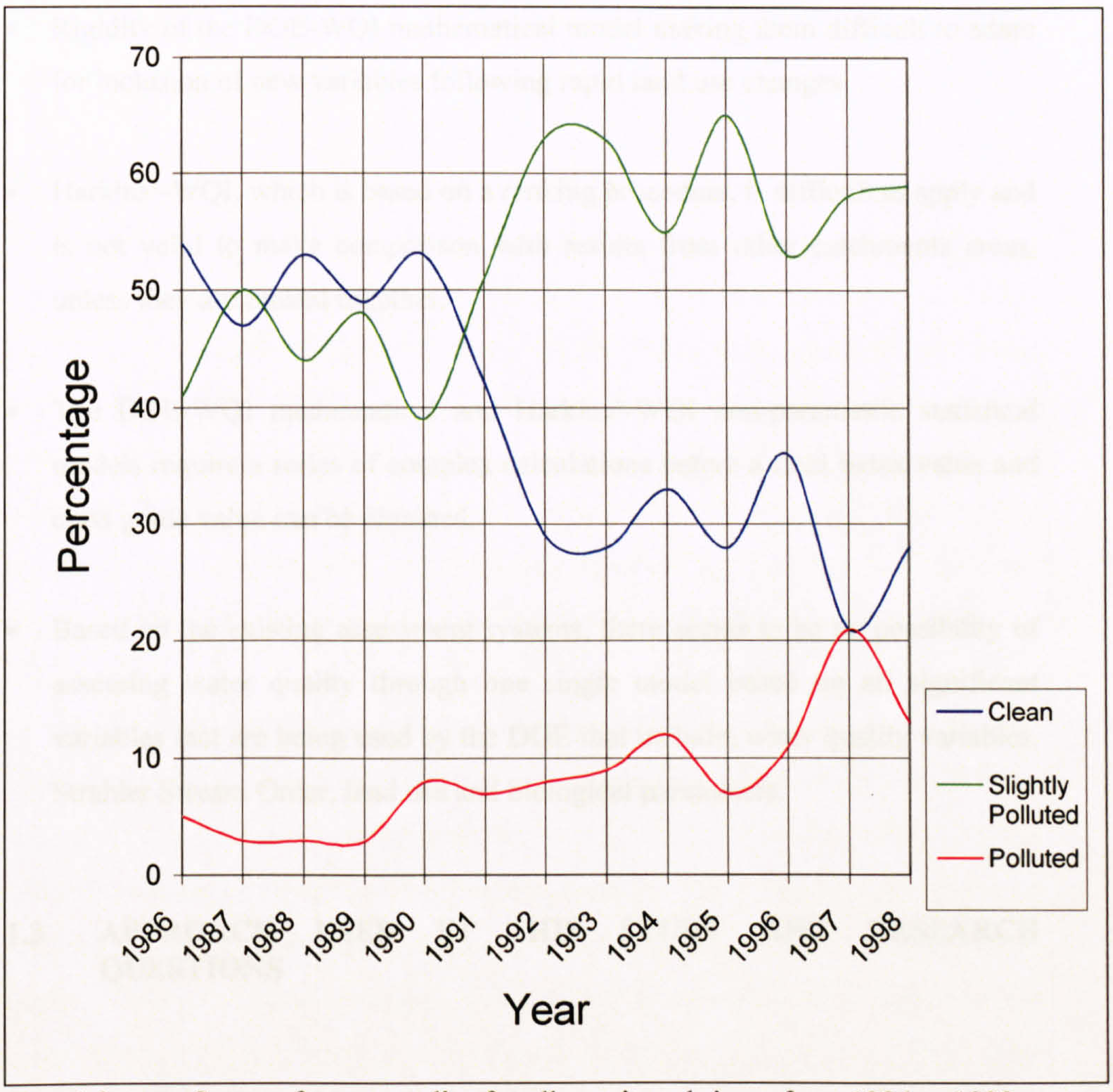
Table 1.2 Projected Cost of Environmental Control in Malaysia in the 1990s: The Medium Growth Scenario (million Malaysian Ringgit)
(Source : ADB, 1994)
(Note: ( ), percentage from previous year)

Provision	Type of Offence	Year							
		1988	1989	1990	1991	1992	1993	1994	1995
16	Failure to comply with conditions of licence	4	8	4	8	7	12	20	15
18	Operation and use of prescribed premises without licence	-	2	-	4	12	6	1	4
22	Emission of wastes into the atmosphere without licence	-	-	-	2	1	4	4	15
24	Emission of wastes onto land surface	-	-	-	-	-	-	-	2
25*	Emission of wastes into any inland water without licence	13	6	9	10	42	75	113	84
31	Failure to comply with written notice	-	-	1	-	1	4	5	4
34A	Failure to submit EIA	-	-	-	-	-	1	4	-
37	Failure to furnish information	1	1	1	-	3	1	6	5
	Total	18	17	15	24	66	103	153	128

Table 1.3 Offences prosecuted under the EQA, 1974, number by type, 1988-1995
(Source: DOE, 1995).
(Note: * Water Regulations of EQA, 1974)

The analysis of the status of water quality from 1986 to 1998 (Box 1.2), indicates that the clean rivers (blue curve) are constantly being polluted whereas the numbers of slightly polluted (green curve) and seriously polluted rivers (red curve) are increasing (DOE, 1995, 1996, 1997, 1998). In general, it shows that the status of water quality for all rivers monitored throughout the whole country is in the state of gradual deterioration. These results provide an indication that no signs of significant improvement exist since the development of water quality criteria and standards was established in 1985.

As discussed in the preceding section, the issues of water quality and quantity are closely related to land use factors. Since these factors are strongly related, water quality assessment systems should also be viewed on the basis of land use factors. The selected locations of the sampling stations determine the type of land uses that exist in the vicinity of the respective catchment or sub-catchment area (GEMS, 1978). With an appropriate technique of analysis, assessment of water quality can be done in both ways, either by using the existing water quality parameters or by separately incorporating land use factors. Therefore, in order to pursue this approach, it is possible to investigate the main type and magnitude of land use activities that contribute significantly to the change in water quality of the receiving water body.



Box 1.2 Status of water quality for all monitored rivers from 1986 to 1998. (Source: DOE, Malaysia, 1995, 1996, 1997, 1998)

1.2.4 Limitations of Existing Approaches

The existing techniques of water quality assessment possess some limitations although they are seen to work quite well. The results obtained being accepted without any form of complaint or challenge from other parties. These limitations are based on their fundamental designs that may reduce its accuracy of assessment (DOE-WQI) and also on the validity of its application (Harkins'-WQI). These limitations are summarised as follows:

- Rigidity of the DOE-WQI mathematical model making them difficult to adapt for inclusion of new variables following rapid land use changes.

- Harkins'-WQI, which is based on a ranking procedure, is difficult to apply and is not valid to make comparison with results from other catchments areas, unless they are ranked together.

- The DOE-WQI mathematical and Harkins'-WQI non-parametric statistical models require a series of complex calculations before a final index value and class grade value can be obtained.

- Based on the existing assessment systems, there seems to be no possibility of assessing water quality through one single model based on all significant variables that are being used by the DOE that include; water quality variables, Strahler Stream Order, land use and biological parameters.

1.3 APPROACH USED IN THIS STUDY AND RESEARCH QUESTIONS

1.3.1 Artificial Neural Network Technique

The advantages and disadvantages of the existing indexing and classification systems based on the DOE-WQI mathematical and Harkins'-WQI statistical formulae is briefly described in Section 1.2.4 and the details will be discussed in Chapter Three. Based on their limitations in application, it seems appropriate to explore other water quality assessment techniques that may be more flexible, robust to noisy data, highly adaptable to new form of environmental data, capable of providing direct and prompt results for classifying of river water quality. One prospect for future research concerns is the use of Artificial Neural Network (ANN). ANN can be applied since most of their approaches are based on the concept of 'pattern recognition'. Therefore, it is timely to examine its capability and effectiveness in classifying water quality.

The ANN is a technique that is modelled on the structure of the biological nervous system. It can be applied to other scientific issues in view of its capability to resolve problems based on small number of real world data that are non-linearlities in characteristics and those highly fluctuating data such as water quality (Dayhoff, 1990; Carling, 1992). The technique employed can be developed from data without an initial system model, able to handle noisy or irregular data, provide prompt answers to complex issues, easily and quickly updated, able to interpret information from huge number of variables simultaneously and may readily provide generalised solutions (Haykin, 1999).

In this thesis, Back-Error-Propagation technique (White, 1989a; Tsai and Lee, 1999) was applied to create a trained network structure based on the INWQS values. The observed data were activated through this trained set using the ANN Simulator where computations performed promptly. The output results presented both as probability and class values that described the status of the river water quality. Using the same principle, several catchment areas were classified and those possess similar water quality classes were grouped together. They were tabulated in such a way to search for common land use parameters that may cause significant changes in water quality classes. Based on the values of these common land use parameters, a new training set was created. Applying the same technique, classification of water quality can be performed using the land use parameters, thus avoiding the use of water quality variables. The anticipated results were the quantitative classification of the changes in water quality due to changes in land use activity. Thus, a list of values of common land use parameters was created and can readily accepted to be equivalent to that of water quality classes created as in INWQS Table. Based on this list, the future water quality of a catchment or sub-catchment area can be predicted according to its land features and land use activity. To fulfil this aim, this research attempts to meet the following specific objectives:

1. To review existing approaches and identify their limitations as tools for monitoring and planning;

2. To classify rivers using Back-Error-Propagation of ANN (BEP of ANN) as a technique for preliminary assessment of compliance of a water body with the standards adopted by the DOE, Malaysia, for the various classes of beneficial uses (Class I to V) base on physico-chemical variables;

3. To investigate the accuracy and reliability of Back-Error-Propagation of ANN technique in river classification against the two methods being applied by DOE, Malaysia, the DOE-WQI mathematical and Harkins'-WQI statistical models;

4. To compare the results of classification obtained from DOE-WQI mathematical model, Harkins'-WQI non-parametric statistical model, Back-Error-Propagation of ANN technique, Maximum Likelihood Classifier, Mahalanobis Distance Classifier and Decision Tree Classifier;

5. To investigate the land and topographic features, the type and magnitude of land use activities that contribute significantly to the changes in water quality based on the same technique of Back-Error-Propagation of ANN technique as in river classification;

6. To predict the water quality based on land topographic features, the type and magnitude of land use activities; and

7. To assess the suitability of the technique relative to existing methods.

1.4 MAIN CONTRIBUTION TO RESEARCH

The results of this study may contribute into three aspects of knowledge. Firstly, it provides a practical approach in classification of river water quality. Within a single ANN computation, the results obtained were categorised into two portions, the probability value and the class grade value. Thus, it shortens the process of calculations as acquired by the traditional classification methods. The result obtained for each sample displayed the magnitude of probability distribution that acquired by each class. The second aspect is, it is operationally simple to perform and relatively flexible. This flexibility in the sense that it can readily modified to cater for the diverse geographical regions or regions with rapid land use activity. Obviously, the importance or representativeness of specific water quality variables and their standard values are different from one geographical region to another. Thus, the technique of assessment applied should be relatively flexible where new variables can readily be added or deleted from inclusion for a particular region.

The third contribution is that it provides a new approach in classifying water quality based only on land use parameters. This application is critically suitable for remote areas where road access for monitoring purposes is difficult. In addition, it may provide vital input on the estimate of water quality for water resources management and development planning purpose such as a new township. This estimate can be segmental where the changes in water quality can be performed and determined effectively in terms of the percentage changes in township area (either industrial, residential, agriculture or forest), population or other significant changes in land use parameters. Therefore, areas to be designated as conservation, forest reserve or special site for scientific interest can be determined effectively at the earlier planning stage.

1.5 STRUCTURE OF THE THESIS

This thesis consists of seven chapters. The first three chapters described their respective theories and concepts. The following last four chapters described the methods of research approaches, the results and the conclusion derived from the study. A summary of each chapter are presented as follows:

- **Chapter One** highlights the main aims and objectives of the study. It provides the background information and the brief description of the water quality classification techniques that are being applied in Malaysia. The limitations of these techniques and the issues surrounding the problem of monitoring water quality that relates to land use changes are also highlighted. The introduction of ANN technique, its capabilities and effectiveness over the existing techniques is presented;

- **Chapter Two** described the theory and concept of the development of water quality index system. The designed and applications of various models that are being used, its advantages and limitations are discussed in details. Another form of assessment based on classification scheme, its development mechanism and applications is also highlighted. Based on certain models of index system, the linkages and the transformation from numerical index value to the class grade value are addressed in details. This chapter also discussed the objectivity and subjectivity between index system and classification scheme, its relationship and the effectiveness of assessing water quality based on physico-chemical and biological variables;

- **Chapter Three** provides an overview of water quality management programme in Malaysia. The two main techniques of assessment, the DOE-WQI mathematical and the Harkins'-WQI non-parametric statistical models and their mechanisms of classification based on the physico-chemical variables of the INWQS are discussed in detail. Assessment based on Strahler Stream Order, which incorporates land use factors as well as the application of biological variables, is also presented. In view of the problems of water quality management in Malaysia, the limitations of the existing techniques are described;

- **Chapter Four** described the theory and concept of pattern recognition in ANN. This concept relates to the five-banded classes of INWQS that exist arbitrarily in multi-dimensional space separated by decision boundaries. The decision boundary constitutes the effectiveness of discriminant function of various classifiers in separating different class region. The two main methods of classification, supervised and unsupervised approaches are discussed. The supervised approach of Neural Classifier indicated by the Back-Error-Propagation (BEP) technique is highlighted together with the discussion of its advantages and limitations. This BEP of ANN model will be applied in the later chapters dealing with classification of water quality;

- **Chapter Five** is the Pilot Study of a selected catchment area in Malaysia. Several models of classification techniques are employed and the results are compared. Emphasis are given to three models; the DOE-WQI mathematical, Harkins'-WQI non-parametric statistical and BEP of ANN model. Analyses are based on general findings, trend analysis, accuracy or reliability testing and sensitivity analysis;

- **Chapter Six** concentrates on the application of BEP of ANN model in classification of eight selected catchment areas. These catchment areas are grouped together based on similar classes of water quality and tabulated to search for common land use parameters. A new training set based on land use parameters is created, and using the same BEP of ANN model, classification of water quality is performed. Analyses on reliability and sensitivity are carried out. Based on the results of sensitivity testing, those water quality variables, land use parameters and hydrological features that are sensitive to slight changes can be determined; and

- **Chapter Seven** presented the overall conclusions of the study. The reliability, effectiveness and limitations of applying BEP of ANN model is described in detail as compared to the existing approaches being used by the Malaysian Department of Environment. Brief discussion on classification results as compared to other classifiers is also made. The experiences gained during the experimentation with BEP of ANN model specifically on classification of water quality are discussed. Suggestions for further research within the same scope of study are presented.

CHAPTER TWO

THE DEVELOPMENT OF WATER QUALITY ASSESSMENT SYSTEM

2.1 BACKGROUND

Many different types of water quality assessment schemes have been developed over the last century. Among the most widely accepted are the water quality index systems and the banded classification schemes. Most countries, as members to the international or regional organisations, have to abide to agreements or directives associated with the management of their surface water quality. Political pressures from these organisations and the non-governmental environmental groups have encouraged these countries to take positive measures and to step up water quality monitoring programmes (EEC, 1976, 1981; UNESCO, 1978, 1982; WHO, 1987; Newman, 1988; UNEP, 1992).

The water quality assessment schemes developed by different developers differ greatly from one scheme to the other. Their applications are modified accordingly to suit the recipient countries. Assessment can be calculated directly from individual water quality variable and from a group of selected variables, which provides a single numeric value that carries specific meaning. This numeric value can readily be transformed into banded classes that normally relates to the beneficial uses of water. With so many different types of water quality assessment schemes developed and with their wide applications, the aim of this chapter is to examine the general concept of the development of the assessment schemes with emphasis on the index systems and banded classification schemes. Based on these general findings, an overview of the main types of assessment schemes will be highlighted.

Generally, the index systems and banded classification schemes are introduced to cater for physico-chemical and biological variables, which are modified by different countries to suit their local requirements (NWC, 1976; SDD, 1976; Newman, 1988). These schemes are capable of reducing large quantity of data down to its simplest form by averaging or aggregating all the selected significant variables, while retaining the essential meaning from which the data are drawn (SDD, 1976; Ott, 1978; Newman, 1988; OECD, 1989; UNEP, 1992; WRI, 1995). In relation to these two schemes of assessment, the water quality index system is the most popular technique of assessment that is widely being used. Basically, the water quality index system was based on the concept of the first formal water quality index developed by Horton in 1965.

Beside these systems, a "water quality profile" is sometime used in reporting the state of water quality. Water quality profile is a set of water quality conditions that exists between water quality indices and single-parameter indicator. Specifically, water quality profile is termed as an unaggregated water quality indicator, presented at the same time to reflect the state of water body (WRI, 1995). Normally, it is presented in generalised form, as bar charts or simple bar graphs that do not display its technical details. Water quality profiles have been criticised heavily in such that the presentations of the status of water quality were too complex in that it contains too much information for the users to understand and interpret (Ott, 1978; WRI, 1995).

2.2 WATER QUALITY CRITERIA AND STANDARDS

The water quality assessment scheme is one of the several components under water resources management. The strategy in water quality management begins with the setting up of the main objectives based on the requirement of the respective country in order to provide greater protection to surface water as illustrated in Appendix 2.1 (Thanh and Tam, 1990; Viessman and Hammer, 1998). These objectives are designed within a fixed time frame and normally do not specify the means by which they should be achieved, nor do they imply any legal requirement to carry out enforcement activity (Thanh and Tam, 1990). Objectives are supported by a set of criteria, expressed in numeric terms and more refined than the objectives. According to Chapman (1992) and Gray (1999), this set of criteria comprises five categories of specific water use as indicated in Table 2.1.

Based on the selected criteria for intended uses, water quality data taken from different data sets can be compared to indicate the suitability of the respective water body. In complement to objectives and criteria, are the water quality guidelines. Guidelines are also based on numerical terms such as concentrations or in general statements. Guidelines are detailed and forceful statements than the criteria but have no legal provision in support of enforcement activity. Guidelines are also regarded as an achievement and are compliance-oriented.

Category of Specific Water Use
1. Raw water sources for drinking supply,
2. Public recreational waters and aesthetic,
3. Agricultural supply,
4. Industrial supply,
5. Preservation of freshwater, estuarine and marine ecosystems.

Table 2.1 Water quality criteria
(Source: Chapman, 1992; Gray, 1999)

The objectives, criteria and guidelines do not have any legal status to support enforcement activity, and to ensure that the river water quality is not polluted and maintained at desired concentrations. In complementing these three approaches, standards are designed to provide legal requirements and supports. Thus, standards are rigid indicators, which are absolutely stated in numerical terms that are either met or violated. It provides an authority with power for monitoring and enforcement activity. Generally, only few developed countries such as the United States have implemented and enforced their own standards, and others may only established criteria or guidelines (Thanh and Tam, 1990). In general, standards are based on three basic requirements, which include; technological capability; discharges of effluent and the condition of the receiving stream.

Standards based on technological capability are the application of best technology for reducing the harmful pollutant before it is discharge into the water body. Most of the European Union countries are guided by limit values set-up under best available technology (BAT) or BAT not entailing excessive costs (BATNEEC), whereas the United States is guided by the BAT or best practical technology (BPT) (Alloway and Ayres, 1993; Twort et al., 1994; Pohanish, 1997). The effluent standards are the minimum allowable concentrations for potential pollutants measured at discharge point where the waste discharge starts to mix with the receiving water body. The receiving stream standards are based on the capability of the receiving stream to under go self-purification.

Most of these assessment schemes are linked to the water quality criteria and standards. This will support the enforcement activity and legal action can be taken accordingly. The selection and formulation of criteria and standards is a critical process that need to be carefully balanced with the planning inputs such as the economic factors, the existing technology and the manpower capabilities. If too high standards are set, this will cause great problems to comply with. If standards are too low, then this may impair on the human health and cause extinction of the aquatic species. Thus, objectives may not be achieved if inappropriate standards are selected and finally exert negative impacts on economics achievement (Thanh and Tam, 1990; DOE, Malaysia, 1990).

In standard setting, emphasis is placed on those common pollutants and highly dangerous chemicals that are being discharged into the receiving water body. The existence of these pollutants is closely related to the type of land use activity such as industrialisation, agricultural practices, commercialisation, deforestation and the population behaviour. Based on critical substances discharge, different countries have established their own list of priority substances. For example, the European Union legislation under EC Dangerous Substances Directive provides

List I (known as Black List) and List II (known as Grey List), which contains the list of all dangerous substances that can be discharged into the aquatic environment (EEC, 1976, 1981). List I contain the most dangerous substances that should be eliminated due to their toxicity and bioaccumulation characteristic, whereas List II should be reduced since it may provides deleterious effect on the aquatic species. In addition to EC Directive, the Department of Environment, United Kingdom introduced the Red List of priority pollutants that can be discharged into the aquatic environment (DOE, UK, 1988; Alloway and Ayres, 1993). The Environmental Protection Agency of United States has classified hazardous substances under the directive of Identification and Listing of Hazardous Wastes Code of Federal Regulations, 1986. These hazardous substances are divided into four components, which include; pollutants from non-specific sources (F-type); pollutants from specific sources (K-type); acute hazardous pollutants (P-type) and general hazardous pollutants (U-type) (Manahan, 1991; Alloway and Ayres, 1993; Pohanish, 1997).

2.3 WATER QUALITY INDEX SYSTEM

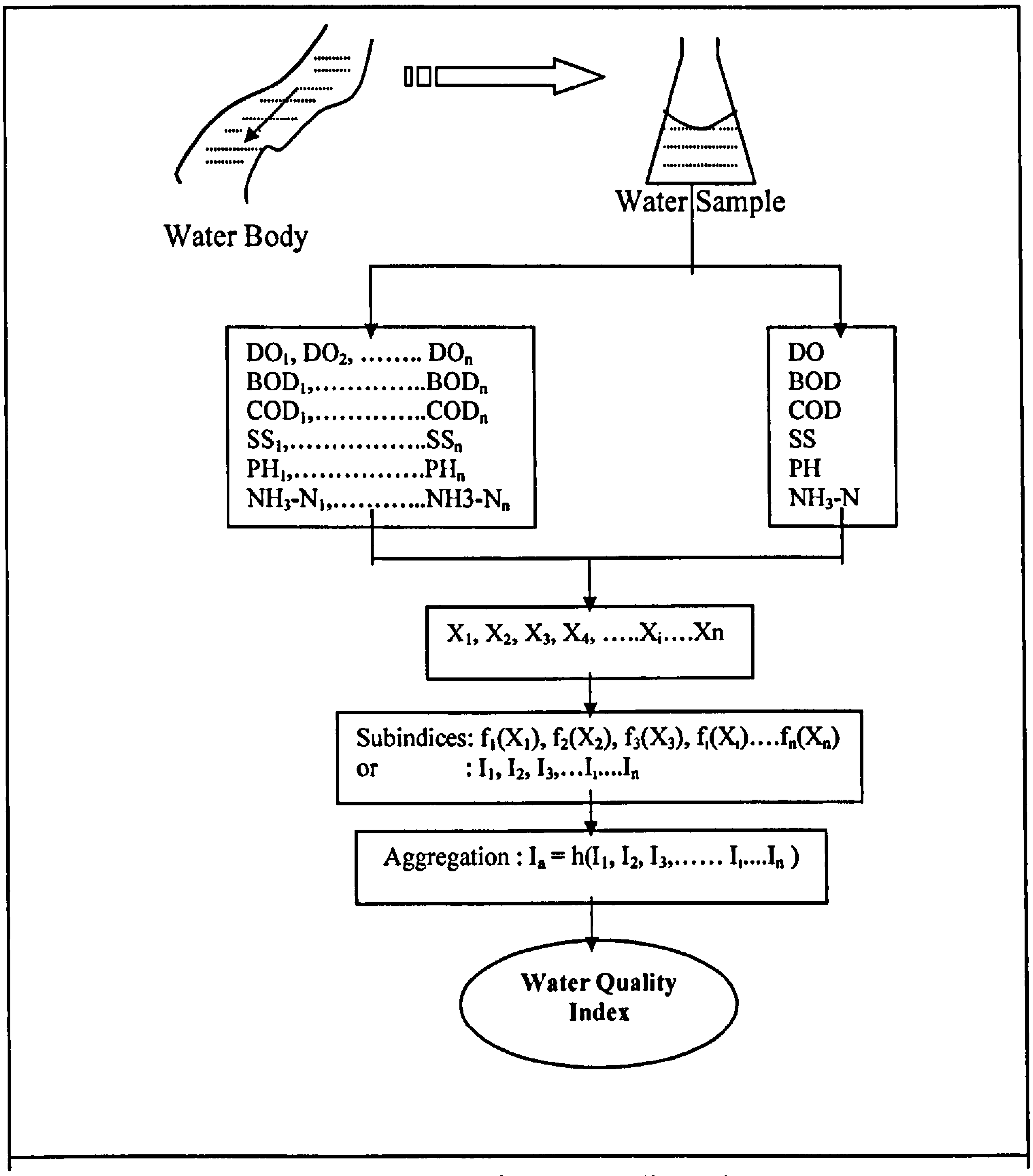
The water quality index system that is widely being used consists of two variable components; the physico-chemical and biological variables (Dojlido and Best, 1993). Physico-chemical indices are the numerical values describing the status of water quality based on the physical and chemical variables such as temperature, turbidity, suspended solids, dissolved oxygen, toxic compounds, heavy metals, organic and inorganic compounds (Chapman, 1992; Dojlido and Best, 1993). The advantages of these physico-chemicals include their preciseness, and ability to discriminate and quantify factors relevant for water resources management (Newman, 1988; Dojlido and Best, 1993). Biological indices are numerical values describing the status of water quality based on the living communities of macro-organisms and microscopic organisms in a particular water body. Examples of these biological indicators are fish, benthic organisms and plants species (Boon et al., 1992; Walling, 1994). Biological indicators are temporally independent, which is an advantage over physico-chemical indicators, since the effects of water pollutants provide an integrating assessment of water quality. However, biological indicators may potentially suffer limitation of being less accurate and capable of discrimination, since the pollutants may be involved in a complex, and delicate ecosystem especially in areas of biologically diverse (Newman, 1988; Walling, 1994; Boon et al., 1992).

2.3.1 Theory and Concept

The conceptual and theoretical basis of water quality index system was based on Horton (1965) who initiated the first formal water quality index (WQI). His concept and theory was modified by many developers and were documented by Ott (1978). Following Ott (1978), a handful of new approaches were introduced. They were modelled as mathematical or statistical expressions and are now being used by various water resources organisations. With the recent advancement in computer technology, these models were transformed into computer programs that can speed-up the complex mathematical and statistical formulae for the assessment of water quality (Singh, 1995; Wanielista et al., 1997).

2.3.2 The Development of an Index Structure

The water samples collected from monitoring stations can be divided into two sets of observations as illustrated in Box 2.1. The first set represents a series of observations that can be grouped according to similar type of variables and the second sets are grouped into a mixture of different variables. The significant variables that contribute to water pollution are selected for water quality index development. Based on Box 2.1, the structure of water quality index is made up of the basic subindex structure, which comprises of individual variable and the aggregation of these subindices, which comprises of several individual variables that are bind together with some form of mathematical function to produce a single numeric value (Ott, 1978; Bolton et al., 1978; Ball and Church, 1980; Lohani and Norhayati, 1982; Lohani and Todino, 1984).



Box 2.1 The development of Water Quality Index
(Sources: Modified from Ott, 1978; Ball and Church, 1980; Lohani and Norhayati, 1982)

2.3.2.1 Subindex Structure

The concentration of each variable in the water body as indicated in Box 2.1 may have different effects on human health and aquatic species. This concentration is a measurable value and the value of effects it carries is unitless that needs to be quantified. This unitless value is the subindex value and is obtained from subindex structure, which is the basic structure that relates to the effect of concentration for a specific variable. According to Horton (1965)), the existence of some pollutants in water environment, such as heavy metal or toxic chemicals, is intolerable. Others may exist in the water body but may not cause any detrimental effect.

In order to obtain a subindex value, the concentration of each variable should be transformed into a common scale so that the subindex value it carries in relation to other individual subindex value can easily be compared and interpreted. The simplest approach is to construct a rating curve for each variable where subindex value can readily be obtained. Some examples of these rating curves developed by DOE, Malaysia are represented as in Appendix 2.2. Although different scales have been developed, the most popular rating scale being used is the one with the range of values from 0 to 100, indicates that the higher the values, the better is the quality of waters (also termed as decreasing scale). Based on this rating scale, indices can be distinguished into two types; an index with an increasing value which is termed as pollution indices, commonly apply in air pollution, and the one with decreasing value as quality indices which is widely used in water quality indices (Ott, 1978; UNEP, 1992; WRI, 1995). This rating scale can be interpreted by the non-technical people. The accuracy and sensitivity of these scales varies accordingly and were discussed in details by Ball and Church (1980), and House (1986).

The use of each rating curve for each subindex becomes cumbersome and complication will arise when large numbers of variables are employed. Each variable or each subindex will be aggregated with other variables or subindices to give a final water quality index value as indicated in Box 2.1. Rating curve may not be applicable in the aggregation of these subindices. Thus, each rating curve needs to be transformed into mathematical or statistical equations in order to aggregate it appropriately. In the mathematical approach, the relationship between variable concentration (X_i) and the subindex value (I_i) is linked with some kind of a function as illustrated in Box 2.2. In water environment, different variables possesses different characteristics, thus different subindex functions have been applied. These functions take the form of linear, segmented linear, non-linear and segmented non-linear.

A. Linear and Segmented Linear

The characteristic of subindex as in Equation 2.1 in Box 2.2, is determined by the function f_i that it carries. One of the simplest forms of subindex function f_i may take the form of linear (McDuffie and Haney, 1973) and segmented linear (Horton, 1965; Nemerow and Sumitomo, 1970). This linear function can be transformed into Equation 2.2 as represented in Appendix 2.3. Linear function subindex is simple to compute, however this function may seldom exist. In another situation, linear function may acquire extreme condition with serious effects. This takes the form of segmented linear function, either in a situation known as 'hockey stick' function or 'staircase step' function as indicated in Appendix 2.4a and Appendix 2.4b respectively. This segmented linear function is also seldom exist in subindex of water quality, except for dissolved oxygen (DO) designed by Horton's (1965) as described in Appendix 2.4b.

B. Non-Linear and Segmented Non-Linear

Normally, the non-linear function dominates in a situation where the rate of change of the subindex value changes gradually with an increase in the level of variable concentration. In this case, the relationship between the subindex and the variable is not a straight line when represented graphically. The subindex value for non-linear function can be determined directly from the curve of a graph (implicit function) or from the best-fit mathematical equations (explicit function). However, in most situations, the rating curves it represents are joined with one or more curves at its breakpoints either these curves are segmented. Thus, these segmented curves may consist of mixture of both the non-linear and segmented non-linear functions, which possesses different characteristics. These curves can be transformed into several best-fit equations as in Appendix 2.5. Most commonly, variables used in the design of water quality index may comprises of mixed linear, nonlinear, segmented nonlinear and exponential functions that may takes the form of positive or negative slopes that constitute the increasing or decreasing scales of the respective subindices as indicated in Appendix 2.6.

The relationship between variable concentration, X_i and the subindex value, I_i can only be established when it is linked with a function f_i as illustrated in Equation 2.1. In other words, the subindex, I_i is a function of variable X_i, represented as $I_i = f_i(X_i)$, which carries specific individual information within a particular water body. All selected significant variables are assigned subindex values as $I_1, I_2, I_3,\ldots I_i \ldots I_n$ or is written as $f_1(X_1), f_2(X_2), f_3(X_3), \ldots\ldots f_i(X_i) \ldots f_n(X_n)$ respectively.

$$I_i = f_i(X_i) \qquad \text{------ Equation 2.1}$$

where I_i = sub-index
X_i = a pollutant variable
f_i = function of variable

Box 2.2 Subindex structure
(Source: Ott, 1978)

The rating curve and the subindex equations as indicated in Appendix 2.5 and 2.6 are linked directly to water quality criteria and standards for which the index values obtained can be segmented into range of values or quality limits. These quality limits can be transformed into classes that relates to the beneficial uses of water (DOE, Malaysia, 1986, 1990). However, these models create problems at the lower portions when transformed graphically, thus renders it to be less accurate. The effect of this lower portion designed in the subindex structure is not applicable for waters of moderate to highly polluted waters as described in Appendix 2.7. Thus, it is less responsive in areas of low water quality.

The segmented non-linear function can be referred to an implicit function curve drawn for pH variable developed by Brown et al. (1970). This curve was obtained from averaging of several curves supplied by water quality experts. The subindex value was obtained directly from this curve without the use of any mathematical equation. However, the four segments of the pH curves can be transformed into four best-fit explicit non-linear equations as indicated in Appendix 2.8. In contrast to AN curve (Appendix 2.6), the pH curve exhibits the problems of the upper portion that tends to be more suitable for waters of low quality. However, based on Interim National Water Quality Standard (INWQS) as in Table 2.2, the lowest threshold value was set to pH 5.0. Below this value it exerts similar effects on human and aquatic species (DOE, 1990). In such situation, the criteria and standards, which reflect the beneficial uses of water, work quite well in assessing water quality with that of mathematical formulae for only a small segment along the pH curve.

Parameters	Unit	Class I	Class II	Class III	Class IV	Class V
1. AN	Mg/l	0.1	0.3	0.9	2.7	> 2.7
2. BOD	Mg/l	1.0	3.0	6.0	12.0	> 12.0
3. COD	Mg/l	10.0	25.0	50.0	100.0	> 100.0
4. DO	Mg/l	7.0	5.0	3.0	1.0	< 1.0
5. PH	-	7.6	6.0	5.0	5.0	5.0
6. SS	Mg/l	25.0	50.0	150.0	300.0	> 300.0

Table 2.2 General INWQS with five different classes
(Source: DOE, Malaysia, 1990)

Another form of non-linear function is represented by an exponential function where the concentration of variable X is taken as exponent of a constant as indicated in Appendix 2.9. Generally, the variable in non-linear function is raised to a power greater than one where the curve of slope increases rapidly. When this power is double, the concentration of variable X is also double, thus subindex I increases fourfold. However, the problem of this exponential curve is similar to the AN curve (Appendix 2.6), the problem created at the lower portion.

2.3.2.2 Subindex Aggregation

The second step is the aggregation of these subindices into a final index. The respective subindices as in Box 2.3 are aggregated, which indicates that all information they carry are simplified into a single number. Similar to the process of subindex construction, subindices can only be bound together using an aggregating function, which takes the form of addition, multiplication, maximum and minimum operator. In general, the main index function is represented as in Equation 2.15, Box 2.3.

$$I_a = h(I_1, I_2, I_3, \ldots\ldots I_i \ldots I_m) \quad \text{----Equation 2.15}$$

where I_a = overall aggregated Index
h = function of overall sub-indices.

Box 2.3 Aggregation of subindices
(Source: Ott, 1978)

A. Additive Function

The additive function is the simplest aggregation function, consists of three types of functions; unweighted linear sum, weighted linear sum and root-sum-power (Brown et al., 1970). The basic linear sum can be represented as in Equation 2.16 in Appendix 2.10 and an example of the unweighted linear sum is shown in Appendix 2.3. It is shown that when two variables are aggregated and summed up, the result is an exaggeration of index value as represented by Equation 2.17, Appendix 2.10. Although these graphs are set at the most appropriate points to avoid any standard violation, ambiguous condition emerged, which contributes to standard limit violation. However, ambiguous condition can be avoided for dichotomous subindices (involvement of two variables) but exaggeration still occurs as indicated Appendix 2.11. Thus, the linear sum function may exaggerate and creates an ambiguous water quality value.

The exaggerated and ambiguous region can be reduced or eliminated by multiplying a coefficient known as 'weight'. Weight is multiplied to the subindex to make it unity, a value equivalent to 1. The weighted linear sums are represented as in Equations 2.18 to 2.21 in Appendix 2.12. However, these examples show that the weighted linear sum exhibits eclipsing which tends to underestimate pollution level. These problems are the characteristic of the linear additive forms and demonstrate the unsuitability of this aggregation function for representing dichotomous subindices. If more than two variables are used, the magnitude of ambiguity and the eclipsing regions will increase greatly.

The problems of ambiguous region can also be reduced using the root-sum-power that is a non-linear aggregation function as indicated in Appendix 2.13. The ambiguous region persists although greater area has been reduced. This region can be eliminated by the conversion of the root-sum-square into root-mean-square as indicated in Appendix 2.14. In this case the ambiguous region is reduced to zero. However, two eclipsing regions appeared and these contribute to the lost of information.

B. Multiplicative Function

Generally, multiplicative function is more applicable for addressing decreasing scale index and is widely used in designing the water quality index. This function was first developed by Landwehr (1974) based on the additive function. In decreasing scale index, the highest index value represents the highest water quality, which resembles a natural condition of water body where no pollution occurs. A maximum scale of 100 units is normally being used and zero value is the lowest value, either the most polluted condition. The application of additive forms to aggregates subindices creates the problems of ambiguous and eclipsing regions. Ambiguous region can be eliminated, but eclipsing remains within the index structure when different functions are applied. The unweighted additive function may cause the index to exaggerate, thus overestimate pollution level. Similarly, these exaggeration problems remain when unweighted multiplicative function is used. Another approach in reducing such problems is the application of the weighted product function, which is commonly being used in most of the multiplicative aggregation functions.

Generally, the weighted product is expressed as in Equation 2.32, Appendix 2.15. This equation indicates that if any of the subindex value is zero, the overall index is zero and this will eliminates the eclipsing problem. Therefore, if any subindex exhibits low water quality, the overall index will indicate low water quality. In a moderately low water quality, the multiplicative function of weighted product when used in decreasing scale may still produce eclipsing region of its subindices.

Thus, the weighted product function is not applicable for all situations in assessing the status of water quality but can minimise the eclipsing region. However, in an extremely low water quality, weighted product does not produce any eclipsing region.

In addition to the weighted product function, geometric mean is also applied when the weights are equal as in Equation 2.33. Geometric aggregation function can be expressed as in Equation 2.36 and 2.37 as in Appendix 2.15. The sum of all weights is unity (1) and this weight becomes very small when the index is aggregated with large number of subindices (example 9 or 10 subindices). With smaller weights, the curvature of the line graph gradually changes to an abrupt shape, towards right angle as indicated by a series of curves in Appendix 2.15. With these characteristics, for a very small change in the value of subindices, the overall index value will increase almost half of its total range. This shows that the geometric weighted product tends to transform the subindices with relatively small weights, into non-linearity properties. This produces an objectionable distortion since it becomes relatively confused in interpreting the relationship between the subindices and the overall index.

C. Maximum and Minimum Operator

As discussed earlier, the root-sum-power function acquired acceptable properties since it has neither an eclipsing region nor an ambiguous region. Since it also possesses limiting function, it is not applicable to be used. Maximum operator is another function that posses the same properties which is not unwieldy to be used and with no limiting function (Ott, 1978; Smith, 1989). In general, maximum operator can be represented as in Equation 2.38, and Graph A in Appendix 2.16. It shows that if one subindex exhibits low water quality, the overall index exhibits low water quality. Besides that, no ambiguous region occurs for the overall index I since both subindices I_1 and I_2 exist in opposite manner. These properties mainly suit dichotomous subindices. However, the drawback of maximum operator function is that it could not provide the fine degradation of the overall index I and becomes more complex when more then two subindices are aggregated. Therefore, it is difficult to apply, in particular for the evaluation of the changes in water quality over time.

In contrast to maximum operator is the minimum operator function. Its general form is illustrated as in Equation 2.40, and Graph B in Appendix 2.16. The index I in minumum operator is determined by the minimum value of any subindices such that the overall index is zero if one or more of the subindices equals to zero. When two subindices are aggregated to provide an index I, they undergo the same process as in maximum operator, but the plots of horizontal and vertical lines are in opposite direction. The plots will never touch the two axes, thus eclipsing and ambiguous regions will never exist. Again, this function is more applicable for dichotomous subindices. However, the problems exist when more then two subindices are used.

2.3.3. Variable Selection

Variable selection is critically and equally important in index construction. The selection of all monitored variables in index construction is impractical and makes the index unwieldy, and too few in selection will not represent the exact or true condition of the status of water quality. Therefore, it appears that the most practicable way is to select the most significant variables that are being monitored in all national rivers (Horton, 1965; Landwehr, 1974; SDD, 1976; Ott, 1978; Lohani and Norhayati, 1982; Dojlido and Best, 1993). However, in an integrated water quality assessment, the water body is not only assessed on quality but also assessed in terms of its suitability for intended uses of water. Thus, the variable selection will be more meaningful when it is incorporated with intended or beneficial uses of the respective water body and this provides an important input for planning and economic purposes (Lohani and Norhayati, 1982; House, 1986; DOE, Malaysia, 1986).

In selecting an appropriate number of variables for index construction, several approaches have been developed. An approach that is widely being accepted is based on professional judgement from water quality experts. Normally, experts' opinions are sought through a series of questionnaires (Brown et al., 1970; Walski and Parker, 1974; SDD, 1976; Dunnette, 1979; Lohani and Norhayati, 1982; House, 1986; Smith, 1989). Selections are performed based on its importance, together with the estimate of relative weight it carries and the rating curves are drawn. The final selections of these variables, weightings and rating curves are based on their averages after consent are sought from the respective experts. Some examples of the selected variables and rating curves for DOE, Malaysia are illustrated in Table 2.2 and Appendix 2.2 (DOE, Malaysia, 1986). Thus, these relative selections represent the collective opinions from the experts' judgement that can be applied objectively as compared to other approaches.

Another approach in variable selection is based on rejection rationale. All monitored variables are listed and the less significant variables, either that does not cause any harmful effect are rejected (Dojlido and Best, 1993). Variables that are questionable of their significance and the effect they acquired are also rejected (Horton, 1965). This approach was considered as subjective since the judgement was made by a small group of water quality experts (Harkins, 1974).

The methods employed for variable selection based on experts' opinion and the rejection rationale have been strongly criticised by some developers who are using the statistical approach. They argued that statistical methods are more objective in selecting significant variables (Shoji et al., 1966; Harkins, 1974; Schaeffer and Janardan, 1977; Joung et al., 1979; Lohani and Todino, 1984). The correlation technique in statistical approach can be used to identify the possible associations among variables in determining the importance of each variable. The less significant variables will be automatically dropped and their weightings are assigned in parsimonious manner leaving only the significant ones (Harkins, 1974). Although, statistical approach was claimed to be more objective, the process of selection was difficult to perform without the use of computers. The results obtained were difficult to interpret (House, 1986). All monitored variables of concern will be used in statistical calculations and the selected variables may not represent those in needs for intended or beneficial uses of water. Thus, statistical approach is more site-specific which applies to a specific geographical location only.

2.3.4 Statistical Approach Water Quality Index

The development and application of a water quality index from statistical approaches are not many as those produced by mathematical approaches. As claimed by statistical developers, the statistical approach water quality index was to provide an objective index rather than to use the subjective mathematical approaches which seek the opinion from water quality experts (Harkins, 1974; Schaeffer and Janardan, 1977). Some developers felt that those different panels or different disciplines of water quality experts will select different variables and different ratings, thus biases may occur. This will destroy comparability and objectivity of assessment system. To eliminate these biases based on opinion of water experts, Harkins (1974) developed the first index based on statistical method using Kendall's non-parametric multivariate ranking procedures. This method does not require any justification of unrealistic assumptions as compared to that of parametric statistical methods.

In Harkins non-parametric approach, any number of parameters can be used and most often the choice of variable to be selected is based on the objective and availability of monitoring data. If the assessment needs to fulfil a specific objective only, then those unrelated variables should not·be included. In this non-parametric approach, for each variable used, a control value was first chosen together with the respective water quality standards value. Normally the selected control value was set from an ideal water quality value. The observation data including the control and standard value of each variable were ranked in ascending order. Any tie values (same numeric value) exist were split in usual manner. The rank variance for each parameter as in Box 2.4 is computed using Equation 2.42 and the final index is obtained using Equation 2.43.

The use of control values together with water quality standard values in the formula will allow comparison to be made between stations with the same data sets. Thus, any observed index value greater than the standard index value will indicate that the waters were polluted and action needs to be taken. Since ranking procedures were carried out at a particular time for specific data set, index computed at different times or obtained from different data set should not be compared. This was due to the fact that the index calculation was affected by the rank variances that were totally dependent on the number of observations.

$$Var(R_i) = S_i = \left[1/12m_i \ [(m_i^3 - m_i) \cdot \sum_{i=1}^{q_i} (t^3_k - t_k)] \right]^{1/2} \quad \text{......Equation 2.42}$$

where q_i = number of separate occurrences of ties,

t_k = the number of ties encountered

m_i = number of values (observations plus control value) for variable *i*.

$Var(R_i)$ = variance of the rank for variable *i*.

S_i = the standard deviation of R_{ij} for the *ith*.

$$I_j = \sum_{i=1}^{n} (R_{ij} - R_{ic})^2 \ Var(R_i) \quad \text{......Equation 2.43}$$

where R_{ij} = the rank of the *jth* observation for the *ith* variable,

R_{ic}= the rank of the control value for the *ith* variable,

Box 2.4 Harkins' Water Quality Index
(Source: Harkins, 1974)

Other statistical methods that have been used include the multivariate factor analysis, discriminant analysis and the probability approach (Shoji et al., 1966; Joung et al., 1979; Lohani and Norhayati, 1982; Lohani and Todino, 1984). Normally, large numbers of variables were involved and the situation reflected the availability of monitoring data. The main component is the formation of a correlation matrix and the determination of variables mean values and standard deviations. This correlation coefficient value is the weighting scale used for each variable produced from the correlation matrix. Thus, the less important variables will be dropped automatically leaving only those important and significant variables together with their weightings. Although all calculations can be performed using computer, the processes and mechanisms were complex and more difficult to apply. Among the popular statistical techniques used is the principal component analysis developed by Joung et al. (1979). No published reports mentioning the application of this statistical approach have been found.

Water quality variables may also possess stochastic characteristics that exist with certain probability or degree of uncertainty (Lohani and Norhayati, 1982). Thus, probabilistic approach can be applied in water quality assessment system based on the measurement of the likelihood or chances that pollutants may occur with certain probability value. In the development of stochastic water quality index, Lohani and Norhayati (1982) seek the opinion from water quality experts to select the significant variables, weightings and rating curves. These selected variables and weightings were applied into the normal probabilistic concept to obtain a general stochastic water quality index where the result was assigned as values between zero and one or expressed in term of percentage. This approach provides another convenient tool in river classification when it was applied to classify one of the polluted streams in Malaysia. Although, it provides good results, this statistical approach was not used since the variables that were considered as the main contributors to water pollution were not monitored nation wide.

2.4 WATER QUALITY CLASSIFICATION SCHEME

2.4.1 The Background of Classification Scheme

The preceding section described in detail the development and application of water quality index systems for assessing the quality of surface water. Another form of assessing surface water quality from huge volume of monitoring data is based on classification schemes. Newman (1988) defined them as a devised to convert this huge volume of data into water quality classes that can be readily comparable and applicable in demonstrating compliance with the requirements of the respective water quality criteria and standards.

River classification schemes were originally based on the saprobian system developed by Kolwitz and Marsson in 1908 (Hellawell, 1986). The term "saprobian" or "saprobia" is the dependence of aquatic organisms on decomposing organic substances as source of food (Persoone and De Pauw, 1979; Pinder and Farr, 1987; Metcalf, 1994). It relates the effect of aquatic community structure to certain concentrations of organic pollution of a flowing water system. This original saprobian classification was designed as a four-banded scheme which included; oligosaprobic which described a clean and healthy river segment; polysaprobic, which described the zone of extreme pollution that exists near a point discharge; and mesosaprobic, which is the zone of recovery (oxidation) comprising of two segments; the beta-mesosaprobic which is a zone of moderate pollution and finally the alpha-mesosaprobic which is a zone of heavy pollution (Gray, 1992; Chapman, 1992).

In general, the national water classification scheme and water quality index system based on physico-chemical and biological parameters are being applied as separate assessment systems. This acts as a form of 'check and balance' on the accuracy between these approaches. A classification scheme comprises of different number of class bands (SDD, 1976; Newman, 1988; DOE, Malaysia, 1990). Each class band represents the quality of waters that are based on their criteria and standards of the significantly selected parameters as indicated in Table 2.2. This criteria and standards are absolute range of numbers where the highest or the most stringent criteria and standards values represent the highest water quality. The selected pollutants are the main contributors to water pollution that commonly being applied to all national rivers.

Different countries may have used different number of banded classes within their national classification schemes. Within the European Union, this application varies from three bands in Ireland to seven bands in Germany as illustrated in Appendix 2.17 (Newman, 1988). The figures show that the five-banded classification schemes are more popular. Some countries relate these classes into several descriptors and numerical values from water quality index system as shown in Table 2.3. This banded scheme may also relate to different colour use in mapping of river segment for planning purposes. The first descriptor was introduced by the National Sanitary Foundation of the United States (NSF US) which relates both the water quality index and classification schemes and has been proved elsewhere to correlate quite well between these two systems (Ott, 1978; House, 1986). The Scottish Development Department (SDD) index particularly the geometric weighted formulation correlated quite well with the National Water Council (NWC) and Thames Water Authority (TWA) classification schemes (House, 1986).

Water Authority	Descriptor	Numerical Range	Class Designation	Colour
NSF WQI (Ott, 1978)	Very Bad	0-25	5	Red
	Bad	26-50	4	Orange
	Medium	51-70	3	Yellow
	Good	71-90	2	Green
	Excellent	91-100	1	Blue
NWC/TWA, UK (SDD, 1976; NWC, 1981)	Gross Pollution	0-20	5	Red
	Moderate Pollution	21-40	4	Orange
	Slightly Polluted	41-70	3	Yellow
	Very Good	71-90	2	Green
	Excellent	91-100	1	Blue
Union Benelux Treaty (Newman, 1988)	Very Poor	13.6 – 15.0	5	Red
	Poor	10.6 – 13.5	4	Orange
	Average	7.6 – 10.5	3	Yellow
	Good	4.6 – 7.5	2	Green
	Very Good	3.0 – 4.5	1	Blue
DOE, Malaysia (1986)	Heavily Polluted	0 – 31.8	V	Red
	Polluted	31.9 – 55.8	IV	Orange
	Slightly Polluted	55.9 – 75.7	III	Yellow
	Good Quality	75.8 – 92.5	II	Green
	Excellent	92.6 - 100	I	Blue

Table 2.3 Examples of descriptor and numerical range being used in river quality classification.
(Source: SDD, 1976; Ott, 1978; NWC, 1981; DOE, 1986; Newman, 1988)

2.4.2 The Development of Classification Scheme

Generally, the early attempt of river classification scheme was initiated due to the seriousness of water pollution caused by large volume of organic matter discharged from sewage outfalls. Based on the report of Royal Commission, United Kingdom, the biological oxygen demand (BOD) was found to be the most significant chemical indicator in describing the status of river quality (SDD, 1976; NWC, 1981). Thus, BOD was used as a measurement of water pollution as it indicates the amount of dissolved oxygen used up by the micro-organisms in decomposing the organic matter that is present in the sewage effluent. This means that the greater the volume of organic matter discharge, the higher will be the amount of BOD concentration. In describing the status of water quality based on BOD concentration, a class standard descriptive system was designed by the Commission using general statement as: very clean; clean; fairly clean, doubtful and bad water quality. Along with this system, a standard designated as 20/30 was applied for all sewage effluents. This 20/30 standard meant that after a particular treatment, all discharges should have a maximum of 20 mg/l of BOD and 30 mg/l of suspended solids (sediments). Thus, the early attempt of water pollution control was based on this standard measured at discharge outfalls.

Following the assessment based on BOD concentration, various water authorities have added other significant variables in the development of their own classification schemes. Some water authorities have modified this classification scheme using four-banded classes with the inclusion of variables such as dissolved oxygen and ammonia (SDD, 1976). Problems arise where rivers of different water quality were oftenly placed in the same class. In resolving these problems, another class was added so that classification can be based on intended uses of water particularly for portable water supply (TWA, 1976; YWA, 1978). This classification scheme relates both potential uses and environmental measures. This model was modified further by the National Water Council (NWC) of United Kingdom, such that each variable and each of the five classes as shown in Table 2.4, is assigned by class limiting criteria that should be achieved by 95 percent (or percentiles) of samples taken from monitoring activities (NWC, 1981). The selected chemical components are the dissolved oxygen, biological oxygen demand, ammonia and toxicity to fish.

In selecting the class limiting criteria, some countries may apply 90 % (percentile) and this depends on the priority and requirement set-forth in water quality management and control. For a particular station, if the 90 % or more of the sample falls within the criteria and standards range such as in Class 1A (Table 2.4), then the sample taken from that respective station will be assigned Class 1A and this may apply to other samples taken. Finally, based on simple statistics such as the highest frequency of occurrence, the respective class is assigned as class value for a particular station. The same statistical calculations are carried out for other stations. Thus, a general trend of water quality can be drawn for all of the respective stations along the river stretch for a certain period of time.

NWC Class	Descriptor
1A	Good Quality
1B	Good Quality
2	Fair Quality
3	Poor Quality
4	Bad Quality

Table 2.4 NWC UK five-banded classification scheme (Source: NWC, 1981)

The second type of classification scheme that commonly used is the Point Score system. For example, the Benelux countries (Belgium, the Netherlands and Luxemberg) are using a common single classification scheme based on score points assigned to the five-banded classes as illustrated in Table 2.5. Score points are given to each of the three variables and summed up to give an overall score. The total points vary between 3 to 15 which imply that the lower values indicate higher water quality. The total points are divided by the total number of variables used and the score obtained is referred to the range of values as in first column indicated in Table 2.6. This score relates to a specific class value indicative of the respective water sample taken from a particular station. Samples taken from other stations are examined using the same process. Finally, all stations are designated water quality classes and a trend curve is drawn from the statistics obtained.

Classification scheme incorporate ideas about specific intended uses of water. Since water has manifold uses, such classification scheme provides limited application and posed more complication when dealing with manifold intended uses of water. Thus, a more robust version, the General Quality Assessment (GQA) is being used alongside with that of NWC/TWA of United Kingdom, which serves to provide a comprehensive assessment of the status of water quality (Saeger, 1994). This version as indicated in Table 2.7 is based on six classes and considered as sensitive to changes in water quality. Concurrent to the development of GQA is the application of criteria and standards as stipulated in the Use Classification. This Use Classification contains standards based on EC Directives for the protection of various intended uses of water (Saeger, 1994). As indicated in Table 2.7, the GQA is applied along a river stretch and a class value is assigned based on the highest frequency of occurrence of a particular class. Calculations are performed based on the 90 percentile data values for each variable.

Grade/Points	Dissolved Oxygen (% Saturation)	Biological Oxygen Demand (mg/l)	Ammonia
1	91-110	≤ 3	< 0.4
2	71-90 111-120	3.1 – 6.0	0.5
3	51-70 121-130	6.1 – 9.0	1.1 – 2.0
4	31-50	3.1 – 15.0	2.1 – 5.0
5	≤ 30 and > 130	> 15	> 5.0

Table 2.5 Scoring and grading system for the assessment of water oxygen balance (Sources: Newman, 1988)

Total Point Score For Water Oxygen Balance	Quality Class	Description	Colour Code
a) 3 – 4.5	1	Very good	Blue
b) 4.6 – 7.5	2	Good	Green
c) 7.6 – 10.5	3	Average	Yellow
d) 10.6 – 13.5	4	Poor	Orange
e) 13.6 – 15.0	5	Very poor	Red

Table 2.6 Relationship between scoring point, quality class and descriptor (Source: Newman, 1988)

Grade/ Points	Dissolved Oxygen (% Saturation) (10-percentile)	Biological Oxygen Demand (mg/l) (90-percentile)	Ammonia (mgN/l)
A	80	2.5	0.25
B	70	4	0.6
C	60	6	1.3
D	50	8	2.5
E	20	15	9.0
F	<20	-	-

Table 2.7 Scoring and grading system for the assessment of water oxygen balance (Sources: Saeger, 1994)

2.5 WATER QUALITY ASSESSMENT USING ARTIFICIAL NEURAL NETWORKS

The preceding sections described in detail the development and application of water quality assessment based on index systems and classification schemes. Another new form of water quality assessment is based on ANN techniques. Review on the literature revealed that the application of ANN in water resources mostly confined to river flow forecasting, runoff-rainfall relationship and other hydro-physical processes. However, research on water quality assessment based on the ANN's techniques was less rigorous as compared to the studies based on hydro-physical processes (Dawson and Wilby, 1998, 1999, 2001; Thirumalaiah and Deo, 1998; Jain et al., 1999; Kneale and Abrahart, 2004). This is due to the fact that the application of ANN's techniques for running water using chemical, biological and associated ecological parameters is a complex analysis (Minn and Hall, 1993; Kneale, 2004). Among of these three parameters, the ecological and biological parameters have frequently been used as compared to chemical parameters.

Generally, the ANN's techniques are software simulations of networks that run on conventional computers (SRI Business Intelligence Consulting, 2003). These conventional computers processes huge and complex computation effectively based on the rules, programs or algorithms as instructed through the central processing unit (CPU). However, ANN does not use any rules or programs. Instead, the computations are based on the network weights and interconnections which are adjusted through training processes until the network gives the desirable output in respond to sample input data. The general comparison of the functions of ANN to that of the conventional computers is shown in Table 2.8. Therefore, the ANN appear to be suitable for applications that have no formal and articulated rules, which make them useful in situations where exact instructions are difficult to formulate (SRI Business Intelligence Consulting, 2003). The other unique attribute is the capability of the network to train and learn to recognise specific patterns or to perform specific tasks when it is computed to the proper data and processes. If the neural network fails to function, the performance degrades gradually and smoothly rather than stopping abruptly. The concept and application of ANN in pattern recognition is discussed in detail in Chapter Four and Chapter Five.

Point of Comparison	Conventional Computer Programs	Neural Network
1. Problem solving approach	Rule-directed	Trained
2. Source of knowledge	Input data and rules	Trial and error from training examples.
3. Advantages	(a) Swift and precise for computation, (b) Well developed technology, (c) Commodity prices.	(a) Useful where rules are difficult to articulate, (b) Adequate solutions to difficult problems; ability to deal with unclear or noisy data.
4. Disadvantages	Necessity of explicit rules for every possible case.	(a) Nascent technology, (b) Inexact results, (c) Difficult to explain the rationale for computational decision.

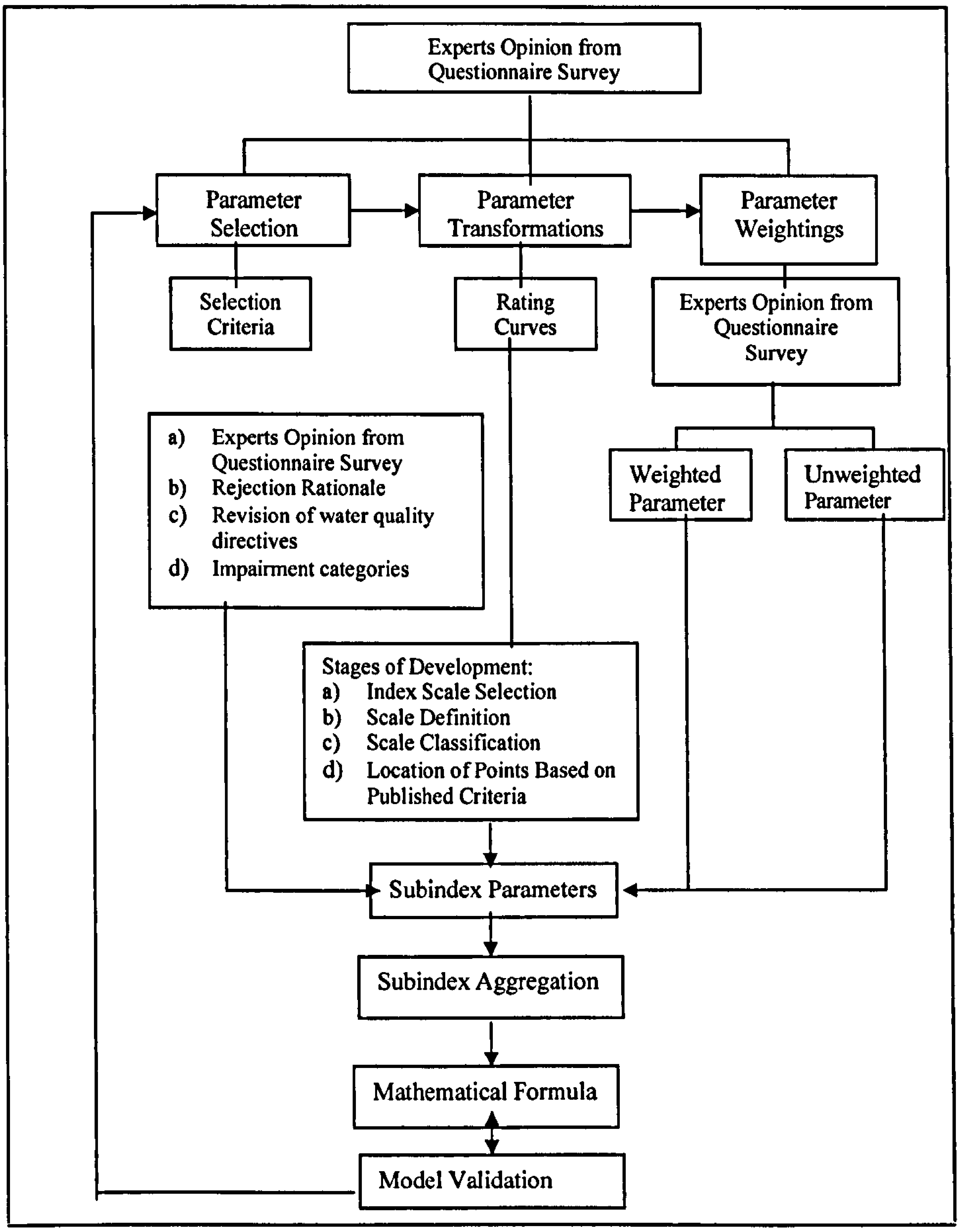
Table 2.8 Comparison of neural networks and conventional computer programs
(Source: SRI Computing Business Intelligence, 2003)

2.6 DISCUSSION AND RESEARCH AGENDA

2.6.1 Water Quality Index Systems

Several mathematical and statistical approaches have been applied in designing water quality index. The index structure begins with the design of a basic subindex structure for an individual variable that carries specific individual information. Following the construction of this basic structure is the evaluation and selection of variables, transforms and weightings. Variable selection is one of the critical factors in the development of an index structure (Brown et al., 1970, 1973; O'Connor, 1972; Landwehr, 1974; SDD, 1976; Ott, 1978; Lohani and Norhayati, 1982; Bhargava, 1983; House, 1986; Smith, 1989; Dojlido et al., 1994; Palupi et al., 1995). Several methods are being applied and those based on professional judgement from many experts are widely being used. These experts were selected from a wide variety of professional backgrounds and from many different geographical locations. The general process of evaluation and selection is illustrated in Box 2.5. The subjectivity of this approach, such as the effect of personal and regional biases was minimised by taking their mean opinion. It has been shown statistically that the experts involved were appropriate, based on the overall results obtained (Landwehr, 1976; Lohani and Norhayati, 1982; House, 1986).

In the index approach, selected individual subindices are aggregated together using mathematical or statistical methods to form a final index structure that produces a single numeric value, which carries the overall information describing the status of water quality. The final water quality index structure is considered objective when these selections and evaluations are performed in an objective manner. Based on the reliability of the water experts' judgement, most of the water authorities are applying them directly and some may have modified this approach despite of some disagreement of its application between small groups of index developers and other water-related scientists (Ott, 1978; House, 1986; Dojlido et al., 1994). Other approaches to variable selection are based on the opinion of individual developer or individual organisation, which normally considered as being relatively subjective, thus their application becomes less popular.



Box 2.5 The development of WQI
(Sources: Modified from Brown et al., 1970, 1973; Ott: 1978; Lohani and Norhayati, 1982; DOE, Malaysia, 1986; House, 1986; Smith, 1989).

The selected water quality variables that exert greatest impacts on humans and aquatic species were the most vulnerable and considered as pollution indicative. The number of variables selected is crucial for a mathematical index system as it cannot cater for large number of variables. If different number is chosen, the final index result will be different. As concluded by Horton (1965), if too many are selected, the index becomes unwieldy. Therefore, it would be more practical to use only those variables that are of greatest significance in most parts of the country. However, there is no limit of the number of variables that can be used in statistical approach. In compliance to statistical requirements, all monitored variables have to be included. The drawback of statistical approach is that the weightings acquired by each variable would tend to converge and their importance would be diminished (SDD, 1976; House, 1986; Dojlido et al., 1994). These weightings determine the degree of importance of each selected variable. However, some developers do not consider weighting to be necessary because the occurrence or significance of these selected variables varies across the national scale or between different geographical locations (Lohani and Todino, 1984; House, 1986; Smith, 1989; Dojlido et al., 1994). Statistically, weightings have little effect if the samples are taken from areas of high water quality or if samples come from relatively low water quality areas (SDD, 1976; House, 1986; Dojlido et al., 1994).

All selected variables need to be transformed into a common scale of index value so that the change in water quality in relation to other selected variables can be compared. Several approaches in applying variable transform have been applied, which include the use of rating curves, mathematical functions and statistical techniques. A rating curve is applicable only for the design of an individual subindex where the values can easily be determined. Rating curves such as that shown in Appendix 2.2 have been used extensively by Brown et al. (1970, 1973); Prati et al. (1971); Walski and Parker (1974); Landwehr and Deininger (1976); SDD (1976); Lohani and Norhayati (1982); and House (1986). Most of these developers concluded that for an index system to be acceptable, the rating curve should be sensitive to changes in water quality, include information on water quality criteria and standards, and effectively relate index values with beneficial uses of water so that they are easy to interpret by the non-technical person. A common problem arises in designing an individual rating curve is that a single variable may exert significantly different effect on human and aquatic species, thus, an individual rating curve may not be applicable to all species in all situations. Therefore, selected variables are often grouped differently based on the objective of the index construction. This gives rise to the construction of general and specific water quality indices, as illustrated in Table 2.9. However, in developing a general water quality index that incorporates beneficial uses of water, as well as emphasis on safety and health measures to both human and aquatic species, developers generally assign the highest criteria and standards to the highest value of water quality.

In the design of the basic subindex structure, the rating curve can be represented as mathematical function, as described in Section 2.3.2 (Appendix 2.2). The simplest mathematical function is the linear and segmented linear (Horton, 1965; Nemerow and Sumitomo, 1970; McDuffie and Haney, 1973). However, most of these functions seldom exist for most of the water quality pollutants, except for dissolved oxygen (Horton, 1965). This is due to the chemical nature of water pollutants that are being discharged where the rate of change of the index value changes in a gradual manner with an increase in the level of pollutant concentration. The most common water quality subindex function exists as non-linear or segmented non-linear function (Prati et al., 1971; Dinius, 1972; Walski and Parker, 1974; Stoner, 1978). However, in real situation, a single rating curve for a particular water quality variable may consist of several curves joined at breakpoints (Appendix 2.5 and 2.6). Therefore, this single curve may consists of mixed functions comprises of linear, segmented linear, non-linear and segmented non-linear function. As illustrated in Appendix 2.2, the application of this single rating curve with mixed characteristics becomes more complicated and therefore less practical. In addition, there is no information on the procedures or guidelines that can include the criteria and standards within a single rating curve; consequently this makes it difficult to incorporate the possible potential uses of water (House, 1986).

Other criticisms made by many developers on rating curves concerns the lower portion of the quality scale where the subindex value may become extreme (SDD, 1976; House and Ellis, 1981; House, 1986). This has resulted in the fact that many rating curves are only suitable for waters that are less polluted or waters of high quality. In addition, if the subindex value is to obtain directly from rating curve, the potential of selecting a wrong reading is high. These problems can be avoided by transforming the rating curves into mathematical equations as shown by Brown et al. (1970); Prati et al. (1971); Dinius (1972); Walski and Parker (1974); Landwehr and Deininger (1976); Lohani and Norhayati (1982); and House (1986). Water quality criteria and standards can readily be incorporated into these mathematical expressions that provide information on potential uses of water. This will be of great help in planning purposes. Although the use of mathematical expressions seems to be complicated to apply, especially when it involves larger number of variables, computers can speed up the processing time. As a result, mathematical functions are being used more widely.

The other important feature of a rating curve is that the index score or scale is usually drawn on the y-axis of the plotted curve. Different developers may construct different subindex scale for each of the selected variable. This difference in design is to account for greater accuracy, especially towards the lower end of the rating curve. This scale may vary from –100 to 1000 (Table 2.9). Too large and too small a scale range makes the subindex difficult to interpret. However, most of the subindices developed, use a scale of 0 to 100, which is considered to be more practical, easy to compute and readily interpretable by non-technical persons. The 100 subindex score means that the water body resembles to that of natural or undisturbed condition. Whereas, the zero score is confined to the most polluted condition that does not posses any economic value. It should not be used for public supply and sensitive aquatic species could not survive in such condition.

A broad range of scale values (0-100) provides adequate description of water quality condition and at the same time can display subtle changes that may occur within a water body. The scale of 0-100 was designed to divide the subindex scales into several segments that consist of both the description of water quality based on certain range of threshold values. Normally, these threshold values are the range of values defined by the water quality criteria and standards that relate to a list of potential uses of water. These segments of numerical range can be described in general as descriptors, or transformed as class values as illustrated in Table 2.3. However, the 0-100 scale approach may incur certain drawbacks, where information that requires the smaller or larger subindex values may not be considered, thus some vital information may be lost. An index system with an appropriate scale range that can hold most information in all situations is difficult to design.

The practicability of an index system as concluded by Horton (1965) is that the system should be simple and the result displayed is easily understood by non-technical persons. The inclusion of zero score at the lower end of the scale may be included. However, it is often considered as unnecessary, since it may affect the accuracy of the assessment of the lower end of the scale (House, 1986). Although the water body posseses an index value of zero, it still has an economic value, either as a means for transport or for other related uses, therefore it should not be rated zero (Dunnette, 1979; House, 1986). Thus, this scale was modified in the range of 10-100 for general uses to resolve the problem that occurred at the lower end of the rating curve. The sub-division was similar to that of 0-100 scale, except that the base starts with value of 10. It was segmented into several ranges, where each range reflects the possible uses of water based on the recommended criteria and standards. A subindex score of 10 can indicate the transport of crude sewage and the flow of effluent. This score of 10 can be taken as equivalent to that of zero score for the scale of 0 – 100. Based on Table 2.9, other ranges of scale have been used. Normally, small scales are attributed to subindex assigned for specific-use, involving toxic substances. Some developers have assigned negative score in order to justify its toxicity effects, where the existence of these variables is intolerable (Horton, 1965).

Subindices can be aggregated to produce one single deterministic numeric value that describes the overall status of water quality for a particular water body. As discussed in Section 2.3.2, aggregation is based on mathematical and statistical formula. The accuracies of these mathematical formulae are based on the type of functions it carries, which include the weighted and unweighted arithmetic, multiplicative, maximum and minimum operator, and geometric formula. These functions link-up all the selected subindices together, and relate the combined effect into a single numerical index value, in a manner justified by the developers. However, different functions possess different characteristics that exhibit different forms and involve different magnitudes of information loss. This loss is in the form of exaggeration, ambiguous and eclipsing regions, when data are presented graphically. Some of the examples of these losses were summarised by Ott (1978), as illustrated in Appendix 2.18.

Based on the simplest mathematical function in aggregation of subindices, the unweighted linear sum creates ambiguity that tends to exaggerate the level of pollution (Prati et al., 1971; Landwehr, 1974; SDD, 1976). Ambiguous regions will cause the result of an aggregated index to display poor water quality state, although there is no individual subindex having such poor water quality value.

Table 2.9 Summary of WQI development

Name of Index Developer (Year)	Country	Index Name[a] / No. of variable	Range (Best to Worst)	Formula
A. General WQI				
1. Horton (1965)	US	Quality Index (10)	100 to 0	$QI = [\sum_{i=1}^{n} W_i I_i / \sum_{i=1}^{n} W_i] M_1 M_2$
2. Brown et al. (1970)	US	Water Quality Index (NSF) (9)	100 to 0	$NSF\ WQI = [\sum_{i=1}^{n} W_i I_i$ or $\prod_{i=1}^{n} I_i^{W_i}$
3. Prati et al. (1971)	US	Implicit Index of Pollution (13)	0 to 14	$IIP = 1/n [\sum_{i=1}^{n} I_i]$
4. Dinius (1972)	US	Social Accounting System (11)	100 to 0	$I = 1/n \sum_{i=1}^{n} W_i I_i$
5. McDuffie & Haney (1973)	US	River Pollution Index (8)	0 to 1,000+	$RPI = 10/(n+1)[\sum_{i=1}^{n} I_i]$
6. Scottish Dev. Depart. (1976)	UK	Water Quality Index (10)	100 to 0	$WQI = 1/100[\sum_{i=1}^{n} W_i I_i]^2$ or $1/100[1/n\sum_{i=1}^{n} q_i]^2$
7. Ross (1977)	UK	Water Quality Index (5)	10 to 0	$WQI = [\sum_{i=1}^{n} R_i / \sum_{i=1}^{n} W_i]$
8. Dunnette (1979)	US	Water Quality Index (Geographical) (6)	100 to 10	$WQI = PT_o W_o + PT_f W_f + PT_n W_n + PT_t W_t + PT_b W_b + PT_p W_p$

Note: [a]: when an index name is not available, the index characteristic is used.

Name of Index Developer (Year)	Country	Index Name[a] / No. of variable	Range (Best to Worst)	Formula
9. Bhargava (1983)	India	Water Quality Index (9)	100 to -10	$WQI = \left[\prod_{i=1}^{n} f_i(P_i) \right]^{1/n} \times 100$
10. House (1986)	UK	Water Quality Index (9 & 4)	100 to 10	$WQI = \prod_{i=1}^{n} q_i w_i$ & $[\sum_{i=1}^{n} q_i w_i]$ & $[\prod_{i=1}^{n} q_i]^{1/2}$ & $\sum_{i=1}^{n} q_i$
11. Palupi et al. (1986)	Indonesia	Water Quality Index (9)	100 to 0	$WQI = [\prod]^{1/9}$
12. DOE, Malaysia (1986)	Malaysia	DOE Water Quality Index (6)	100 to 0	$WQI = \sum_{i=1}^{n=6} W_i q_i$
13. Smith (1989)	New Zealand	General Index (8)	100 to 0	$GI = Min \{I_1, I_2, I_3, I_4, I_5, I_6, I_7, I_8\}$
14. Dojlido et al. (1993)	Poland	Water Quality Index (7 & 19)	100 to 0	$WQI = \sqrt{n / [\sum_{i=1}^{n} 1/(x_i^2)]}$

Note: [a]: when an index name is not available, the index characteristic is used.

Name of Index Developer (Year)	Country	Index Name[a] / No. of variable	Range (Best to Worst)	Formula
B. Specific-Use WQI.				
1. Nemerow and Sumimoto (1970)	US	Index for Three Water Uses (14)	1+ to 0	$I_j = \sum_{i=1}^{n} W_i I_i$
2. MITRE's Corporation) : Greely et al. and Truett et al. (1972-1975)	US	a) Prevalence Duration Intensity Index (b)	1 to 0	$PDI = [P \times D \times I] / M$
		b) National Planning Priority Index (10)	1 to 0	$PPI = \sum_{i=1}^{n} s_i f_i (X_{ij})$
		c) Priority Action Index (4)	1 to 0	$PAI = \sum_{i=1}^{n} W_i q_i$
3. O'Connor (1972)	US	a) Fish and Wildlife Index (9)	100 to 0	$FAWL = \sum_{i=1}^{n} W_i I_i$
		b) Public Water Supply Index (13)	100 to 0	$PWS = \sum_{i=1}^{n} W_i I_i$
4. Dee et al. (1973)	US	Environmental Evaluation System (78[c])	1000 to 0	$EES = \sum_{i=1}^{n} W_i I_i [w] - \sum_{i=1}^{n} W_i I_i [wo]$
5. Zoeteman (1973)	Netherlands	Potential Pollution Index (3)	0 to 1,000+	$PPI = [NG/Q] \times 10^{-6}$

Note: [a]: when an index name is not available, the index characteristic is used.
b: any number of variables can be included.
78[c]: water quality variables account for 14 of the 78 variables used in the system.

Name of Index Developer (Year)	Country	Index Name[a] / No. of variable	Range (Best to Worst)	Formula
6. Walski and Parker (1974)	US	Index for Recreation (12)	1 to 0	$WQI = [\prod_{i=1}^{n} fi^{w} (Pi)]^{1/\Sigma w_i}$
7. Inhaber (1975)	Canada	Canadian National Index (7 & 8)	0 to 1	$I_{water} = \sqrt{[(I_{it})^2 + (I_{amb})^2]/2}$
8. Deininger and Landwehr (1976)	US	Index for Public Water Supply (11 & 13)	100 to 0	$PWS = [\prod_{i=1}^{n} Ii^{w_i}]^{1/n}$
9. Johanson and Johnson (1976)	US	Pollution Index (b)	100+ to 0	$PI = \sum_{i=1}^{n} W_i C_i$
10. Stoner (1978)	US	Index for Dual Water Uses (31)	100 to −100	$DWU = \sum_{i=1}^{n} I_i + \sum_{j=1}^{n} W_i I_j$
11. House (1986)	UK	a) Potable Water Supply Index (13)	100 to 0	$PWSI = 1/100[1/n(\sum_{i=1}^{n} q_i)]^2$ & $1/100[\sum_{i=1}^{n} q_i w_i]^2$
		b) Aquatic Toxicity Index (9)	0 to 10	same as above
		c) Potable Sapidity Index (12)	0 to 10	same as above

Note: [a] : when an index name is not available, the index characteristic is used.
b: any number of variables can be included.

Name of Index Developer (Year)	Country	Index Name[a] / No. of variable	Range (Best to Worst)	Formula
C. Statistical Approach WQI:				
1. Shoji et al. (1966)	Japan	Composite Pollution Index (18)	2 to -2	$CPI = \sum_{i=1}^{n} B_i Z_i$
2. Harkins (1974)	US	Harkins' Index (Kendall Ranking) (b)	0 to 100	$HIj = \sum_{i=1}^{n} Z_{ij}^2$
3. Schaeffer and Janardan (1977)	US	Beta Function Index (4[b])	0 to 1	$BFI = 1/b\,[S / T + S]^{1/2}$ $S = \sum_{i=1}^{n}\sum_{j=1}^{m_i} Z2_{ij}$ & $T = \sum_{i=1}^{n}\sum_{j=1}^{mi-1} R_{ij}$ $b = [2\sum_{i=1}^{n} m_i^2 \Big/ 3\sum_{i=1}^{n} m_i^2 + \sum_{i=1}^{n} m_i - 2n]^{1/2}$
4. Joung et al. (1978)	US	a) Index of Partial Nutrients (5)	100 to 0	$PNI = \sum_{i=1}^{n} W_i I_i$
		b) Index of Total Nutrients (5)	100 to 0	$TNI = \sum_{i=1}^{n} W_i I_i$
5. Lohani and Norhayati (1982)	Malaysia	Stochastic Water Quality Index (12) (Probability Approach)	100 to 0	$SWQI = WQI\alpha_i = \sum_{i=1}^{n} [\text{Prob. } \{X \geq f\}] \geq \alpha_i$
6. Lohani and Todino (1984)	Thailand	Water Quality Index (13)	100 to 0	$I(i) = \sum_{j=1}^{n} [a(ji)\, \gamma(j) / \lambda(i)]$

Note: [a]: when an index name is not available, the index characteristic is used.
b: any number of variables can be included.
4[b] : any number of variables can be included and only 4 variables are selected.

This exhibits an overestimation of pollution levels. If based on these results, an inappropriate management strategies and enforcement activities will be imposed to reduce water pollution. Ambiguity regions and exaggeration of pollution levels can be reduced by multiplying weight so that each subindex becomes unity. Although the weighted linear sum may reduce the effect of an ambiguous region or the exaggeration of pollution levels, it may creates a serious eclipsing region, that underestimates the pollution levels (Brown, 1970; Deininger et al., 1971; O'Connor, 1972; Landwehr, 1974; Nemerow, 1974; SDD, 1976; Stoner, 1978; Dunnette, 1979; Joung et al., 1979; Lohani and Norhayati, 1982; DOE, Malaysia, 1986). This underestimation resembles a situation where at least one or two subindices of high concentration or where the standards greatly exceeded, but the overall index does not reveal these violations. It will also lead to a wrong decision by the water pollution management authority.

Another function that eliminates the problems of ambiguity and eclipsing is the used of the root-sum-power function. Root-sum-power is another additive form that is only applicable in non-linear aggregation functions. This method can entirely eliminate the problems of ambiguity and eclipsing, as the power increases to infinity. However, since it posses a limiting function, the results may be unwieldy, if it is applied as an index aggregation function. Only Inhaber (1975) has used the root-sum-power to incorporat four aggregated indices functions together into a single water quality index, as an input into the general Environmental Quality Index (EQI) for the Canadian waters (Table 2.9). To date, there are no published reports on the application of this root-sum-power based on Inhaber's approach. In general, the additive functions do not appear well suited to aggregation of decreasing scale subindices (Landwehr, 1974; SDD, 1976; Ott, 1978; Bhargava, 1983; House, 1986).

The advantage of root-sum-power method is that it can eliminate both the ambiguous and eclipsing regions. However, it acquires a limiting function and this limits it application. Another function that resembles the properties of root-sum-power is the maximum operator, commonly used for air pollution in the context of an increasing scale index. With the maximum operator, if one subindex exhibits poor quality, the overall index exhibits poor quality. Such an approach is more suited to dichotomous conditions. However, problems will arise when more than two subindices are aggregated. Another limitation is that it could not provide the fine degradation of the overall index. Thus, it could not display the trend in water quality assessment. Based on the published reports, there are no examples of the application of maximum operator function being used by any water authority except the minimum operator developed by Smith (1989) in classifying rivers in New Zealand. Smith argued that the suitability use of waters is largely governed by the 'poorest' characteristic of the selected variables. It is linked with the legislative requirements and the classification scheme so as to make it more acceptable. In contrast to the maximum operator, it is more applicable for decreasing scale of water quality index. In certain respects, the properties are quite similar to that of maximum operator, where eclipsing and ambiguous regions do not exist. It indicates overall poor water qualities when at least one of its subindices shows high concentration value or violates the standards. The other advantage is that there are no restrictions on the number of variables used. Otherwise the disadvantages are similar to that of maximum operator.

Both the maximum and minimum operator cannot provide a practical approach in the assessment of water quality. They cannot provide the fine degradation of the overall index and becomes more complex when more then two subindices are aggregated. The approach is only to evaluate the subindex variable having the highest concentration value or the most polluted variable. This approach does not show the collective effect of the selected variables and may resemble that of toxic substances.

The elimination of weightings, as in the minimum operator function developed by Smith, can be supported by another additive formulation developed by Dojlido et al. (1993, 1994), who developed index system based on the harmonic square mean function. Both developers noted that the use of constant weights assigned to the selected variables may lead to improper evaluation since different variables may exerts different effect in rivers of different geographical locations. Therefore weightings should be assigned differently for different rivers, even though the selected variables are common on the national scale. This will cause some difficulty in comparing the results when different weights are assigned to the same selected variables for different rivers. Therefore weightings should be eliminated and the possible approach of reducing ambiguity and eclipsing problems is the averaging of subindices based on harmonic square mean function.

With the harmonic square mean function as illustrated in Table 2.9, the mean value provide a high statistical value for the variable that is least favourable, taking into consideration of other variables. However, this index system involves a large number of variables that are divided into two groups; the basic variables (comprising of seven variables) and the use of additional variables in special cases only (Dojlido et al., 1993, 1994). Additional variables are only considered when the index value obtained from the basic variables shows poor water quality. Additional variables include those relating to toxic substances that are considered intolerable by Horton (1965) and most other developers, and should be designed separately. Although this approach seems to be a single system, it can be considered as two separate index systems. The index calculation involving the basic variables seems to be more applicable in areas of high water quality. The use of additional variables is more applicable to areas of low quality, only when the overall index result is low. The result of Summarised Index Value is then evaluated using the criteria that it should not fall below 90 percent of its maximum value. This approach seems to be quite objective and provides more information, but the results obtained generally cannot be compared with other water bodies using other data set or other rivers.

Information loss from the application of additive forms of index can be reduced by applying the multiplicative approach. However, the weighted multiplicative form is more widely used than the unweighted form, due to the inherent ambiguous region. This causes great problems in unweighted multiplicative form, and thus exaggerates pollution level. Although, most developers agreed that the weighted multiplicative approach retains most of the information, eclipsing may still exist, but in a reduced form as compared to the unweighted additive formulation. This happens when it is applied to a decreasing scale of water quality index for high and moderately low water quality. However, eclipsing is eliminated in an extremely low water quality (Landwehr, 1974; House, 1986). In this situation, the overall index exhibits poor water quality if one of the subindices exhibits poor water quality or violates the standard limits. Conversely, the ambiguity region is eliminated if any of the subindex values are zero, which indicates that the overall index will be zero. This indicates that the weighted multiplication function is not always applicable for all conditions of water quality (Landwehr, 1974; Ott, 1978; House, 1986).

If equal weightings are applied, the multiplicative formulation becomes the geometric mean function. This is considered as a special case of the multiplicative form, since the sum of the weights is unity. Applying the geometric mean function to aggregate large number of subindices will reduce each weight to become relatively small value. Consequently, as weights become smaller, it approaches the characteristics of non-linearity where it may cause objectional distortion and confusion for the user (Walski and Parker, 1974; Ott, 1978). To overcome these problems, a modified version of geometric mean was developed by Walski and Parker (1974), and Bhargava (1983), where the weighting is replaced by a sensitivity function. Although, in most of the modifed versions of the weighted multiplicative and geometric formulation, there is a reduction in ambiguity and eclipsing, information lost persists. This accumulates when more than one variable is applied. However, this lost of information does not cause the index value to be entirely distorted or totally misinterpreted if the development of index is properly designed.

Some developers criticised the way in which the earlier mathematical index systems were designed and considered them as subjective in their approach (Harkins, 1974; Schaeffer and Janardan, 1977; Joung et al., 1979; House, 1986). They claimed that the major limitations are the selection of variables, weightings and rating curves, which were solely dependent on the opinion of the water quality experts. Different experts may rank and select variables differently (Shoji et al., 1966; Harkins, 1974; Schaeffer and Janardan, 1977; Joung et al., 1979; Lohani and Todino, 1984). Therefore, the indices may subject to biases and will undermine the comparability and objectivity of assessment system. Within a flowing water body, the physical, chemical and biological variables are in a state of dynamic interaction. These interactions may sometimes become so complex that a stress on one variable frequently affects the other variables as well. Based on those experts' opinions of the earlier index systems, the inter-relationships between variables themselves are usually ignored. When only one or two variables are considered at a time, the overall relationship between combinations of variables and water quality itself is not clear. As a result of such debates, several indices have been developed using statistical methods that they claimed to be more objective in relation to the process of variable selection and the way weightings were performed (Shoji et al., 1966; Harkin, 1974; Schaeffer and Janardan, 1977; Joung et al., 1979; Lohani and Todino, 1984).

Several statistical methods have been applied such as the use of factor analysis, by Shoji et al. (1966), and Lohani and Todino (1984), Kandell's non-parametric multivariate ranking procedure by Harkins (1974), and the probabilistic approach by Lohani and Norhayati (1982). For practical applications of statistical methods, all monitored variables should be included so as to determine which are less important and a clear indication of the interaction and interdependence between monitored variables. However, this was not always the case, since some of the least important variables considered by developers were screened-out earlier and those considered important were used in the statistical calculations (Harkins, 1974; Joung et al., 1979; Lohani and Norhayati, 1982; Lohani and Todino, 1984). Although it seems to be objective, somehow the early screening of the least important variables shows an element of subjectivity. If all variables are used, the magnitude of the weights on the output result will be different when compared to those weights obtained from the result of the more important variables. The manner in which the weights were produced becomes too dependent on the information provided where the developers have to decide upon the threshold score above which a variable will be selected. Inevitably, this approach still contains an element of subjectivity that will affect the accuracy of the output result.

As large numbers of variables are used for the statistical index construction, the procedure for determining the transformation and weighting becomes so complex that the validity and interpretations of the end results become questionable (Joung et al., 1979; Lohani and Todino, 1984). Normally, developers based their calculations on those data collected from a single river within a single catchment area, thus covering a specific area in certain limited period of time and survey. Therefore, the final index values based on these weightings should not be made comparable both temporally and spatially. If it needs to be compared with other data set from other rivers or catchment areas, all of these data set needs to be incorporated into a single calculation. Then only the comparisons can be considered as valid. Therefore, the formulations have to be reviewed from time to time (Lohani and Todino, 1984; House, 1986).

Harkins (1974) has commented on the subjective approach of the mathematical formulae index construction, particularly on the weightings of the selected variables. However, he could not provide an alternative method that can reduce this subjectivity (Landwehr and Deininger, 1976). Instead, Harkins has applied an approach based on Kandell's non-parametric multivariate ranking procedure. Harkins and other statistical developers have considered that the non-parametric approach was more applicable in computing environmental data, especially that of water quality data, where fluctuations in concentration occur. The non-parametric estimation method should be used in situations where the underlying distribution is unknown and where it could not be transformed to make it normal. Thus, the validity of such indices does not depend on the data being drawn from any particular statistical distribution (Berthouex and Brown, 1994). However, the advantage of this approach is that it could be used with any data set, although the results obtained were not as precise as that of parametric method. The disadvantage is that it may incur a loss in the precision of the estimated value, because there was no constraining assumption made regarding the population distribution.

If statistical methods are to be used for the development of national water quality index systems, and to determine the highest weightings or to determine a group of the most significant variables, all data taken from all rivers at national scale would have to be used. This will be laborious and impractical, although it can be done with the most powerful computers. Based on these justifications, it was rejected by House (1986) in her evaluation of a practical and comprehensive index system. She concluded that the statistical methods lack objectivity and reproducibility. The possible inclusion of all types of variables monitored, so as to capture its objectivity approach, seems neither practical nor feasible in water quality assessment that makes statistical methods to be less favourable. To date, only Harkins statistical approach is still being used by some water authorities (DOE, 1986).

The development of water quality index systems based on mathematical and statistical techniques has produced several ingenious indices, where their practical application and effectiveness depend on the objective of water uses. Their effectiveness can be determined when they are capable of being used for more than one purpose. Based on these uses, indices developed can be divided into three components that include; the general-use, specific-use and those developed based on statistical approaches. Some of these published indices are illustrated in Table 2.9. They may differ fundamentally in both structure and development. Basically, most of the indices developed are based on the intended use of a particular water body. The most significant problem facing the creation of water quality indices is that the uses for water are manifold, and the quality of water demanded for each purpose varies tremendously. Most of the general and specific-use indices use the weighted linear sum aggregation function that exhibits serious eclipsing problems (underestimation of values) when used in decreasing scale indices. A high value of a certain variable may be desirable in one instance and indifferent or even detrimental in another.

The general-use indices are based on the intention that the indices developed are applicable to all forms of intended water usage. Generally, the intended uses of water are for public water supply, aquatic wildlife and fisheries, irrigation, recreation and industry (Ott, 1978; House, 1986; DOE, Malaysia, 1990; Chapman, 1992; Viessman and Hammer, 1998). However, some water experts do not accept the concept of general water quality (Deininger and Maciunas, 1971; O'Connor, 1972; Stoner, 1978; House, 1986). They believe that each index should be designed for a specific water use. These specific-use indices can be divided into two sub-components; the specific-use and the planning indices. Specific-use indices include those indices developed for portable water supply, for protection of fish and wildlife populations, for irrigation and recreational purposes. The planning indices are specifically designed for management decision-making especially in water pollution monitoring programs. The structure may be based on variables other than those routinely measured by water pollution monitoring programs, such as the degree of economic activity within an area, the average flow rate and the investment allocated to a particular catchment area (Mitre Corporation, 1971; Dee et al., 1973; Zoeteman, 1973; Walski and Parker, 1974; Inhaber, 1974; Landwehr and Deininger, 1976; Johanson and Johnson, 1976). The statistical approach to indices comprise of all indices developed by the application of statistical techniques, such as factor analysis and probability. However, based on several findings, some indices that are categorised under specific-use can also be applied as general-use indices. These were due to their structure and performance that were not sufficiently different from those of general-use water quality indices to warrant its use.

Among the three components, the general-use indices are widely being used by most water quality controlling authorities. These general-use indices may encompass those of specific-use and planning-use. As concluded by Brown et al. (1970, 1973), in developing the most practical water quality index, the disadvantages would have to be weighed up against the economic goals of individual studies. Obviously, in view of the drawbacks, and the results from the comparative studies of Brown et al. (1970, 1973), Lohani and Norhayati (1982), Bhargava (1983), Deininger and Newsome (1984), House (1986), Smith (1989), Dojlido et al. (1993, 1994), and Palupi et al. (1995), concluded that it would be more profitable if time was spent in perfecting a sensitive general-use water quality index, rather than producing several specific-use indices.

2.6.2 Water Quality Classification Schemes

Most of the national water quality classification schemes that are being applied vary between countries. Normally, in a classification scheme, both the physico-chemical and biological methods are used together to assess the country's water quality status. These two assessment techniques have advantages and disadvantages, as summarised by Newman (1988) and Gray (1999) (Appendix 2.19). Although the physico-chemical technique may incur greater costs, the main advantage is that it is more precise, discriminating and quantitative. It is therefore, appropriate for application in water quality management and conservation. It is more applicable to water licensing authorities, since it provides the important information for the assessment of compliance with prescribed standards. In contrast, biological assessment techniques tend to be less precise, in that they do not always indicate the exact cause of pollution (Hellawell, 1986; Newman, 1988; Gray, 1999). However, the biological approach can assess effectively the overall ecological damage caused, not only by the pollutants present, but also those due to the residual effects of the earlier pollution incidents. These effects may have been accumulated by the indicator species (Cook, 1976; Hellawell, 1986; Hilsenhoff, 1987; Metcalf, 1994).

Based on the advantages and disadvantages of the mathematical and statistical approaches, the best approach is to apply these two techniques together, so that there will be a balance between simplicity, comprehensiveness and general applicability (House, 1986; Reynoldson and Zarull, 1989; US EPA, 1990; Chapman, 1992; Dojlido et al., 1993, 1994; Saeger, 1994; Heinonen et al., 1994; Varga et al., 1994; Viessman et al., 1998; Newman, 1998; Gray, 1999). However, the national classification schemes as discussed provide subjective interpretation. The subjective parts relates to the decisions made from the classification that may not necessarily be reproducible by another user although they may provide an important basic input in water quality management in compliance to water quality criteria and standards. It may exhibit the general trends of water quality based on changes in class value such as the change from Class 2 to Class 1 for certain period of time and could only provide an estimate of changes in water quality based on score point system. For example, Class 2 is assigned when it shows high frequency of occurrence of Class 2. This is also applies for the result obtained from the Point Score system where the final score is averaged to relate its corresponding class value. Thus, may lack sensitivity and becomes more difficult to indicate an exact difference between stations having the same class value.

Classification schemes with four or five banded classes may pose another difficulty, which limit the potential uses of water. Within a single class, say Class 2, normally it indicates more than one potential or beneficial uses of water. Since, the criteria and standards that fit into a single class can be so wide, this gap potentially be occupied by various criteria that represent different potential or beneficial uses of water. Thus, a single class should not be confined into a single use and should be carefully designed with an appropriate criteria and standards that can fit into several potential or beneficial uses. Therefore, it seems that the most appropriate way is to assign the highest standards for existing beneficial use, which is normally the standard of drinking water supply as proposed by WHO (1984a, 1984b, 1993) or EC Directives (1976, 1981). Within the range of these standards, subsequently it may cover several other critical beneficial uses such as the propagation of aquatic life needed to maintain the health of the ecosystem.

The selection of appropriate variables that may represent all rivers at the national scale is critically important in water quality and resources management. In general, the least number of selected variables being used in classification scheme is three but it can also exceed five (Newman, 1988). The most basic parameters selected are the dissolved oxygen, biological oxygen demand and ammonia, which determine the health of a water system in terms of sustaining aquatic species. Due to the requirement directed by international or regional agreements and in some cases as mandatory needs for national comparability of data, the national classification schemes, which generally based on three to five main variables is being used by some countries as official documentation for all surface water. However, some national classification schemes may apply more than five basic variables based on their local requirements. This is the case where normally the water experts cannot compromise when choosing the exact number of variables to be included (Ott, 1978). Horton (1965) concluded that in the designing of water quality assessment system, an appropriate number of significant variables need to be chosen, if too many, the approach may be unwieldy. However, for a uniform national water quality assessment system to perform effectively, the classification scheme should not only categorise water according to quality, but also provide an indication of possible economic and beneficial uses. The economic gains or losses to some extent is an indicative of the effectiveness of the water quality management and controlling programmes that may directly linked to its water quality classification scheme (Newsome, 1972).

2.6.3 Water Quality Assessment Using Artificial Neural Networks

The application of ANN in water quality modelling is relatively a new approach. Case studies on water quality model performance are very limited (Kneale et al., 2000). Thus, it is difficult to make a detail comparison on the performance of any ANN's model in relation to the index systems and classification schemes. However, there are advantages and disadvantages of applying ANN's approach over the statistical approach. One of the advantages of ANN over the index system and classification scheme is that ANN does not make use of any assumptions about the underlying statistical properties of a data set. All types of data on different time or spatial scales can be used to assess the status of water quality. This shows that ANN is a flexible technique of data usage and model development (Abrahart, 2004). This flexibility allows the economic and environmental variables to be linked in a manner that would not be clear in a process model. Thus, it can be applied to manage the river basin and select the feasible strategies to meet environmental quality goals. The output from ANN's application may generate multiple scenarios which provide the input to a hydrological drainage, water quality and runoff model (Kneale and Howard, 1997). The other advantage is that ANN can cater for non-linear situation which is useful in view that most of the environmental variables are non-linear in characteristics. This non-linearity characteristic and flexibility, makes ANN to be an attractive approach for the forecasting of complex multi-disciplinary hydrological problems such as crop and fish stock management, pesticide leaching, runoff and rainfall, and groundwater pollution and abstraction interactions (Keale and Howard, 1997; Tansel et al., 1999; Morshed and Powers, 2000: Tingsanchali and Gautam, 2000; Abrahart and See, 2002; Abrahart, 2003). It can search for patterns in the data and capable to create the formulation which describe the condition and processes operating on the area under investigation.

Studies also revealed that ANN's approach acquired some limitations. One of these limitations is viewed from the result produced which is not precise as compared to the statistical approach where the assumption about the underlying statistical properties of a data is known. The other limitation is that the causal relationships between each variables or group of variables are difficult to quantify or not understood (Lek and Guegan, 1999). In search for the better performance and capability of resolving the non-linearity of the environmental data and to reduce or resolve those limitations, the application of ANN technique needs to be investigated further, particularly in areas of water quality assessment such as the use of physico-chemical variables. These physico-chemical variables can be more precise as compared to biological or ecological variables when it is applied in different scenarios, either in compliance to water quality criteria and standards. The concept of ANN as pattern recognition is described in details in Chapter Four and Chapter Five presented the details of the application of ANN model in water quality classification using physico-chemical variables in compliance to water quality criteria and standards.

2.7. SUMMARY

The water quality index system has been criticised due to:

- the lack of consensus or agreement on a common design approach,
- the inherent data lost through aggregated formulation,
- the erosion of expert knowledge,
- misuse, and
- the failure to provide information of economic implications.

In contrast of using the classification schemes, results presented in terms of class grade is much easier to understand and interpret. Although classification schemes may considered as subjective approach, it has been accepted and applied in most countries to help them comply to international or regional environmental directives. In certain cases, it is taken as mandatory matter that needs to be enforced.

Thus, on one hand, water quality index system with some of its inherent limitations has been accepted as an objective tool for water quality assessment, and on the other hand, national classification schemes is being applied, although it is seen as subjective way of assessing water quality. Since most countries are applying both of these two systems as 'cross-check' for consistency and accuracy, it may well be the most practical for the best management practices that these two systems can be integrate or incorporate into one single assessment system. Studies conducted by House (1986) concluded that the SDD index system correlated quite well with that of classification schemes. As most developers have noted that with so many index systems and classification schemes have been developed in response to recent legislation, a more standardised approach to the classification of water quality is practically desirable (Ott, 1978; House and Ellis, 1981, 1987; Lohani and Norhayati, 1982; Bhargava, 1983; Newman, 1988; Saeger, 1994). An efficient classification system not only provides information on the trend of water quality, but the result may help the water management authority to decide and provide an adequate protection for potential uses of water.

The assessment system being used by the DOE, Malaysia incorporates the use of weighted arithmetic formulation (Table 2.9) and the five-banded classification schemes. This assessment may possibly be improved further to reduce the inherent loss of information that exists in its mathematical structure and the subjectivity effect of the classification schemes. The DOE-WQI model is too rigid to allow the addition of new variables or the exclusion of obsolete variables. This rigidity poses critical issues in water resource management especially in areas of rapid urbanisation and industrialisation, where new types of pollutants (such as phenolic compounds, arsenic, mercury) not monitored before being discharges into their river system. At some point in time and space, the index and classification values calculated from the rigid system may not represent its true values, leading to an erroneous interpretation.

The water quality assessment systems that are based on water quality criteria and standards may have limited applicability in countries with diverse climatic conditions, and the existence of several geographical regions. This is due to the fact that in different geographical regions, the concentrations of variables that exist under natural conditions are different. These natural concentration values may exceed the values in water quality criteria and standards from other geographical regions. This is one reason why different water quality standards have been adopted in different geographical regions. Therefore, water quality assessment system should be flexible to allow different criteria and standards to be used. The difficulty of applying a uniform index and classification system nation-wide may also arise due to the existence of various water controlling authorities with different water-related legislative requirements. Consequently, their span of control of water bodies varies considerably. If, however, a uniform or standardised index is introduced, it is difficult to avoid 'customising' among water authorities, where the water quality results can be modified at their ease. Thus, application of a uniform index can be problematic (Ott, 1978).

The Harkins'-WQI, which is based on a ranking procedure, is difficult to apply and is not valid to make comparison with results from other catchments areas, unless they are ranked together. The five-banded classification scheme is subjective in nature. However, based on the objectivity of the DOE-WQI model and the subjectivity of the classification schemes, these two approaches were incorporated as one assessment system as being applied by the DOE, Malaysia (1986) for the classification of national rivers. The index value can readily be transformed into class grade value that incorporates beneficial uses of water.

Based on the DOE's, Malaysia incorporation concept, new approach and technique may be explored that can be flexible, universally acceptable, possibly using an existing mode as indicated in Table 2.10. This new techniques should be easy to understand, simple, capable of providing prompt results and applicable to geographical regions that differ in their legislative water quality criteria and standards. Therefore, a segment of river can be assigned to various beneficial uses according to the highest known existing uses. Any review and improvements to be made on the corresponding criteria and standards should consider the geographical regions and the site-specific effects. These criteria and standards can readily be complied and achieved, and at the same time it can be reviewed for further enhancement in the future (Thanh and Tam, 1990). Based on the needs of the new technique of water quality classification, artificial neural network approach seems to fit these criteria. The neural network do not require rules for operation, making them useful in situations where precise instructions are difficult to formulate, trainable to reduce the computation errors, capable to learn and recognise specific patterns or can perform certain tasks through exposure to the proper data and feedback.

Since the water quality assessment systems were introduced in 1985, no review has been made on the effectiveness of the existing assessment systems by the DOE of Malaysia. These assessment systems are the DOE-WQI model, the Harkins'-WQI non-parametric statistical model and the classification scheme. The six selected variables, which include; ammoniacal nitrogen, biological oxygen demand, chemical oxygen demand, dissolved oxygen, pH and suspended solids have also never been reviewed to determine their effectiveness in water quality assessment. Thus, the application of artificial neural network technique may complement the concepts and fundamentals of the existing water quality assessment systems being applied by the DOE, Malaysia. In the next chapter, the details descriptions of the management of water quality in Malaysia through the application of the water quality index system and classification scheme are discussed. Other approaches based on biological variables, river geomorphological features and land use variables are briefly highlighted.

Method	General Implications
1. Mathematical WQI	a) data is lost during aggregation process b) objective c) can be too rigid d) reproducible e) more refine f) provides trends g) indication for potential uses of water
2. Statistical WQI	a) more objective than mathematical WQI b) complicated and laborious in calculations c) reproducible d) more refine e) cannot compare with other data sets f) provide trends
3. Classification Scheme	a) subjective b) reduce reproducibility c) provides trends d) compliance to criteria and standards e) indication for potential uses of water.
4. WQI & Classification Scheme	a) data are lost during aggregation process b) objective for WQI c) mathematical formula can be too rigid d) reproducibility e) result presented both in refine index and class value f) provides trends g) reduce subjectivity in classification h) indication for potential uses of water. i) conform to National Water Quality Criteria and Standards
5. Expected New Approach	a) objective b) reproducibility c) flexible d) conform to National Water Quality Criteria and Standards e) indication for potential uses of water f) results are more refine g) easily understandable and ease of interpretation h) must be in agreement with expert opinion i) capable in providing water quality trend j) capable in assessing water quality with relatively small amount of data k) results obtained can be compared temporally and spatially.

Table 2.10 Summary of the advantages and disadvantages of applying the index system and classification scheme in water quality assessment.

CHAPTER THREE

WATER QUALITY MANAGEMENT PROGRAMME IN MALAYSIA

3.1 BACKGROUND

The water quality monitoring programme in Malaysia was first started in the early 1970s. Most of the monitoring activities were carried out by the Drainage and Irrigation Department (DID), the Public Works Department and the Ministry of Health. The scope of monitoring activities carried out by these agencies was however limited, focussing only on the supply of domestic freshwater. Monitoring activities carried out by the Health Ministry are associated in the surveillance of water-related diseases, especially cholera and malaria (MOH, 1996).

As a result of the outcome of Stockholm Conference on Human and Environment, 1972, grants for funding major economic development projects in developing member countries required the incorporation of environmental protection into the structural planning process (UNEP, 1992). To comply with this requirement, in 1973 the Malaysian Government directed that all planning for major development projects includes consideration on environmental effects. This was to reduce environmental deterioration and at the same time to enhance the quality of life. Environmental protection was further enhanced with the establishment of the Environmental Quality Act, 1974 (EQA), which was followed by the establishment of the Department of Environment (DOE) in 1975. However, only in 1985, the water quality management programme was initiated in Malaysia. Environmental measures were then incorporated into mid-term development planning in 1976, The Third Malaysia Plan (1976-1980), and into a long-term development planning through the First Outline Perspective Plan (1981-1990) (GOM, 1976 and 1981).

The Malaysian water quality programme covers a broad spectrum of activities, which fall under several main sub-programmes. These sub-programmes may also link with other water-related activities, which fall under the jurisdiction of other ministries and departments. For example, the Public Works Department and the Health Ministry are mainly associated in monitoring and managing the water intake stations, where water are processed before distributed as public water supply. However, the overall water quality management programme remains in the control of the DOE. **As such, the aim of this chapter is to briefly examine the obligations of the DOE in managing and controlling the country's water quality programme with main emphasis on water quality assessment techniques that are being used.**

3.2 THE MALAYSIAN WATER QUALITY MONITORING PROGRAMME

The establishment of EQA in 1974, gives authority to the DOE to enforce water quality monitoring programmes, and to control and manage all water quality monitoring stations previously handled by the DID. These programmes cover a broad range of activities, which include:

(a) The Network of Water Quality Monitoring Stations
(b) Analysis of Water Samples
(c) Standard Analytical Methods
(d) Reporting of Analysis
(e) Water Quality Assurance Programme

3.2.1 Point and Non-Point Source of Water Pollution

The current enforcement of water pollution control and management is based on the Effluent Discharge Standards stipulated under Water Regulations of the Environmental Quality Act, 1974. Based on these regulations, water pollution control and monitoring should first starts at the point source of pollution. Thus, in the early enforcement control of water pollution, the monitoring activities were confined to all industrial outlets that discharge their effluent directly into the receiving water body. During that time, the critical problems that needed immediate actions were to resolve the effluent which have been discharged directly from the main industry, the palm oil mill and rubber factory. This effluent has polluted heavily most of the country's main rivers, deteriorated the environment badly and incurred high cost for the river basin cleaning campaigns (DOE, 1990). Those violated the Water Regulations of the EQA 1974 were prosecuted. However, despite the fact that the industries have complied with the effluent discharge standards, continuing degradation in water quality is being experienced in these watercourses. The situation becomes worst in view of the rapid industrial and socio-economic growth.

The effluent standards that measure the pollutants at point source are no longer valid to ensure the health of the river system in the country. Thus, in the context of wider environment, this is no longer adequate for the protection of the ambient water resources in regions with rapid industrialisation and high socio-economic growth. In addition to the point source pollution, the contributions from the non-point source of water pollution are difficult to monitor and control. The major non-point sources come from agro-based activities, land clearing and deforestation, tin-ore mining and small-medium industries. The pollutant loads being discharged into the watercourses have increased beyond the assimilative capacity of the receiving water body. As a result, the DOE decided that an effective and practical means for the protection of water resources from point and non-point sources of water pollution is to control the discharge of effluents based on the water quality objectives or standards required for the protection of the identified beneficial uses of the water sources. Taking into consideration of these initiatives, the Water Regulations of the EQA 1974 were amended in 1996. Although it means more stringent, this initiative complements the needs for a practical and workable water quality assessment system in protecting and conserving the health of the river system in the country. Therefore, the existing water quality index system and the classification scheme have included the contribution from both the point and non-point sources of water pollution.

3.2.2 The Network of Water Quality Monitoring Stations

At the beginning of DOE's monitoring programme, the total numbers of sampling stations (sites) was 400, which covered 49 catchment areas in the Peninsular Malaysia. Another 110 (in 21 catchment areas) and 124 sampling stations (in 25 catchment areas) were in Sabah and Sarawak respectively. The number of sampling stations increased rapidly, and by 2003 there were 926 sampling stations in 120 catchment areas across the whole country.

In the first stage of the monitoring programme, data were collected from rivers known to receive wastewater discharges, particularly from palm oil and rubber factories which is the point source of water pollution, or which have been the subjects of complaints from the public. Rivers were classified as being of high priority or low priority, on the basis of the severity of pollution and the number of complaints received. High priority rivers were sampled monthly and low priority rivers from four to six times per year. In addition to the routine sampling, data were also collected for specific short-term projects including compliance with the existing criteria and standards (DOE, 1994). Since most of the routine samples were collected on monthly basis, these data were used to monitor the long-term trends in water quality, but could not provide information on short-term variation of water quality.

The DOE sampling network was set up with sites located downstream of known wastewater discharges from palm oil mills and rubber factories, which are the major sources of water pollution. However, the locations of these sites were subsequently reviewed, and stations were relocated. Sites were chosen based on the guidelines provided by World Health Organisation (WHO) Promotion of Environmental Planning and Applied Studies (PEPAS) in Malaysia, which produced operational guidelines for water quality monitoring, as part of the Global Environmental Monitoring System (GEMS) programme for developing countries (WHO, 1987). These guidelines include the recommendations for the selection of monitoring sites, sampling procedures, analytical methods, analytical quality control, hydrological measurements and data processing. WHO/PEPAS also assisted the DOE in reviewing for the optimisation of the national water quality monitoring and management programme (Nakamura, 1983, 1984). It was recommended that the DOE adopt a prioritisation system, in which certain sites and certain analyses should be given a high priority in order to streamline the collection, analyses and reporting of water quality data.

3.2.3 Analysis of Water Samples

As stated in the National Water Quality Monitoring Programme (NWQMP) of DOE, all analyses of water samples collected was undertaken by the seven laboratories of the Department of Chemistry (DOC), located throughout the country. The analytical test methods under the NWQMP were reviewed in compliance to the quality control procedures for sensitivity enhancement, improved efficiency, data accuracy and reliability. The reviews also covered the methods for *in situ* and field measurements, and all aspects such as instrument preparation, calibration and operational procedures (DOE, 1990).

3.2.4 Standard Analytical Methods

Under the NWQMP of DOE, decisions about the choice of analytical methods for water quality testing were set-up by DOC. This has generally been satisfactory, in recognition of the fact that the DOC was an established agency responsible for official chemical testing in the country. In recent years, DOC has also been actively involved in a number of international programmes for water quality monitoring, specifically the Global Environmental Monitoring Scheme (GEMS) on Water Quality, and the World Meteorological Organisation's Monitoring Programme of Rain Water (DOE, 1996).

The analyses of the water quality were based on five main variable groups, which include; physical parameters; inorganic non-metallic constituents; trace metals; organic pollutants; and microbiological contaminants. Test methods were mostly adopted from 'Standard Methods for the Examination of Water and Wastewater' by the American Public Health Association (APHA, 1992, 1995), American Water Works

Association (AWWA), and the Water Pollution Control Federation (APHA, AWWA WPCF, 1985).

3.2.5 Reporting of Analyses

The results of analyses are sent to DOE headquarters on standardised report forms. These results are then transferred into the DOE's computer systems. Simple statistical analyses are performed which permit the calculation of minimum, maximum values and various percentile compliance frequencies for each parameter at each site. The data are printed out, and visually checked against the analytical result sheet to identify any typographical errors. In the early stages of the monitoring programme, there was no computer programme for checking data entry. This is no longer the case. The database was also used to prepare annual reports of the status of the country's river water quality, which can be used internally and for public release.

3.2.6 Water Quality Assurance Programme

The volume of water quality monitoring data being generated has recently increased over time. The reliability of these data needs to be checked and tested at certain point of time, to gain confidence in the analyses on the output. In 1988, the DOE appointed a consultant to conduct a study on the development of water quality assurance programme. The aim was to improve or assure the quality of measured data on pollutant concentrations, and also to comply with user's requirements, measured in terms of completeness, precision, accuracy, representativeness and comparability, as well as reduce quality costs. This programme has formulated the quality assurance manuals and quality assurance plans, which contains general and specific requirements for each of the component in the programme (DOE, 1990).

3.3 THE DEVELOPMENT OF WATER QUALITY CRITERIA AND STANDARDS

In the early stages of the DOE's water quality management programme, water pollution control was based on the effluent discharge standards stipulated in the respective regulations of the EQA, 1974 (DOE, 1990). However, this approach is no longer adequate for the protection of the ambient water resources, in regions with rapid industrialisation and high socio-economic growth. The pollutant loads being discharged into the watercourses have often increased beyond the assimilative capacity of the receiving water bodies. Despite the fact that the industries have complied with effluent discharge standards, continuing degradation in the water quality was experienced in rivers throughout the whole country (DOE, 1990). The effectiveness and practical means for the protection of the water sources under such circumstances was therefore to control the discharge of effluents based on the water quality objectives or standards required for the protection of the identified beneficial uses of the water sources (DOE, 1994).

The beneficial uses of water are designated as Water Quality Objectives (WQOs) and the limits that must be complied with, in order to sustain the WQOs are referred as Water Quality Standards (WQSs) (DOE, 1990). The DOE defined water quality criteria as the concentration limitations of pollutants established purely on the basis of scientific knowledge for the protection of specifically identified beneficial uses of the ambient water resources (DOE, 1994). Criteria and standards for the identified beneficial uses are based on those that are being applied in the member states of the European Community (EC) Directives, the WHO, UNEP and the United Kingdom (EECD, 1978; WHO, 1984a, 1987, 1993; HMSO, 1987).

Based on the water quality criteria and standards developed, and the need to incorporate beneficial uses in water quality management, and at the same time capable of enforcing compliance, the Malaysian DOE has introduced Interim National Water Quality Standards (INWQS) as transitory reference for the establishment of a more practical system of quality standards. Using the Saprobic system, five-banded classes of INWQS were recommended for water quality classification as indicated in Table 3.1. These correspond to the most sensitive and highest beneficial uses set-up for domestic water supply, fisheries and aquatic life propagation, livestock drinking, recreation and irrigation. This Malaysian National Water Quality Classification System (MNWQCS) Table is the referenced Table for the classification of all rivers throughout the country.

Based on Table 3.1, Class I is confined to water bodies of excellent quality that resembles the standards set for the conservation of natural environment in its undisturbed states. This category carries the most stringent requirements for human health and aquatic protection. Practically, it can be used for public water supply with no treatment necessary. The Class II was subdivided into two categories, Class IIA and Class IIB, both represents water bodies of good quality. Class IIA is set for the protection of human health and sensitive aquatic species that exist in these waters. It is not allowed for any body contact activity in these waters so as to prevent the transmission of probable human pathogens. In Class IIB, body contact is allowed and designated for recreational and protection of sensitive aquatic species. Class IIA and Class IIB was later combined into one class as Class II for the use in classification of rivers. Practically, Class II can be used for public water supply with minimum treatment or required only conventional treatment.

Class Designation	Beneficial Uses of River
Class I	Conservation of Natural Environment, Water Supply I – practically no treatment necessary (except by disinfection or boiling only), Fishery I – very sensitive aquatic species.
Class IIA	Water Supply II – conventional treatment required, Fishery II – sensitive aquatic species.
Class IIB	Recreational use with body contact
Class III	Water Supply III – extensive treatment required, Fishery III – common of economic value and tolerant species, Livestock Drinking.
Class IV	Irrigation
Class V	Water unsuitable for specified beneficial uses.

Table 3.1 Malaysian National Water Quality Classification System (Source: DOE, Malaysia, 1990)

Class III is assigned for the protection of the common and moderately tolerant aquatic species that brings economic value. This class is also suitable for livestock. Water bodies in this class can be used for public water supply, but they need to be treated extensively using advanced treatment facilities. Class IV is assigned mainly to major agricultural irrigation activities that may not allow for sensitive crops. This type of water body should not be used for public water supply. Class V describe water bodies that do not meet any of the five uses. The condition of water body is very polluted, and should not be used for public water supply.

In line with the selection of criteria and standards was the selection of the most common water quality variables that significantly contributes to water pollution. In selecting these variables, the DOE considered the research findings of Norhayati's (1981), using questionnaires to seek the opinion of local water quality experts. Thus, the following factors have been considered in deciding the range of variables to be included in water quality assessment, which include:

a) The primary parameters representative of the major pollution concerns in Malaysian rivers are; AN, BOD, COD, DO, pH and SS;

b) Other quality parameters which are important for the different beneficial uses are; phenols, oil and grease, and detergents;

c) The availability of sufficient monitoring data, e.g. data for total and faecal coliforms, and trace organic pollutants are absent or are very scarce; and hence they are not included in the classification schemes despite of their importance; and,

d) The impacts of toxic trace elements on river water quality, which can be considered as relatively minor for most river basins.

Finally, 30 significant water pollutants were listed and categorised into three lists as illustrated in Table 3.2. List I, which comprised of the six variables, considered to be the most significant variables selected by the local water experts. List II and List III are also significant variables, but less frequently monitored compared to List I. Their presence needs to be given due consideration especially in areas of rapid industrialisation and manufacturing activities.

List	Parameter
List 1	NH_3-N, BOD, COD, DO, pH, SS
List 2	Colour, Oil and Grease, Detergents (MBAS), Salinity, Conductivity, Total Coliforms, Faecal Coliforms, Cadmium, Arsenic, Mercury, Chromium, Lead, Manganese, Aluminium, Copper, Sulphide, Cyanide, Nitrate Nitrogen, Phosphate (as Phosphorus), Pesticides and Phenolics.
List 3	Sodium, Boron and Chloride.

Table 3.2 Three lists of variables according to their importance. (Source: DOE-UM, 1986)

The complexity of using these standards as a direct application in water quality management and programmes makes them very difficult to apply, especially in a newly developing country like Malaysia. As described earlier, only the United States and some other developed countries are capable of implementing and enforcing these standards directly (Thanh and Tam, 1990). However, these constraints of assigning water quality standards can be resolved by integrating and incorporating it as an indirect way into the country's classification schemes. In this case, the selected criteria and standards of the respective parameters were assigned to appropriate classes of water quality, based on the highest known existing beneficial uses of water as illustrated in Table 3.1.

3.4 THE DEVELOPMENT OF RIVER BASIN MANAGEMENT INFORMATION SYSTEM IN MALAYSIA

As the result of the huge volumes of environmental data from Water Resources and Monitoring Programme, the INWQS and classification schemes, the DOE developed the integrated river basin information system (IRBIS), which is a computer system that is capable of storing, collating and analysing these data needed for reporting purposes. However, the IRBIS was found to be useful only for limited range of applications. Various problems were encountered in the application of this system, which was originally designed using the dBASE III+ programming language (DOE, 1990). In 1991, a new system was introduced known as River Basin Management Information

System (RB-MIS) based on dBASE IV (Version 1.1). The RB-MIS was considered to be more user-friendly, flexible and capable of processing additional information.

The RB-MIS provided access into six main modules that include; water quality, pollution sources, aquatic ecology, flow catchment, land use data and socio-economics. Among these six main modules, the most fundamental is that for water quality. This module was the first to be completed (DOE, 1994). It processed 55 water quality parameters, of which 30 parameters are considered the most significant for the purpose of water quality classification (Table 3.2). The structure of RB-MIS is shown in Appendix 3.1. This RB-MIS was also installed with the Geographical Information System (GIS) so as to cater the needs of the planning application, especially the mapping of classes along river segments. Two types of GIS package being used in the RB-MIS; GENASYS and ARC-INFO.

3.5 WATER QUALITY CLASSIFICATION SYSTEM BASED ON PHYSICO-CHEMICAL VARIABLES

In its water quality monitoring programme, besides enforcement activities, the DOE's main emphasis is the classification of rivers throughout the whole country. The results provide inputs for short and long-term planning, implementation of environmental policy, and also provide general information on the status of water quality for the public and interested parties. By 2004, a total of 16 catchment areas have been officially classified since the water quality management programme was started in 1985 (DOE, 1990, 1994). Basically, the selected parameters being used in classification system are based on both physico-chemical and biological variables, quite similar to other national classification system. However, the techniques being applied are different as compared to other countries.

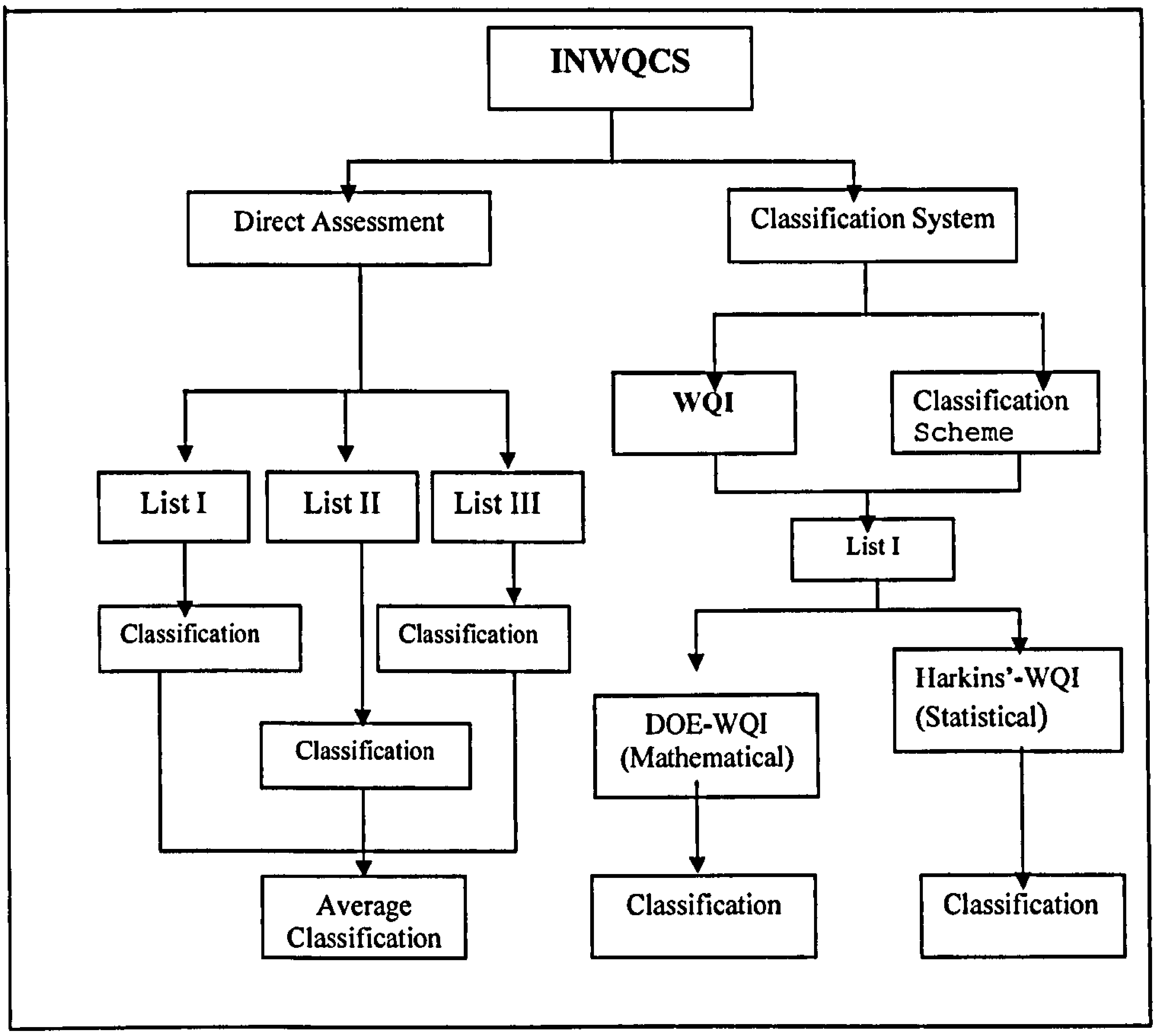
3.5.1 The Concept of National Water Quality Classification System

As discussed in Chapter Two, the design of the mathematical water quality index system, may exhibit the inevitable existence of exaggeration, ambiguous and eclipsing regions. Various mathematical models may exhibit different magnitude of information loss and the statistical models are difficult and impractical to perform. However, the DOE has accepted both approaches, based on the weighted arithmetic formulation and Harkins' statistical model for the assessment of the country's water quality. In complement to these two systems and in compliance to the international directives, the assessment based on national classification scheme is also being used. This classification scheme is an effective approach, particularly for checking the compliance of water quality criteria and standards for the issuance of licenses. Thus, the Malaysian concept of water quality assessment programme can be explained as in Box 3.1, which includes three components; the Direct Classification Assessment, Classification based on Department of Environment-Water Quality Index (DOE-WQI) and Classification based on Harkins' Water Quality Index (Harkins'-WQI).

3.5.1.1 The Direct Classification Assessment

One of the simplest methods of assessment being used is the direct classification assessment, which applies to all 30 variables as mentioned in the three lists in Table 3.2 (DOE, 1986). The measured concentration for each parameter is referred to the INWQS for the classification. This is to investigate the compliance of each variable to the water quality criteria and standards that incorporate safety purposes. Based on this assessment, actions can be taken for those who violate the criteria and standards as stipulated in the EQA, 1974. These classified variables are finally averaged to provide an estimated class.

However, along with this classification, the percentile approach is applied to the number of data collected to each variable. In such situation, the cost-effectiveness in water resources management can be determined, as it is not practical to take action every time a particular standard is exceeded. Therefore, the more cost-effective approach is to allow the standard to be exceeded for a proportion 10 % (normally) of the data (DOE, 1986). Thus, 90-percentile value is the concentration, which is exceeded by only 10 % of the data. Action will be taken only if more frequent exceedance occurs, indicating a critical problem where management efforts such as enforcement activity need to be step-up. If 100 Percentile is selected, it implies that no data exceedance is allowed and the standards imposed become more stringent.



Box 3.1 National River Classification Systems in Malaysia (Source: Modified from DOE, Malaysia, 1986, 1990, 1994)

3.5.1.2 Classification Based on the DOE-WQI Model

The water quality index system based on the aggregation of the six main parameters using the DOE-WQI model is the main approach being used in the national river classification system (List I in Table 3.2). As discussed earlier, the basis of the index classification system is the compliance to the INWQS (Table 2.2). The DOE-WQI model as indicated in Box 3.2 was designed by the local water quality experts through a lengthy process of development. Weighting values were assigned based on their significance and the magnitude of the impacts it carries as a result of water pollution. The six main parameters are computed into this model (Equation 3.1) and a single index number is obtained that correspond to the respective class standard value as indicated in Table 3.3.

$$\textbf{DOE-WQI} = 0.22*\text{SiDO} + 0.19*\text{SiBOD} + 0.16*\text{SiCOD} + 0.15*\text{SiAN} + 0.16*\text{SiSS} + 0.12*\text{SiPH}. \quad \text{.........Equation 3.1}$$

Note: * indicates multiplication

SiDO = Sub-index Dissolved Oxygen
SiBOD = Sub-index Biological Oxygen Demand
SiCOD = Sub-index Chemical Oxygen Demand
SiAN = Sub-index Ammoniacal Nitrogen
SiSS = Sub-index Suspended Solids
SiPH = Sub-index for Acidity / Alkalinity

Box 3.2 The Malaysian Department of Environment Water Quality Index Model (Source: DOE, 1986)

Class	DOE-WQI Standard Value	Class Limit
I	92.6	92.6 - 100
II	75.8	75.8 - 92.5
III	55.9	55.9 – 75.7
IV	31.9	31.9 – 55.8
V	<31.9	0 - 31.8

Table 3.3 Calculated standard values from DOE-WQI and the class limit (Source: DOE, 1986)

3.5.1.3 Classification Based on the Harkins'-WQI Model

In complement to the DOE-WQI, Harkins'-WQI is also being used to compare the results obtained from DOE-WQI. Harkins'-WQI employed the statistical approach, where the order of observations are ranked with respect to a set of control values, usually a set of water quality standards or recommended limits. The DOE has selected the control values based on the INWQS. Harkins (1974) developed WQI based on Kendall's non-parametric multivariate ranking procedure as represented in Box 2.4.

3.6 CLASSIFICATION BASED ON RIVER GEOMORPHOLOGY AND LAND USE VARIABLES

Land use has a direct impact on water quality. With increasing development pressure, the DOE's obligation and responsibilities in monitoring and planning activities has expanded, especially when new catchment areas are being monitored. To ensure that water pollution is contained at a minimum level, an integrated concept of water quality assessment was proposed both for short and long-term strategies. Thus, it was argued that the assessment should not only be based on physico-chemical parameters, but also based on the integration of river geomorphology and land use factors within a particular river basin. Although this approach is seen as qualitative, the results obtained can be compared with that of physico-chemical classification systems.

The approach for river geomorphology is the application of stream order system known as the Strahler's Classification of Stream Orders. This system was designed by Strahler who classified the river system according to the stream size and discharge volume (DOE, 1994). Normally, low order stream discharges a relatively small volume of water and as more streams converge to form a larger stream, gradually the discharge increases. Water pollutants are considered fully mixed in the main river, since this contains relatively greater discharge volume. If water pollutants exist in high concentration, where every branch of the streams is seriously polluted, then the self-purification capability of the receiving main river ceases to function effectively. This will contribute serious water pollution in the downstream receiving water body. Thus, the Strahler Stream Order reflects the quantity of water discharge while the land use activity indicates the possible contribution of point and non-point sources. The procedures and assumptions used by the DOE for the classification in the Strahler Stream Order are illustrated in Table 3.4.

The land use ranking method is based on an estimate of area and type of land use activity within a particular catchment area. Most undeveloped forested catchments would have good water quality while the developed catchments with human activities may exhibit moderate or low water quality. Using this approach, the qualitative judgement on the degree of pollution based on land use ranking is greatly simplified as illustrated Table 3.5.

Strahler Stream Order	Description of Stream
a) Low Order	Stream segments represent more than 50 % – 60 % of the cumulative lengths of a river basin. This means that the channels act as the primary conduits for water, sediment and other materials that are routed from hill-slopes to higher order rivers. The discharge from low order streams is small compared to higher order streams. Strahler Order of 1 to 2.
b) Mid Order	Stream channels with Strahler Order of 3 to 5. The channels from mid-order streams are characterised by moderate to steep gradients. A large part of the sediment received is delivered to high order streams. Deposition of sediment could occur in the stream channels and adjacent floodplains if the streamflow velocity is low and the terrain gradient is low.
c) High Order	Large rivers with Strahler Orders 6 and above. High order channels occur at lower elevations and the river widths are wider. Transport of sediment normally decreases. River discharge is considered to be large compared to mid and low order streams and riverbanks are easily breached during heavy rainfalls.

Table 3.4 Sub-basins definition based on Strahler Stream Order (Source: DOE, 1994)

Description of Landuse	Ranking Number	Category of River	Pollution Class
1. Fully forested sub-basin,least contributing to pollution.	1	Clean River	1
2. Greater than 50 % forest covers and recreational activities.	2	Fair	2
3. less than 50 % forest covers and agricultural activities, villages or towns.	3	Moderately Polluted	3
4. greater than 50 % agriculture, irrigation, town centres and industrial areas.	4	Polluted	4
5. Highly urbanised, commercial and industrial areas.	5	Severely Polluted	5

Table 3.5 Pollution ranking based on land use (Source: DOE, 1994)

Based on the combination of land use ranking with Strahler's three groups of sub-basins orders, the final ranking is shown as in Table 3.6. The general qualitative concept of this integrated system is that, if the ranking of land use pollution is the same for the two given sub-basins, then higher stream order may have a better water quality class due to greater volume of discharge.

Landuse Ranking	Sub-basins Stream Order: Final Pollution Class		
	Low Order	Mid Order	High Order
1	Class 1	Class 1	Class 1
2	Class 3	Class 2	Class 1
3	Class 4	Class 3	Class 2
4	Class 5	Class 4	Class 4
5	Class 5	Class 5	Class 5

Table 3.6 Combination of land use ranking with Strahler Stream Order (Source: DOE, 1994)

3.7 CLASSIFICATION BASED ON BIOLOGICAL VARIABLES

Biological monitoring programmes are closely related to the beneficial uses of water that is associated with the conservation and protection of fisheries (small-scale capture fisheries), aquaculture, livestock and crop irrigation. The reliable identification and groupings of these biological parameters was first documented in 1991. Based on several approaches from developed countries such as the European Community (EECD, 1978), Trent Biotic Index of United Kingdom (HMSO, 1987) and the Hilsenhoff of the United States (Hilsenhoff, 1987, 1988), a set of guidelines and procedures for biological classification were prepared, in association with the formulation of water quality criteria and standards. Based on these guidelines and procedures, the selected groups of biological parameters are phytoplankton (periphyton/plankton), aquatic macrophytes, benthic invertebrates and fish. However, among these parameters, periphyton remains the most representative parameter for all rivers. In 1992, a comprehensive biological classification system was started, where 10 water catchment areas were classified along with physico-chemical classification (DOE, 1994).

3.7.1 Biological Monitoring Station

A common methodology for biological monitoring is illustrated in Table 3.7, which described the main biological parameters, the criteria of selection of the monitoring station and the brief description of sampling procedures set up. Since biological monitoring is very costly, monitoring activities are not as rigorous as that of physico-chemical parameters where its frequency was set up to at least once during the dry season. Dry season is more conducive for monitoring since in wet season, most of the benthic macro-invertebrates are swept away by the rapid currents.

Biological Parameters Monitored	Criteria of Sampling Sites	Sampling Procedures
1. Phytplankton / Periphyton, 2. Aquatic macrophytes, 3. Benthic Invertebrates, 4. Fish.	1. DOE's existing water quality sampling stations were chosen, 2. Additional sampling sites were considered based on the need of catchment/sub-basin size, land-use and hydrological characteristics, stream micro-habitats, existing uses and salinity limit, 3. Accessibility of the sampling sites, 4. Existing hydrological and water quality stations, 5. Stream micro-habitats included rapids, riffles and pools along a particular length of river segment, 6. Avoid the coastal waters and the river mouth sampling sites.	1. Frequency of sampling at least once during the dry period, 2. The range of parameters included the sedentary organisms, periphyton/plankton and aquatic macrophytes, benthic invertebrates and fish communities. 3. Mobile zooplankton / invertebrates are avoided in the study, 4. Combination of parameter variables selected for the biological inventory system does not necessarily include a complete set of data for all categories of organisms. For practical reasons, it is envisaged that periphyton community could be an appropriate indicator species/taxa for some river basins,

Table 3.7 The methodology used for River Basin Biological Inventory System (Source: DOE, 1990)

All existing DOE's water quality stations were chosen for biological monitoring and the needs for additional sampling sites were based on specific cases such as major project being carried out within the respective catchment area. The results obtained provide a comparison with those results from physico-chemical assessment approach. Sampling has not been carried out near the estuary or in any coastal waters. Unlike the physico-chemical parameters where monitoring activities have been handed to a private agency since 1995, the biological monitoring are being conducted by the consultant groups represented by respective five local universities.

3.7.2 Analysis of Water Samples

The aquatic biological sampling and laboratory analyses involve several methods. Different methods as indicated in Appendix 3.2 are being used. The selections of these methods were based on the geographical locations, the existence of species abundance and types of species. The sampling methods and laboratory analyses are referred to the Standard Method of APHA (APHA, 1985, 1995; DOE, 1992). In sampling techniques, the grabbed samples are mainly used for bacteria and aquatic macrophytes, benthic invertebrates were based on Eckman grab and for fishes were the casting net.

3.7.3 Biological Classification Methods

The DOE, Malaysia has selected several approaches in the calculations of the biological index diversity, where different species nay use different biological index system. Based on the monitored biological variables, the DOE is applying the following three main types of biological index and classification system.

3.7.3.1 Shannon-Weiner Index

The Shannon-Weiner Index has been used for calculating the diversity of the phytoplankton and zooplankton, especially the periphyton (Box 3.3). The plankton were identified up to the level of genus and species, and separated into algal sub-divisions. Indices calculated were species diversity, richness and evenness. This index can be used to compare the impact of water pollution both spatially and temporally. Normally, the results of diversity index decreases downstream from the wastewater outfall. As the distance increases away from the outfall, the index value gradually increases with increasing in the quality of water. However, Shannon-Weiner Diversity Index cannot be used for direct comparison with the physico-chemical classification since it involves only three related classes in the description of the degree of pollution as indicated in Table 3.8, whereas, the physico-chemical classification normally involves five classes.

As examples, the scrapped algae taken from the periphyton samples, the density (number of algal cells or units/ml.) was calculated for each genus. These numbers of cells per known volume was converted from replicated counts to number of cell per ml. and were expressed as algal density per unit area of substrate. Based on this counted cells, the plankton species diversity (H') of each sample was calculated using the Shannon-Weiner Index (1949) as in Equation 3.8 and the value of H' obtained is described as in Table 3.9.

$$\text{Diversity Index (H')} = \sum_{i=1}^{n} (P_i \ln P_i) \qquad \text{....Equation 3.8}$$

where, n = number of species in the sample

P_i = proportion of total sample belonging to *ith* species

$\ln$ = natural logarithm.

Box 3.3 Shannon-Weiner Index
(Source: DOE, 1994)

Shannon-Weiner Diversity Index	Degree of Pollution
a. Value greater than 3	Clean water: represent original biological communities.
b. Value between 3 to 1	Moderate pollution: changing but reducing communities.
c. Less than 1	Heavy pollution: decreased communities.

Table 3.8 Descriptor used in Shannon-Weiner Diversity Index
(Source: DOE, 1994)

3.7.3.2 Bio-Monitoring Working Party Index (BMWP)

The BMWP is a biological technique using an index score system. The value of BMWP obtained is classified using Table 3.9 (DOE, 1994). A range of scales was designed for BMWP, where scores obtained relates to the corresponding classes and descriptors of water quality. Since BWMP is based on these five-banded classes, it can be compared with the results of classification obtained from physico-chemical parameters. BMWP is commonly used for benthic macro-invertebrates where the most sensitive organisms to pollution such as the stoneflies was given the highest score of 10, and the most pollution-tolerant organisms such as oligocheate and nematoda worms was given the lowest score of 1. This score was only given once if more than one species present. Finally, an average scores value known as Average Score for Taxon (or families) (ASPT) was calculated by dividing the sum of BMWP scores with the total number of taxa (families/orders). Usually, this result of score comes together in pairs as BMWP/ASPT where BMWP score of greater than 100 are equivalent to ASPT score of greater than 4 that indicates clean water or pollution free (See Table 3.10).

River Class	BMWP Values	FBI Values	Descriptor
I	7.26-10.00	0.00-3.75	Excellent water quality, no treatment is necessary for water supply.
II	5.76-7.25	3.76-4.25	Good quality, requires conventional treatment.
III	4.26-5.75	4.26-5.75	Slightly polluted, requires conventional treatment.
IV	3.76-4.25	5.76-7.25	Moderately polluted to polluted, extensive treatment needed.
V	0.00-3.75	7.26-10.00	Heavily polluted, extensive treatment required.

Table 3.9 The scale that relates to class value for BMWP and FBI (Source:DOE, 1994)

3.7.3.3 Family Biotic Index (FBI)

The FBI is an index based on species diversity where calculation is performed up to family level. There exist several types of FBI and the most common FBI being used by DOE is based on Hilsenhoff Biotic Index (1987). Like the BMWP, the FBI value obtained can be used to compare with the results of physico-chemical parameters. The score system in Hilsenhoff Biotic Index was based on specific tolerance or quality values for the respective families designated in orders from 1 to 10 as illustrated in Table 3.10. When compared to BMWP, the scores were oppositely assigned. For example, score for the most sensitive organisms such as stoneflies was given 1, whereas in BMWP was given 10 and for the most tolerant species was given 10, whereas in BMWP was given 1. These scores, which were assigned for each family represented from a particular water sample, were then multiplied with the number of individuals of each family.

Although these two systems seem to be quite subjective in their approach, the results obtained can be compared with each other. Comparison can be performed with other approaches, such as the Shannon-Weiner Index for the bacteria or algae and zooplankton, the Index of Biotic Integrity for fish and the Sequential Comparison Index, which make used of two or more kinds of organisms. Finally, an overall diversity index can be estimated or classified accordingly based on their frequency of occurrence.

Group of Organisms	**Score**	
	BMWP	**FBI**
1. Stream Mayflies, Stoneflies, Snail-case caddisflies, Aquatic caterpillar (moths)	10	1
2. River shrimps, Glass shrimps, Freshwater crabs, Side-swimmers, Scud, Isopod. Green-eyed skimmers (dragonfly), Common skimmers-dragonflies nymphs, Clubtail dragonflies, Clean-water damselflies.	8	2
3. Mayflies, Spring stoneflies, Primitive caddisflies, Northern caddisflies.	7	3
4. Clean-water snails, Damselflies	6	4
5. Water strider, Water scorpion, Backswimmer (bugs), Water boatman. Predaceous diving beetles, Water scavanger beetles, Longtoed water beetles, Riffle beetles, Rove beetles, Aquatic weevils, Caddisflies adult, Crane flies, Black flies, Freshwater free-living flatworm.	5	5
6. Pollution-tolerant small mayflies	4	6
7. Round-mouthed snails, River snails, Pond snails, Pouchsnails, Orb snails, Seed shells, Leeches, Bivalves.	3	7
8. Midges, Mosquito larvae and pupae.	2	8
9. Aquatic earthworms, free-living roundworms.	1	10

Table 3.10 The score in BMWP and FBI
(Source:DOE, 1994)

3.8 DISCUSSION

The water quality management programme has undergone great changes after the institutionalisation of Environmental Quality Act, 1974 and the establishment of the Department of Environment in 1975. The deterioration on water environment has had considerable impact on economic achievement and substantial funds have been allocated in managing and controlling water pollution. In view of this, the DOE's has had to widen its short and long-term planning strategies so as to ensure that rivers remain clean and free from point and non-point sources of water pollution.

The national water quality monitoring programme involves the incorporation of two main assessment systems; the index system and the classification scheme as illustrated in Table 3.11. In contrast to some countries, these two systems are treated separately. Basically, the results obtained from index system (either DOE-WQI) are more objective than the national classification scheme (House, 1986; Saeger, 1994). In the presentation of results, these two systems are capable of displaying, either:

- as class values that easily be interpreted by the planner and decision-maker, politician or other non-technical persons, and

- or as a single number, where the refined changes in water quality can easily be determined and readily to be used by those technical person. Based on Table 3.12, the WQI obtained from DOE-WQI is readily converted into percentage and the type of beneficial uses can be determined directly from this table.

A comprehensive water quality management programme should, however include every possible way of assessing water quality. Physico-chemical alone cannot provide adequate information for sound management of aquatic resources because they tell us little of the effects of pollution on living organisms (Meybeck, 1989; Metcalf, 1994). In contrast to physico-chemical and geomorphological classification, biological classification is another way of assessing water quality using benthic organisms as variables. The option of selecting biological variables for classification is so wide due to the vast species diversity of tropical waters. DOE has selected four main groups as illustrated in Table 3.7, and periphyton seems to be the most common variables. The advantages of this system are that aquatic organisms integrate the effects of multiple stresses and demonstrate cumulative impact of environmental condition overtime, whereas chemical data are instantaneous in nature which requires large numbers of measurements for an accurate assessment (Sladecek, 1973; De Pauwe et al., 1983). It also provides an early warning function by detecting intermittent pollution and subtle disruptions that would likely be missed by chemical analyses (Howmiller and Scott, 1977; Reynoldson, 1984). In addition, the impacts of water pollution are not necessarily chemical in nature; biological classifications may also be able to detect the impact of flow alterations, habitat destruction, and over exploitation of aquatic resources (Karr, 1981).

Assessment System	**Method**	**Result Presentation**	**Advantage / Disadvantage**	**Remarks**
1. Classification Scheme	a) Basic Statistical	Class value	a) Subjective	Information lost
2. WQI	a) Mathematical	a) Single numerical value	a) Objective	Information loss less pronounce than (1).
	b) Statistical	b) Single numerical value	b) Objective	Difficult to apply. Cannot compare with different data set.
3. WQI + Classification Scheme ***	a) Mathematical	a) Single numerical value	a) Relatively Objective (Reduced subjectivity)	a) Reduces information loss due to classification scheme.
	b) Statistical	b) Class value		b) Statistical method being used is for comparison.

Table 3.11 Water quality assessment approach

Note: *** The Malaysian approach in water quality assessment

<table>
<tr><td>USAGE</td><td>0%</td><td>10 %</td><td>20%</td><td>30%</td><td>40%</td><td>50%</td><td>60%</td><td>70%</td><td>80%</td><td>90%</td><td>100%</td></tr>
<tr><td>GENERAL</td><td colspan="6">VERY POLLUTED</td><td colspan="2">SLIGHTLY POLLUTED</td><td colspan="3">CLEAN</td></tr>
<tr><td>PUBLIC WATER SUPPLY</td><td colspan="4">NOT ACCEPTABLE</td><td>DOUBTFUL</td><td colspan="3">NECESSARY TREATMENT BECOMING MORE EXTENSIVE</td><td>MINOR PURIFICATION REQUIRED</td><td colspan="2">PURIFICATION NOT NECESSARY</td></tr>
<tr><td>RECREATION</td><td colspan="2">NOT ACCEPTABLE</td><td>OBVIOUS POLLUTION APPEARING</td><td>ONLY FOR BOATING</td><td>DOUBTFUL FOR WATER CONTACT.</td><td colspan="2">BECOMING POLLUTED STILL ACCEPTABLE. NEED BACTERIA COUNT.</td><td colspan="4">ACCEPTABLE FOR ALL WATER SPORTS</td></tr>
<tr><td>FISH AND WILDLIFE</td><td colspan="3">NOT ACCEPTABLE</td><td>COARSE FISH ONLY</td><td>HANDY FISH ONLY</td><td>DOUBTFUL FOR SENSITIVE FISH</td><td>MARGINAL FOR TROUT.</td><td colspan="4">ACCEPTABLE FOR ALL FISH</td></tr>
<tr><td>NAVIGATION</td><td colspan="3">NOT ACCEPTABLE</td><td>OBVIOUS POLLUTION APPEARING</td><td colspan="7">ACCEPTABLE</td></tr>
<tr><td>TREATED WATER TRANPORTATION</td><td>NOT ACCEPTABLE</td><td colspan="10">ACCEPTABLE</td></tr>
<tr><td>USAGE</td><td>0%</td><td>10%</td><td>20%</td><td>30%</td><td>40%</td><td>50%</td><td>60%</td><td>70%</td><td>80%</td><td>90%</td><td>100%</td></tr>
</table>

Table 3.12 General rating scale for the DOE-Water Quality Index (WQI) (in percentage). (Source: DOE, 1995).

Some of the disadvantages of biological assessment systems have been described by Hellawell (1986), and Reynoldson (1984, 1989). However, they concluded that no single system would satisfy all requirements, and recommended that several types of these assessment systems can be used together. The biotic assessments respond only to organic pollution and are geographically restricted (Meybeck, 1989; Metcalf, 1994). Thus, it will not be feasible to develop these assessments to be applied to the national scale water quality management schemes. This would require an extensive database such as those prepared by Sladecek (1973) for the European Community countries and Hilsenhoff (1987) for the United States. Some benthic organisms that are being used in the bio-assessments responded to seemingly minor changes in substrate particle size, organic content and even texture. As a result, the discrimination between the effects of pollution and other environmental factors is often difficult to quantify (Sladecek, 1973). The life history of various species of organisms is very complex, thus the results of bio-assessment scores can vary seasonally (Hellawell, 1986).

The other major obstacle to incorporating bio-assessments into water management policies has been the lack of realistic targets with which to compare assessment values and to serve as water quality criteria. The United States EPA (1990) indicated that biological criteria are much more sensitive than chemical criteria. Thus, individual States are directed to develop biological criteria so as to improve water quality standards, to identify impairment of beneficial uses, to assist in setting programme priorities and to detect problems, which might otherwise be missed or underestimated. At present, about twenty States in the U.S. have been using some form of biological assessment and five States (Florida, Arkansas, North Carolina, Maine and Ohio) are currently using biological criteria to define aquatic life use classifications, and enforce water quality standards (US EPA, 1990).

Based on the discussion of the development of various approaches in water quality assessment, the choice to be made of either to use physico-chemical or biological is very difficult. However, based on the progress of water quality management and development, the U.S. EPA, the United Kingdom Water Authorities, the Canadian Water Authorities and most of the European Community countries have been using both of this physico-chemical and biological classification systems together. These systems are used together as a check on each other so as not to depend only on one particular type of classification.

It is therefore timely for the DOE in Malaysia to review and assess the effectiveness of the existing water quality assessment system. The DOE-WQI is the main assessment system being used throughout the whole country, since it was established in 1985. Some of the river basins in the country are geographically diverse such as the Borneo states of Sabah and Sarawak. Due to this diversity effects, a uniform assessment system like DOE-WQI is inappropriate to be used in these two states, since the concentration of the selected variables that exist under natural conditions are different. These natural concentration values may exceed the values in water quality criteria and standards from other geographical regions. This is one reason why different water quality standards have been adopted in different geographical regions. Therefore, the DOE of Malaysia should introduce another method of assessment that is more flexible to allow different criteria and standards to be used. The new method should also cater for the inclusion of different type of variables, such as the biological variables, hydrological features, land use variables, the socio-economic and demographic variables. Thus, in view of this, a set of criterion is developed as shown in Table 3.13.

As discussed earlier, the application of Harkins'-WQI model is only used to make comparison for a specific station. Fundamentally, it should not be used to make comparison with classification results from other catchment areas. In the next chapter, a new approach that seems to acquire the criteria and perhaps may reduce or fill up the gaps of the existing approaches, in particular the DOE-WQI will be discussed in details. This new approach is the Artificial Neural Network.

Criteria for New Assessment Method
1. Objective; 2. Reproducibility; 3. Flexibility; 4. Conform to National Water Quality Criteria and Standards; 5. Indication for potential uses of water; 6. Results are more refine; 7. Results are easily understandable; 8. Comply to expert opinion; 9. Capable in providing water quality trend; 10. Capable in assessing water quality with relatively small amount of data; and 11. Results are comparable temporally and spatially.

Table 3.13 Suggested criteria for new the water quality assessment method

CHAPTER FOUR

APPLICATION OF
ARTIFICIAL NEURAL NETWORKS

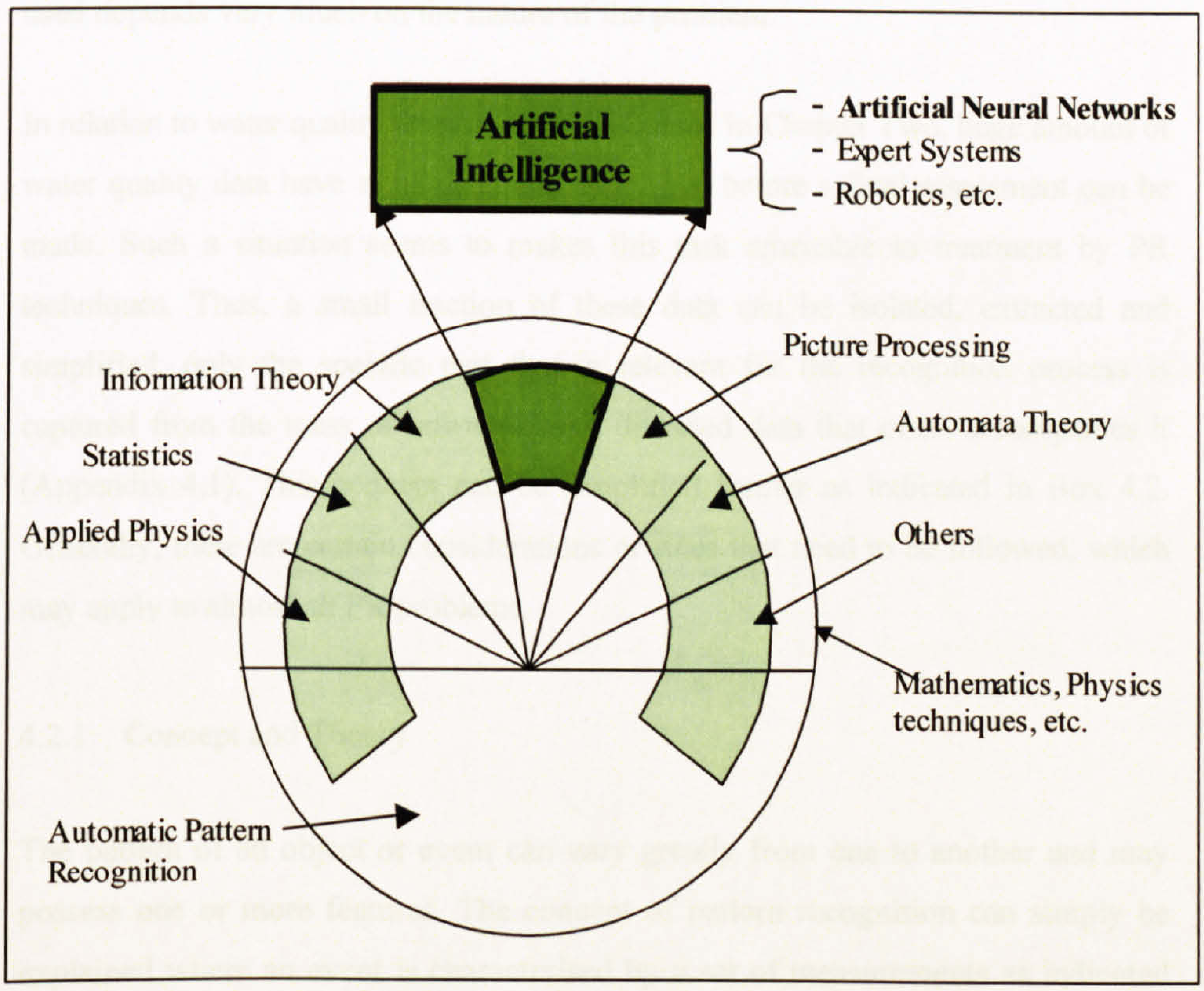
4.1 BACKGROUND

Environmental laws are becoming more stringent in curbing water pollution. However, human activities continue to discharge new pollutants, and therefore increase the frequency of discharging the less common (less significant) pollutants, especially in highly developed areas. As a result, monitoring and reporting systems cannot cope. Some significant variables that were not included earlier in the development of index and classification systems, because of infrequent monitoring, now need to be considered. In such situations, the existing assessment technique of water quality needs to be made more flexible.

The assessment of water quality based on index systems and classification schemes has been used for such a long time (Horton, 1965). Although there are some disagreement among the water scientists on the design of various index systems, and in view of the subjectivity of the classification scheme, their applications and usefulness in water resources management are often undisputed by most of the national water resources controlling agencies. The limitations of these two assessment systems have been discussed in detail in Section 2.6. In response to these deficiencies, new techniques and approaches are being explored, which may produce assessment systems that are operationally simple, flexible and comprehensive, where the results obtained are easily understandable.

One of the new approaches that makes possible in the assessment of water quality is based on the concept of Pattern Recognition (PR). The concept of PR covers broad areas as indicated in Box 4.1 (Verhagen, 1975; Schalkoff, 1992; Theodoridis and Koutroumbas, 1999). Among of these areas, the Artificial Intelligence (AI) seems to provide better performance over the traditional approaches in resolving some of the complex issues of real world. One of the main techniques in AI that is widely being used is the Artificial Neural Networks (ANN). **Based on the performance of ANN**

in many applications, the main aim of this chapter is to explore the possibility or reliability of incorporating the ANN's approach of AI using the theoretical concept of PR in classification of water quality.



Box 4.1 The relationships between Artificial Intelligence and other disciplines. (Source: Modified from Verhagen, 1975; Schalkoff, 1992; Theodoridis and Koutroumbas, 1999).

4.2 OVERVIEW ON PATTERN RECOGNITION

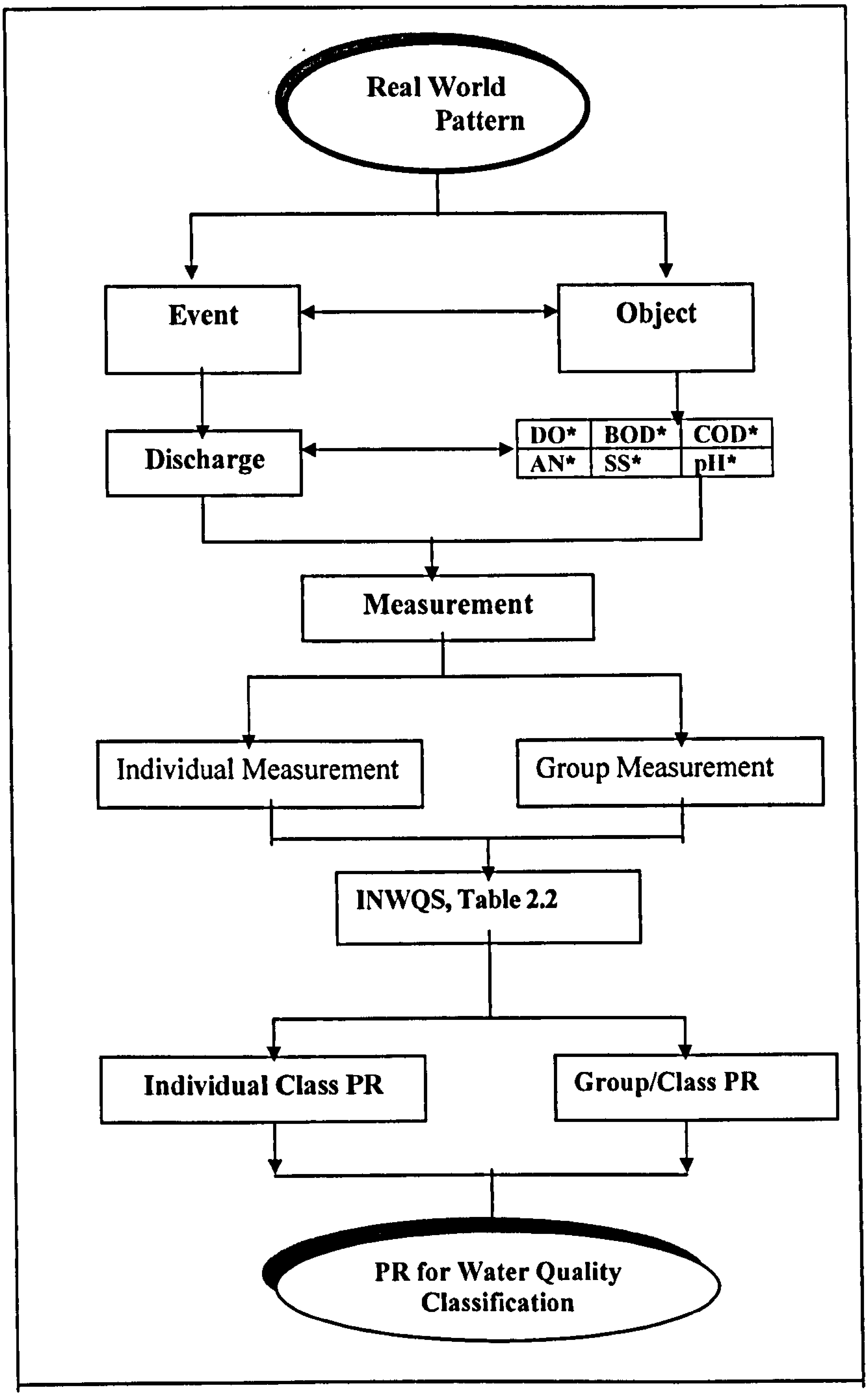
Pattern Recognition (PR) is increasingly becoming an important component of intelligent computer-based systems. Its application is widely used in machine vision, character recognition, computer-aided diagnosis and speech recognition. Pattern recognition is defined as the science that concerns on the description or classification (recognition) of measurements (Varmuza, 1980; Schalkoff, 1992;

Ripley, 1996; Friedman and Kandel, 1999; Mather, 1999). In general terms, the techniques are capable of discriminating effectively between two or more different populations or groups of object or event. Patterns may exist as one-dimensional (waveforms), two-dimensional images, three-dimensional solid shapes or other multi-dimensional shapes. Consequently, the type of pattern being used depends very much on the nature of the problem.

In relation to water quality assessment as discussed in Chapter Two, huge amount of water quality data have to be dealt and simplified before a final assessment can be made. Such a situation seems to makes this task amenable to treatment by PR techniques. Thus, a small fraction of these data can be isolated, extracted and simplified, only the specific part that is relevant for the recognition process is captured from the mass of unwanted and distorted data that often accompanies it (Appendix 4.1). This concept can be simplified further as indicated in Box 4.2. Generally, there are certain considerations or rules that need to be followed, which may apply to almost all PR problems.

4.2.1 Concept and Theory

The pattern of an object or event can vary greatly from one to another and may possess one or more features. The concept of pattern recognition can simply be explained where an event is characterised by a set of measurements as indicated in Box 4.2. For example, an event was characterised with specific pattern when a sample of water taken, contained two different variables with two set of measurements. This event which occurred in a specific time and space, exhibits a virtual point taken in a 2-dimensional co-ordinate system or pattern space with a specific pattern vector. These measurements can also be referred to the standards measurements (concentrations) of the six variables taken from INWQS, Table 2.2, which include; ammoniacal nitrogen (AN), biological oygen dmand (BOD), chemical oxygen demand (COD), dissolved oxygen (DO), acidity or alkalinity (pH) and suspended solids (SS). Based on Box 4.2, a water sample that contained the six variables with six measurements can be represented as a point taken in a 6-dimensional co-ordinate system, which acquires a specific pattern vector.



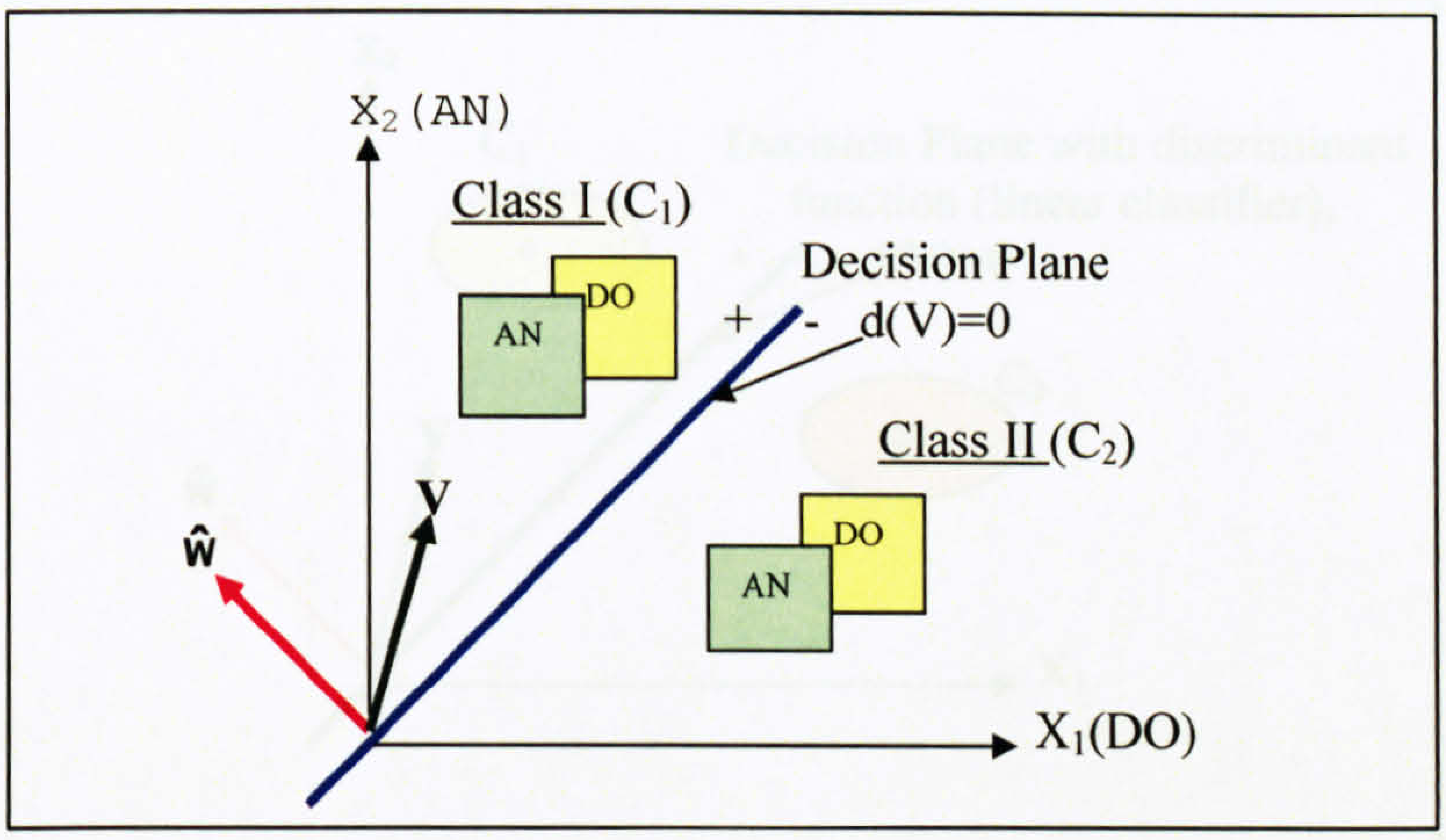
Box 4.2 Application of Pattern Recognition concept for INWQS

(Note: * AN – Ammoniacal Nitrogen; BOD-Biological Oxygen Demand; COD-Chemical Oxygen Demand; DO – Dissolve Oxygen; pH-Acidity or Alkalinity; SS-Suspended Solids)

The water sample of the six standards variables with six standards measurements for each class represents a PR of water quality for that particular class. Since different class standards acquire different PR of water quality, there exist five PR for five classes of water quality classification. The PR for Class I standards posses a specific pattern vector, which represent the highest water quality standards, whereas the PR for Class V posses a specific pattern vector, which represent the most polluted water quality class. These designated classes with specific pattern vector can also be defined as *a priori* of the respective classes. Each *a priori* of the respective class acquire a specific properties with known ranges of values of that class. Thus, there are five *a priori* with five different properties as represented by five banded classes, each with the six selected variables.

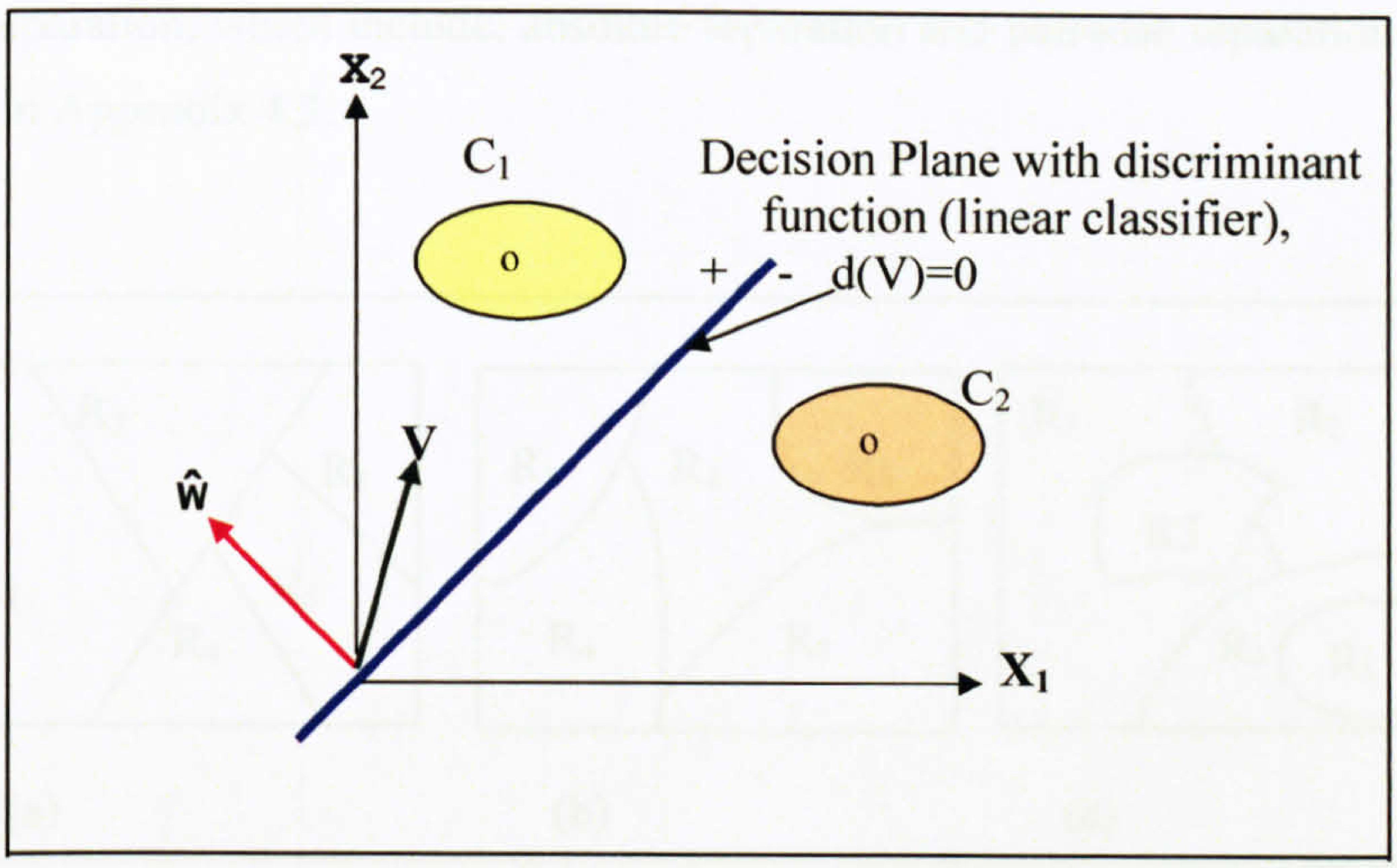
4.2.1.1 Linear Pattern Recognition

A simplest form of PR is the linear PR that can be explained by taking an example from Table 2.2 of INWQS where two water quality variables and two classes are selected for PR. Class I characteristics can be represented by a set of measurements comprises of variable ammoniacal nitrogen (0.1 mg/l) and dissolved oxygen (7.0 mg/l) and Class II characteristics represented by same variables but with another set of measurements (ammoniacal nitrogen, 0.3 mg/l and dissolved oxygen, 5.0 mg/l). These two classes are assumed as two mutually exclusive classes separated linearly by a decision line (or decision plane) as indicated in Box 4.3 and 4.4. The decision line constitutes the linear classifier based on discriminant function and its role is to divide the feature space into regions that correspond to either Class I or Class II. The border of each region is a decision boundary, which classifies the two regions. This concept of classifier and region is more widely applied in statistical PR and Neural PR. This decision line is defined as a decision vector or weight vector ($\hat{w}$) joined in an orthogonal direction to the line (plane) that may pass through the origin (Varmuza, 1980; Friedman and Kandel, 1999). This weight vector that will decide whether an unknown pattern vector (V) falls either on the left or on the right side of the decision line or falls within the decision region of Class I or Class II.

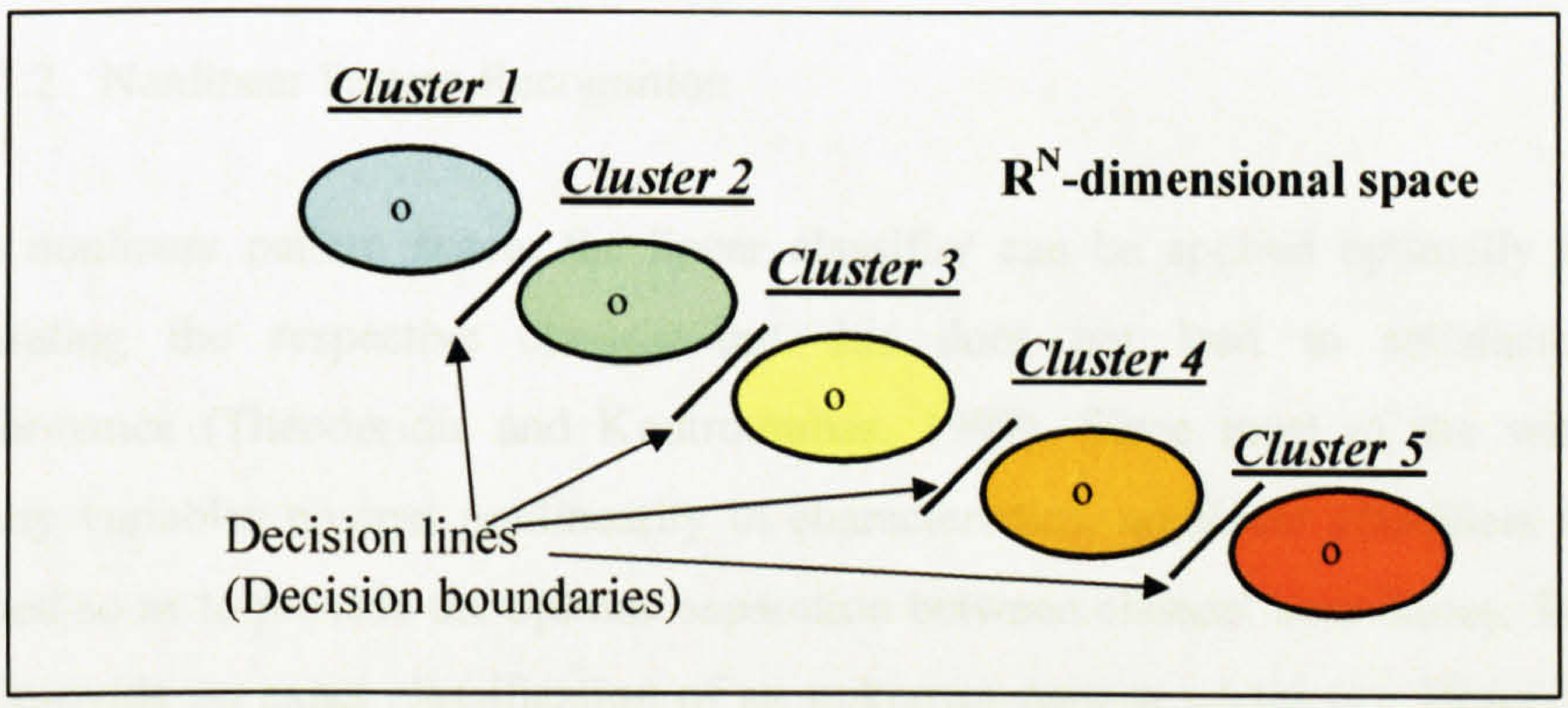


Box 4.3 Two-dimensional pattern space with two groups of clusters (Source: Modified from Varmuza, 1980; Friedman and Kandel, 1999)

Thus, all the five clusters (classes) may exist in a multi-dimensional space (or R^N-dimensional pattern space, where N = 5) and will be separated by linear, non-linear or mixture of linear and non-linear discriminant functions as illustrated in Box 4.5. These discriminant functions may also constitute decision cluster boundaries for the five clusters (five classes). Therefore, in a two-dimensional space, the decision boundaries as in Box 4.5 can also be represented as in Box 4.6a, known as linear (piecewise) decision boundaries, Box 4.6b as quadratic (hyperbolic) decision boundaries or Box 4.6c as general (relative) decision boundaries. Since the relationships of the six water quality variables are non-linear, Box 4.6c may represent the pattern of the five classes of the INWQS (Table 2.2). However, in multi-dimensional (R^5) pattern space, the geometrical shapes will be different and impossible to visualise on paper. However, it is quite possible to visualise the shape in 3-dimensional pattern space separated by a linear decision boundaries for three features as illustrated in Box 4.7. Since water quality variables are dominated by nonlinearity characteristics, in real situation the geometrical shapes and the boundaries are very difficult to visualise.

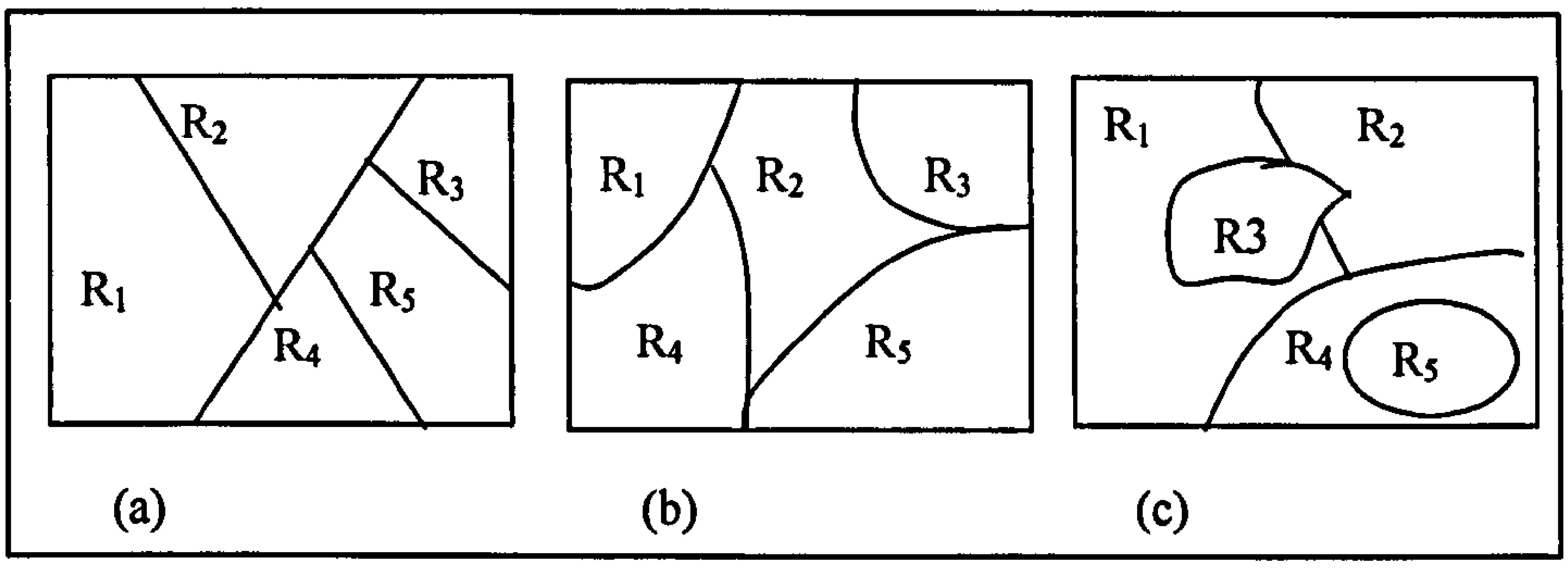


Box 4.4 Two clusters (classes), C1 and C2 with the centre of gravity (equidistance) to decision line (from Box 4.3).



Box 4.5 A simple illustrations of five clusters (classes) of water quality exists in R^N-dimensional space separated by decision lines (planes).

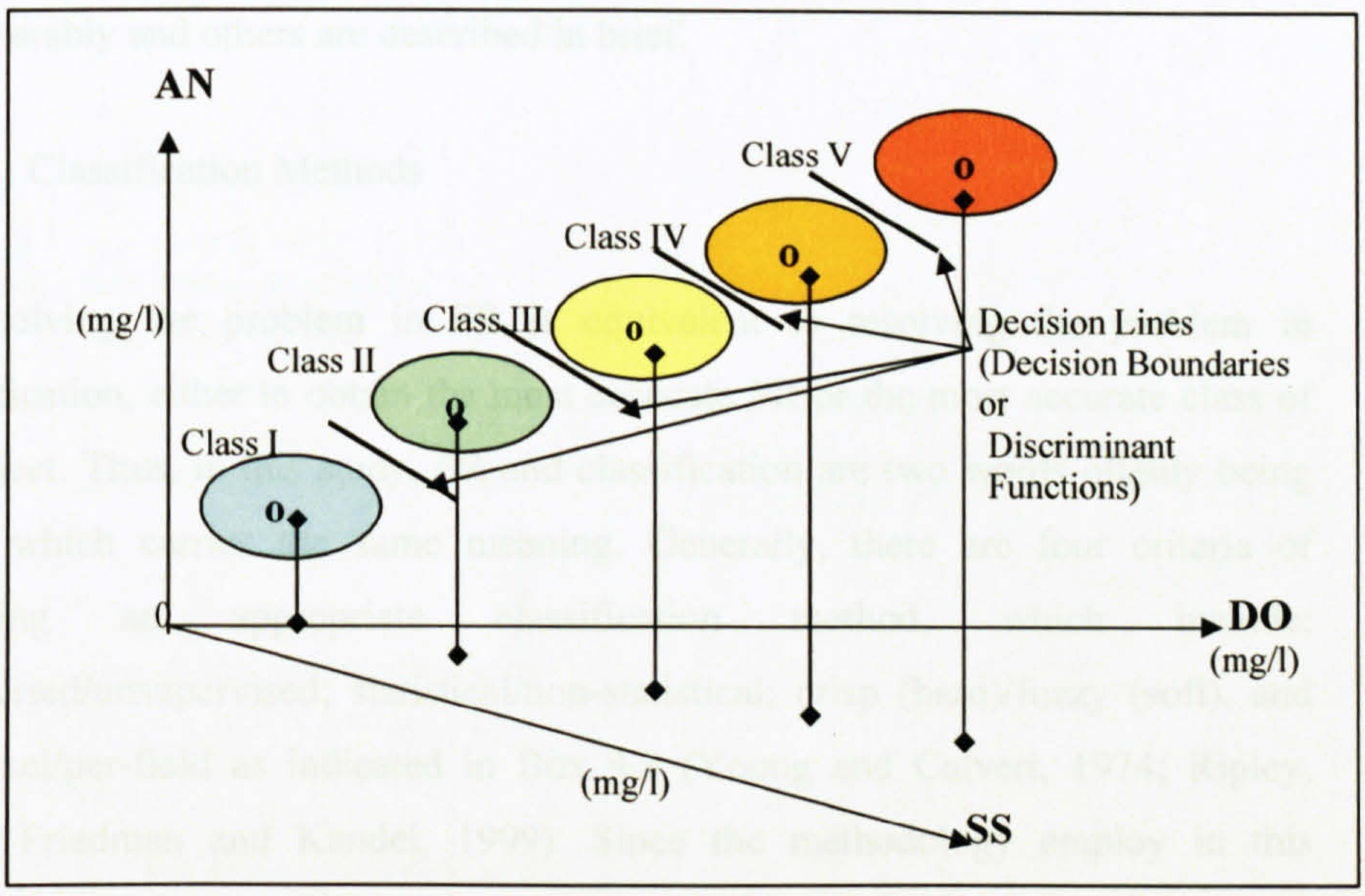
The determination of the discriminant function (decision line), also referred as the classifier, and is fundamental since it determines which region (class) an unknown pattern vector may fall. Therefore, one of the easiest ways is to describe the relationship of two features separated by a decision line (or linear binary classifier) based on two classes, C_1 and C_2 (Box 4.3). This decision line can be determined as indicated in Appendix 4.2, where the decision function for these two classes is separated by the hyperplane which can be represented as Equation 4.2 and for arbitrary vector which may fall either one of the two classes is represented as Equation 4.3. However, this decision line may exist as two main types of separation, which include; absolute separation and pairwise separation as indicated in Appendix 4.3.



Box 4.6 Examples of decision regions in two-dimensional space. (Source: Schalkoff, 1992)

4.2.1.2 Nonlinear Pattern Recognition

In a nonlinear pattern space, the linear classifier can be applied optimally for separating the respective classes, but this does not lead to satisfactory performance (Theodoridis and Koutroumbas, 1999). Since most of the water quality variables possess nonlinearity in characteristics, nonlinear classifiers are needed so as to provide the optimal separation between classes' boundaries. This will provide an exact classification of an unknown pattern vector (V). However, this condition normally creates problem in separating different classes. As compared to linear pattern space, a single straight line can be drawn to separate the two classes in 2-dimensional pattern space as indicated in Appendix 4.4, but not in nonlinear pattern space, where it is difficult to visualise the separation. This nonlinearity problem creates an even and odd parity patterns, which is oftenly known as Exclusive OR (XOR) Boolean function (Pao, 1989; Carling, 1992; Graupe, 1997; Theodoridis and Koutroumbas, 1999). Usually, this Boolean function is used in classification, particularly for linear separation between two classes. Due to this XOR problem, no single straight line can be drawn to separate the two classes in 2-dimensional pattern space as indicated in Appendix 4.4. However, if the centres of gravity of the two classes are assigned, then they can be separated by straight lines as linear classifiers, and this condition is known as AND or OR (as indicated in Appendix 4.4 and Appendix 4.5).

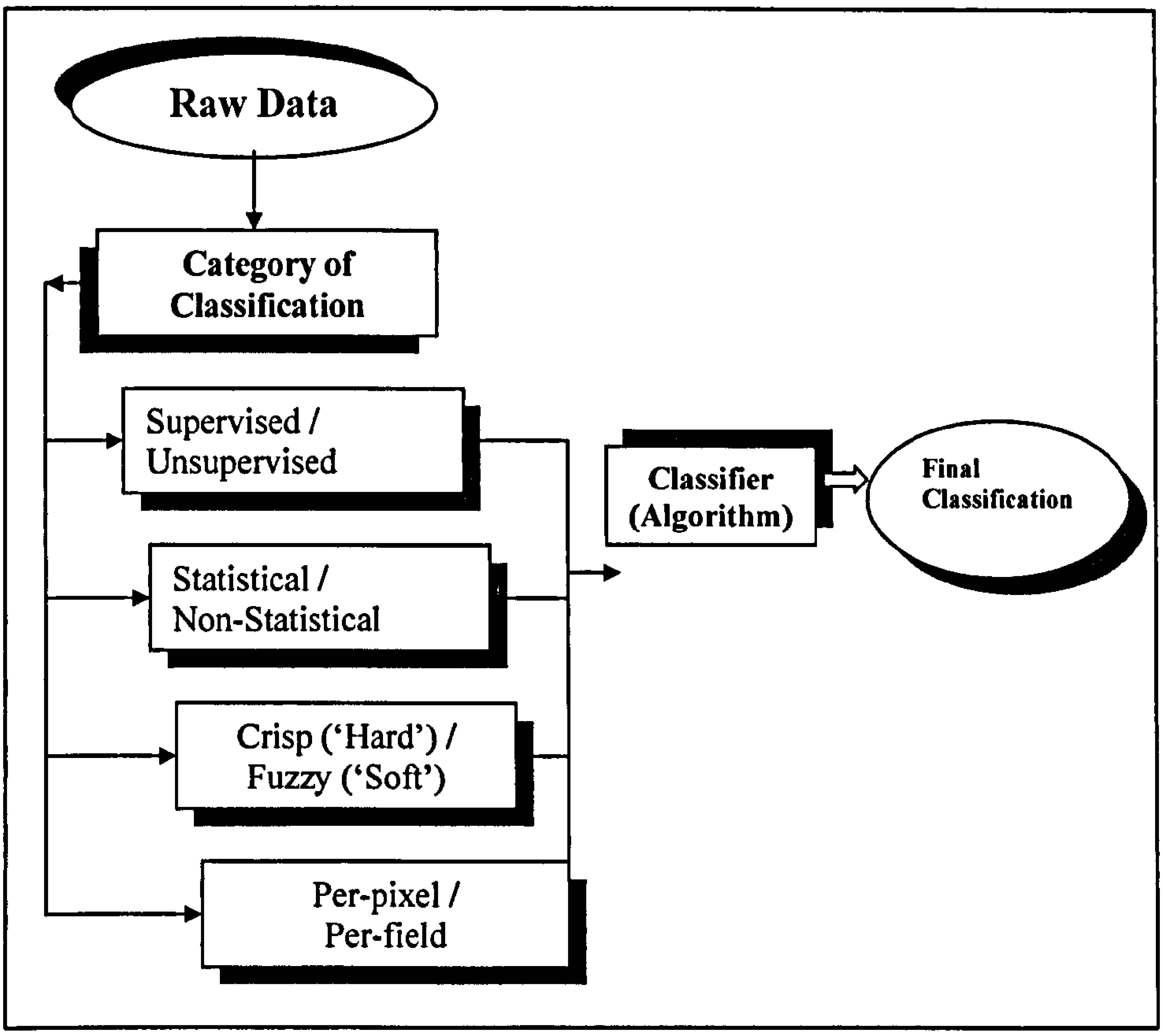


Box 4.7 Concept of three-dimensional pattern space with three features (Source: Modified from Andrews, 1972; Mather, 1999)

In resolving the problems of discriminating boundaries (decision lines) especially in nonlinear PR, classifiers are used. As indicated earlier, the function of classifier in PR is to effectively discriminate the exact boundary of each class, thus provide an exact class for which the object belonged to. Classifier generalise or resolve the XOR problem through the incorporation of AND or OR function. The application of these classifiers depends on the nature of the data available and the purpose of the PR or classification to be performed. There are two types of classifiers that have been developed, which include; statistical classifier and the non-statistical classifier. Statistical classifier is based on purely statistical estimations, which leads to some assumptions. Normally these assumptions refer to the common assumptions based on the frequency distribution or Gaussian (normal) distribution of the data form. In case of non-statistical classifier, no assumptions about the frequency distribution of the data used is made, and do not use the statistical estimates. Examples of the type of classifiers that are commonly being used in PR are; statistical classifier (Minimum-Distance Classifier, Maximum-Likelihood Classifier, Parallelepipied Classifier), Neural-Nets Classifier, Fuzzy Classifier and Syntactic Approach (Friedman and Kandel, 1999). Only the main classifiers that will be applied in this research are discussed considerably and others are described in brief.

4.2.2 Classification Methods

In resolving the problem in PR is equivalent to resolving the problem in classification, either to obtain the most accucate PR or the most accurate class of an object. Thus, in this study, PR and classification are two words oftenly being used, which carries the same meaning. Generally, there are four criteria of selecting an appropriate classification method, which include; supervised/unsupervised; statistical/non-statistical; crisp (hard)/fuzzy (soft), and per-pixel/per-field as indicated in Box 4.8 (Young and Calvert, 1974; Ripley, 1994; Friedman and Kandel, 1999). Since the methodology employ in this research covers most of the supervised/unsupervised and statistical/non-statistical classification, these two methods will be discussed considerably in the next section. The crisp (hard)/fuzzy (soft) and per-pixel/per-field classification are normally being used for land surface classification in the field of remote sensing. Thus, it is beyond the scope of this discussion. However, the concept of per-pixel/per-field classification may resemble the concept in water quality classification. These per-pixel/per-field classification may be returned as per-variable/per-group of variables classification as indicated in Section 2.3 and 3.5 (INWQS Table 2.2 and Box 3.1) that needs to be explored further. When dealing with the raw data, it should be very clear that the most suitable classification method in resolving classification problem is totally dependent on the nature of these data, the objective of the classification and the appropriate classifier as indicated in Box 4.8.



Box 4.8 Four criteria of selecting classification method

4.2.2.1 Supervised Classification

The raw data obtained either from monitoring activities may takes different forms with different characteristics. These data can be classified accordingly to different characteristics and properties. In supervised classification, the process of classifying of unknown objects, events or measurements is based on the information derived from the training data provided by the researcher. The training data is used to compute the properties of each individual class within the training data. In other words, this approach is based on *a priori* knowledge of the data provided by the user before applying to the selected algorithm (Mather, 1999).

Generally, the supervised classification method can be applied using two categories of classifier, which include; statistical and neural classifiers (algorithms). In the statistical supervised classification approach, information required from the training data varies from one classifier to another. However, the supervised neural network technique do not use any statistical information to classify an unknown data, instead all available training data are used. In view of this, no assumption is made about the frequency distribution of the data when supervised neural network technique is used. This approach makes supervised neural network technique more powerful than the statistical technique in resolving the problem of PR. However, there exists a tendency to incorrectly classify the object or event in neural network technique than in the statistical technique. This is in view of the fact that neural network technique take every individual training into consideration, whereas the statistical approach use only the overall properties of the data such as the use of estimation of the mean and the averaging of the effect of misclassification.

Normally, the process in supervised classification involves two stages, which include the training of the data and the classification of unknown data using an appropriate classifier. In training phase, the regions or the range of class measurements are selected and the data properties are statistically calculated. The characteristics of the selected trained data are critically important for the reliability and the performance of a supervised classification process. It should accurately represent the characteristics of each individual variable or the characteristics of a group of variables used in the evaluation. In training of data, among the key importance features are the data representativeness and its size. In classification of water quality, these features are associated with the optimum number of water quality data or the frequency of water quality monitoring activities carried out per year, as required by the Global Environmental Monitoring Scheme (GEMS).

In classification phase, every unknown sample will be matched accordingly with reference to the properties of data calculated in the training phase. Based on INWQS Table 2.2, a single variable can easily be classified; however, the classification for an unknown sample with a selected group of variables can be obtained when it is compared with the reference trained data with specific PR through an appropriate classifier. This will be discussed considerably in Section 4.3. Generally, the supervised classification technique provides more accurate results as compared to unsupervised classification technique. This is due to the fact that the supervised classification technique require more researcher interaction, thus it is more favourable than the unsupervised classification.

4.2.2.2 Unsupervised Classification

The raw data obtained either from monitoring activities does not contain any remarkable characteristics for classification or grouping, for which there is no *a priori* or insufficient ground truth information available. These data can be classified based on the unsupervised classification approach into a number of distinct or separable categories or groups. In view of this approach, through unsupervised approach the data can be identified into natural groups, structures or range of measurements that can be discriminated with different form of classes. Thus, it can generate the specific number of clusters or classes in feature space that corresponding to different characteristics of water pollution level. The determination of the classes is performed by estimating the distances between the each class in feature space. Due to the minimal user involvement, usually this approach is performed in automated procedures. However, most of the real world environmental data exhibits complexity in their nature, they are likely very difficult to discriminate or separate in terms of their class characteristics. In addition to this, it is difficult in practice to satisfy the assumption forming the basis of the unsupervised approach that variables belonging to particular class will have similar properties in feature space, and all classes are relatively distinct to each other in feature space. Thus, the accuracy of the results based on unsupervised classification approach is limited. This approach is more applicable for classification of actual land cover features in remote sensing application and the details are beyond the scope of the study.

4.2.2.3 Statistical Approach Classifier

In supervised classification as stated in Section 4.2.2.1, the training process may be carried out many times so as to obtain an appropriate training data set within minimum errors. The training patterns for various classes may overlap especially those originated from some statistical distributions. In this situation, classification can be performed using statistical approach where respective distribution functions of the classes are known. It is restricted by the need to assume that the frequency distribution of the class membership is normally distributed (Gaussian distribution) for each class. However, such classification may be confronted with the risk of wrongly classified unknown variables. Therefore, statistical classifier such as the one based on Bayes formula of the probability theory can minimise the total expected risk. This classification process works smoothly when, the pattern distribution function for each class is known *a priori* (Friedman and Kandel, 1999). If it is not known, the training patterns should be approximated before applying into the statistical classifier. In this type of statistical approach, the three most common supervised classifications being used are; the centroid, parallellepiped and maximum likelihood classifier (Mather, 1999).

The centroid (k-means) or Euclidean distance classifier is defined as the mean centre of each class based on measuring the Euclidean distance from the predefined points in n–dimensional feature space. The n-dimensional space is divided by a set of straight-line boundaries, equidistant from the two centroids. This classifier allocates an unknown variable to the closest class according to its Euclidean distance in the n-dimensional space. The final shape of each region within which each class falls is dependent on the number and position of the centroids. This approach does not consider the distribution of the training data class as compared to the more complicated standard supervised classification methods, which often require assumptions about the underlying statistical data (Swain, 1978; Richards, 1986). However, this parametric approach is easier to perform than the non-parametric approaches, which are more powerful but require complicated recognition systems and large numbers of training patterns (Swain, 1978).

The geometric of parallelepiped classifier exists as rectangular shape in n-dimensional space. It divides the feature space into rectangle areas or parallelepiped. In the case of the parallelepiped classifier, if the variable falls within a certain range of a training class mean, it is assigned to that class. However, these classes may overlap and one or more variables can falls within one or more parallelepipeds. This produces ambiguous region and can be removed by applying specific decision rule. The simplest rule would assign the variable to the first parallelepiped or may involve variables that are assigned to more complex rule. Quite similar to the centroid classifier, it does not consider the distribution of the training data class as compared to the more complicated standard supervised classification methods.

The geometric of class pattern based on Maximum Likelihood (ML) classifier is defined by ellipsoidal shape when presented in the feature space. The position, size and orientation of this shape are represented by the mean vector variances and covariance matrix of the n features that describe the feature space. This method is restricted by the need to assume that the frequency distribution of the class membership is normally distributed or Gaussian distribution for each class. Its allows the application of the higher order statistics of the data in making class decisions. If the assumed distribution is normal (or Gaussian), then it would be appropriate and sufficient to use second order statistics (such as variance and covariance). This ML classifier uses the assumed multivariate density functions to form a discriminant function for each class and consequently a measure of likelihood of class for which the unknown variable falls. Generally, the results produced minimum probability of error over the entire set of data classified (Swain, 1978). This normal density function may provide a good choice such that its function has been shown to model adequately the probabilistic processes especially for a large number of variables. The classifiers using this assumption tend to be relatively robust, meaning that the overall classification accuracy is not very sensitive to moderate violations of the assumption. However, the application of Gaussian distribution has to be treated with caution such as for cases of clear violation of the normal assumption and the needs for adequate training samples must be provided to accurately estimate the mean and covariance measures for each class, a problem normally arises when the distribution is multi-modal (Swain, 1978). If the assumption of a normal distribution for each class turns out to be correct, then the ML classifier is the optimal choice for the problem. Another classifier that is similar to the ML is the Mahalanobis distance classifier, which is based on the modification of the Euclidean distance classifier (Benediktsson et al., 1990; Ripley, 1996). It measures the closeness of a point in terms of the distribution characteristics of the training data in n-dimensional space (Thomas et al., 1987a, 1987b).

4.2.2.4 Minimum-Distance Classifier

The minimum-distance classifier is one of the simple classification methods that employ the minimum distance or nearest-centre decision rule to label an unknown pixels or class of variables. This classifier is also known as Euclidean distance classifier since it employs Eucledian distance in calculations. The computation measures the degree of dissimilarity between pixels and class centroids computed from training data in multidimensional feature space. The pixel is computed to the least dissimilar class centroid. This classifier does not take all the training data into consideration like the parallelepiped classifier. The main emphasis is the used of the mean value for each class of the training data set, where the output is the mean vector. Euclidean distances are calculated for each mean centre, and then only the shortest distance is determined. Based on this shortest distance, the pixel or the variable is assigned to the class that is the nearest in terms of the estimated multidimensional Euclidean distance from mean centres. However, this approach acquires some limitations due to the use of a simple distance measure. It does not take into consideration of the data distribution in the feature space. This problem can be resolved by replacing the Euclidean distance with the Mahalanobis distance, where the variance-covariance matrices are used for the respective classes present in the training data set.

4.2.2.5 Neural Classifier

The approach use in neural classifier is assumed to be quite similar to other approaches in that *a priori* knowledge of the pattern distribution function for each class is available (Friedman and Kandel, 1999). The neural net is represented by complex architecture networks, which includes the input layer, hidden layer and the output layer. This classifier is characterised by a set of weights and the activation function that controls the flow of information into the hidden layer and output layer. The neural net is trained to produce a set of training patterns through the adjustment of their weights until a correct classification is obtained. This selected set of training patterns will then be used to classify an arbitrary unknown pattern. Several neural net classifiers have been developed such as from the simple perceptron to multi-layer perceptron and advances to feedforward (back-propagation) classifier. This will be described in detail through its application in the next section.

The characteristics of the Neural Classifier can be quite similar to other standard classifiers. However, there are differences in the training and classification algorithms that are performed. The neural net training phase can be comparable to the class mean and covariance matrix calculations in ML. Instead of performing statistical calculations, the network is trained iteratively, which is typical of feedforward algorithm. This training process is only stop when the targeted error is minimised between the desired output (the training classes) and the actual output values of the network is achieved. In classification process, instead of calculating the discriminant functions based on the distributions as determined from the training data as in ML, the network is used in a feed-forward mode. The entire image is fed into the net and a simple metric (such as maximum) is used to process the network output so that unknown patterns can be classified. In non-homogenous data structure, the neural algorithms can approximate highly non-linear and non-monotonic relationships with few *a priori* assumptions about the specific functional form of the input-output relation. The neural network models can be regarded as the logical development of previously established mathematical techniques and as a tool, it is mathematically highly flexible. It is more applicable in situation where the nature of data is highly non-linear with complex settings.

4.2.2.6 Fuzzy Classifier

The classification process may involve some degree of uncertainty. In this case, the outcome of classification may be in doubt in the sense that the target class may fall in some degree into more than one class. This problem can be overcome using fuzzy classifier where a pattern is assigned to be a member of every class with some grade of membership that falls between a value of 0 and 1. In this case, fuzzy classification can be applied using the equivalence relations and the fuzzy clustering approaches. A generalised algorithm is used such as the crisp c-Means, which is then replaced by the fuzzy c-Means. Consequently after the cluster centres are determined, the unknown incoming pattern is given a final set of membership grades, which determine the degrees of its classification in the various clusters (Schalkoff, 1992; Freidman and Kandel, 1999).

4.2.2.7 Syntactic Approach Classifier

In some cases where the information exists in a pattern may not merely in the presence or absence of a features set or of any numerical values. It may not depend on the interrelationships or interconnections of features that yield important structural information that could facilitates structural description or classification (Schalkoff, 1992). Instead of carrying the analysis based on quantitative characteristics of the pattern, it utilises the structure of the patterns and this form the basis of syntactic pattern recognition. Examples of typical patterns that are subject to syntactic approach are characters, fingerprints, and chromosomes. This syntactic classifier is based on the concept of a formal grammar and language that can classify an unknown pattern represented as a string of symbols. Generally, given a specific class, a grammar whose language consists of patterns in this class is designed. For an unknown new pattern, a syntax classifier analyses the pattern (a string) through a process known as parsing and determines whether or not that string belongs to the language (class).

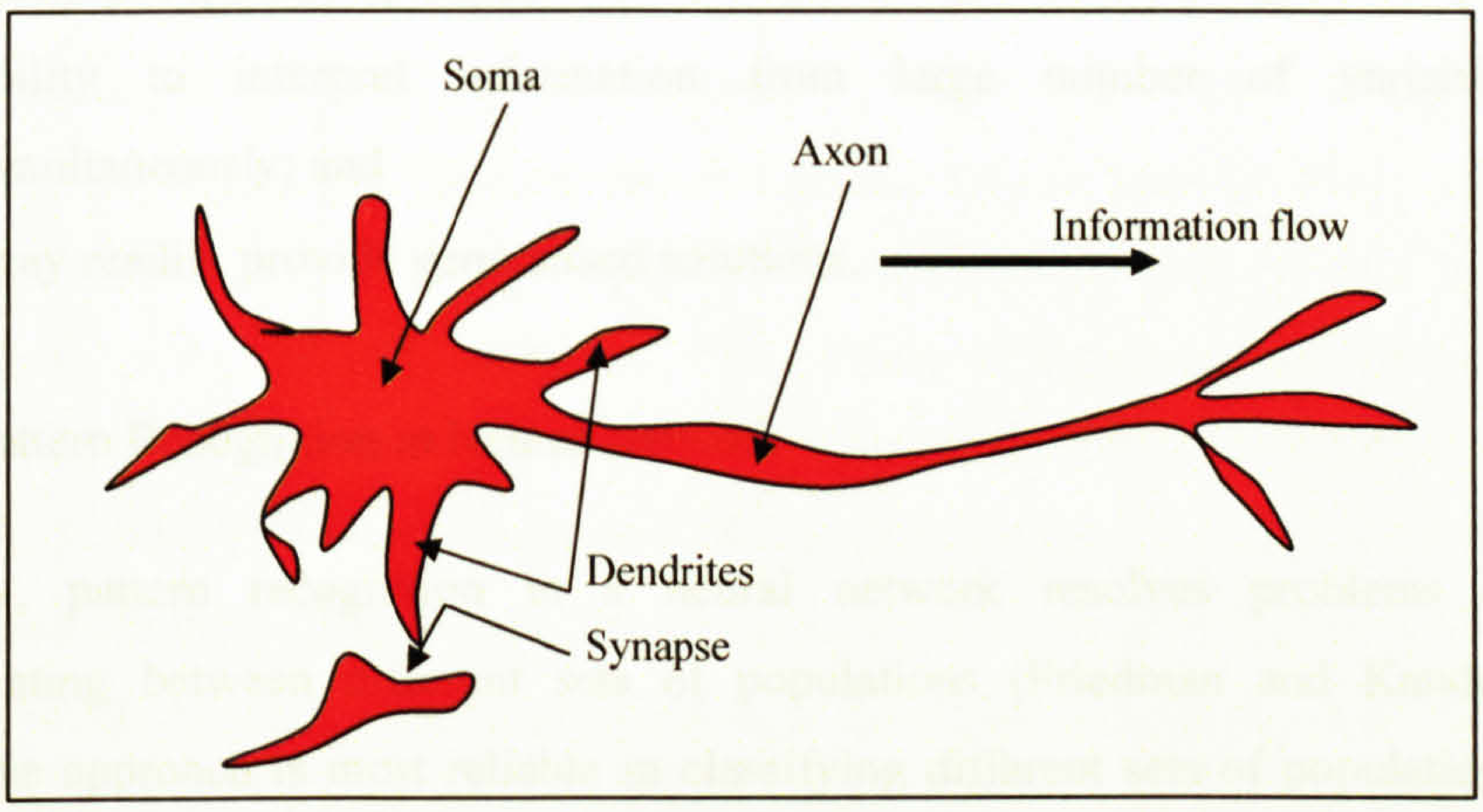
4.3 ARTIFICIAL NEURAL NETWORKS

4.3.1 The Biological Nervous System

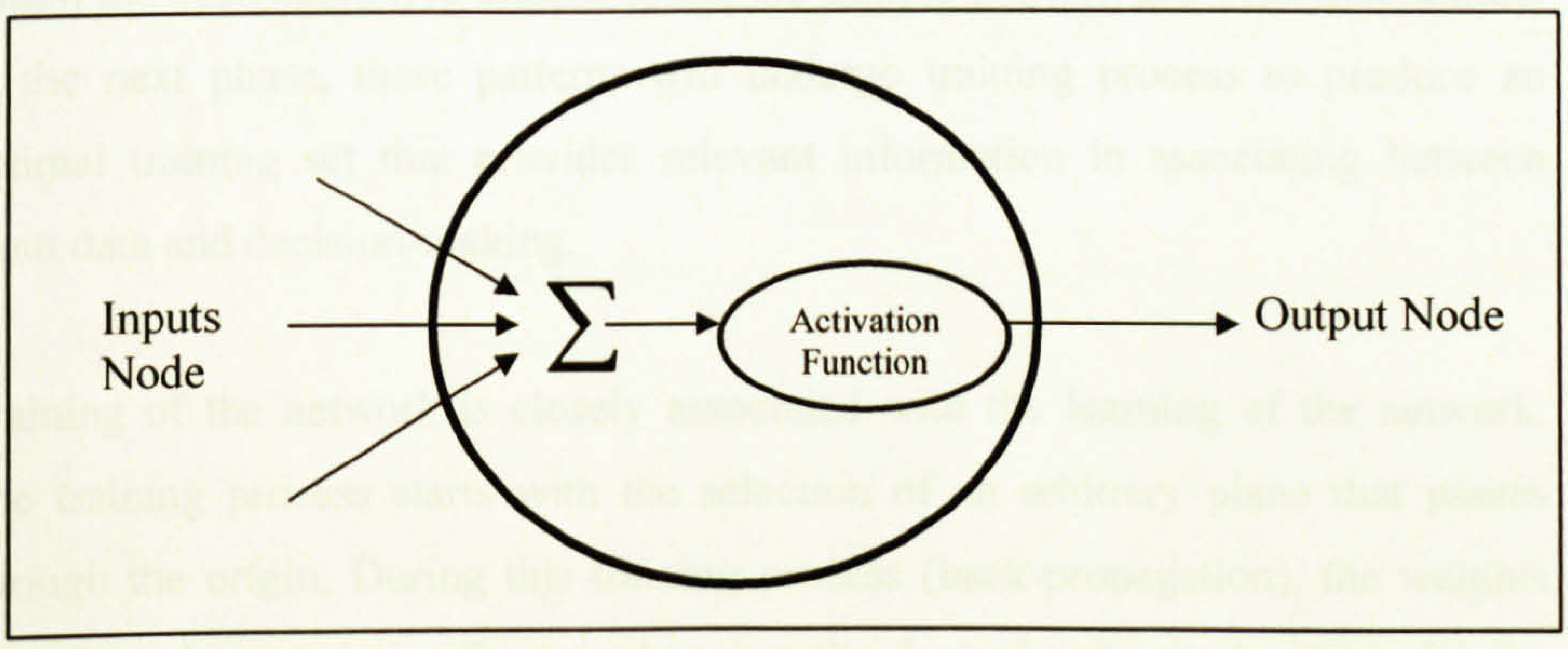
According to Haykin (1994), the biological nervous system of a brain is a massively parallel structure, made up of numerous nerve cells called neurons. These neurons are interconnected to each other and acquire natural capability of storing experiential knowledge that is readily for use (Ripley, 1996). Each neuron is composed of three major parts, a soma, an axon and dendrites as illustrated in Box 4.9 (Eberhart and Dobbins, 1990). A neuron is connected to another neuron through a link called synapse. These neurons are continuously active, receiving and sending pulses via the synapse through the network involving billions of neurons in the brain. In an active neuron, the output produced is in the form of pulse that travels along the axon to the receiver, the dendrite via the synapse. The strength of these pulses is chemically controlled according to the current state of activity of both the sending and receiving neurons. The actual output is then send from one neuron to another depending on a weighting factor that determines the strength of the available output that affects the receiving neuron as an input. In case of two neurons with weak connection or weak association, the potential output will cease to activate, thus renders them to be inactive. In order to deactivate them, the proportion of the output they received is adjusted so as to trigger its strength. This strength is known as the weight (Carling, 1992; Eberhart and Dobbins, 1990).

4.3.2 Artificial Neural Networks Structure.

An Artificial Neural Networks (ANN) is a technique that is modelled from the parallel structure of the natural biological nervous system. This technique simulates the highly interconnected, parallel computational structure with many relatively simple individual processing elements or neurons. The neuron or processing element in ANN is generally considered to be a rough analogous of a biological neuron. The internal structure of this processing element is illustrated as in Box 4.10. Based on this structure and concept, the ANN can be characterised into three components; its architecture, either the way the networks are interconnected in receiving input and sending output; the transfer function of the neurons that is the function that describes the output of a neuron given its input; and the learning paradigm used for training the network (Eberhart and Dobbins, 1990).



Box 4.9 A biological neuron
(Source: Modified from Eberhart and Dobbins, 1990)



Box 4.10 The structure of neural network processing node.
(Source: Carling, 1992)

The ANN technique is distinct from other techniques in which some authors considered it as outperforming the current methods of analysis (Eberhart and Dobbins, 1990; Carling, 1992). Relatively, the advantages of neural network technique are:-

- the ability to resolve the non-linearities characteristics of the world in which we live, particularly that associated with environmental data;
- can be developed from data without an initial system model;
- the ability to handle noisy or irregular data from the real world;
- provide prompt answers to complex issues;
- easily and quickly updated;
- ability to interpret information from large number of variables simultaneously; and
- may readily provide generalised solutions.

4.3.3 Pattern Recognition in Neural Network

Generally, pattern recognition in a neural network resolves problems of discriminating between different sets of populations (Friedman and Kandel, 1999). The approach is most reliable in classifying different sets of populations based on similarity or dissimilarity characteristics. The application of PR concept in water quality classification has been discussed considerably in Section 4.2, where in the preprocessing phase, the *a priori* knowledge of the range of values within the designated five classes forms the sample patterns has been determined. In the next phase, these patterns will undergo training process to produce an optimal training set that provides relevant information in associating between input data and decision-making.

Training of the network is closely associated with the learning of the network. The training process starts with the selection of an arbitrary plane that passes through the origin. During this training process (back-propagation), the weights are adjusted to minimise the error between the desired and actual outputs for the training patterns. As a result of weights adjustment, is the formation of decision boundaries in the feature space that determine the class membership. The detail explanations on the arbitrary decision regions were given in Lippmann (1987), Schalkoff (1992) and Carling (1992).

Training using a two-layer network without a hidden layer can produce hyperplane decision regions in the feature space (Appendix 4.6), whereas, using a three-layer network with a hidden layer can produce any possible unbounded convex region in the input data space as illustrated in Box 4.7. The nodes in the hidden layer produce a series of hyperplane decision regions as in the output layer of the two-layer network. For each node of the output layer will perform a logical AND operation on the created hyperplanes that produced the final convex decision regions for that output as discussed in Section 4.2.1. When a second hidden layer is added, any form of decision region can be created. The output layer may form a set of convex decision regions produced by the previous layer and performs a logical OR operation. This creates arbitrary shaped decision regions. In certain cases, a four-layer network is possible and the advantage is that it can form regions that are disconnected. However, since this four-layer network can produce arbitrary complex decision regions, there is no need for the use of any higher order networks. The analysis of these networks becomes more difficult since the continuous, non-linear activation function will produce decision regions that are usually bounded by smooth curves. The other way to view the capability of neural network is the ability in non-linear transformation of the feature space into a new space in which the data is linearly separable (Pao, 1989). The nodes of the final layer are able to perform a simple hyperplane resolution on the output space of the previous layer.

4.3.4 The Review of the Application of Artificial Neural Networks in Water Resources Management

The ANN approach has shown to be successfully applied in the various scope of scientific research, such as the, chemical research (Kvasnicka, 1990; Wythoff et al., 1990; Smits et al., 1992), medicine and molecular biology (Lerner et al., 1994; Albiol et al., 1995; Faraggi and Simon, 1995; Lo et al., 1995), classification of remotely-sensed multispectral imagery and other GIS applications (Mather, 1999), speech recognition (Rahim et al., 1993; Chu and Bose, 1998), image recognition (Dekruger and Hunt, 1994; Cosatto and Graf, 1995; Kung and Taur, 1995), cybernetics (Siegelmann et al., 1997), meteorology and atmospheric physics (Venkatesan et al., 1997), neurocomputing (Yang and Yu, 1993; Prechelt, 1997), and optical sensing and spectroscopic (Liu et al., 1993). However, some researchers admitted that the research on water resources and management based on the application of ANN was not as rigorous as in other areas, thus the volume of the published research outcomes remain low (Dawson and Wilby, 1998, 1999, 2001; Thirumalaiah and Deo, 1998; Jain et al., 1999). Minns and Hall (1993) relate that hydrological researchers may encounter some difficulties to relate the ANN's concept of pattern recognition and classification into hydrological approaches and techniques.

In most cases the hydrological researcher tends to treat them as 'black-box' models and oftenly ignored the ANN's operation and the effect of its internal parameters (Sarle, 1994). This may result in an inferior model performance. Generally, the hydrological modelling processes were described poorly and this does not mean that it was not carried out correctly (Maier and Dandy, 1999). There were vague areas not encountered and presented, where information were not given explicitly about the modelling processes, thus the optimality of the results could not be assessed properly. In many instances, little consideration is given to potential input data and the internal workings of ANN. Therefore, it was difficult to make meaningful conclusions on the performances of different models. Only, recently that this research has expanded rapidly, especially in hydrological prediction and forecasting, such as rainfall-runoff (Minns and Hall, 1993; Smith and Eli, 1995; Dawson and Wilby, 1998, 1999, 2001; Abrahart, 1998; Maier and Dandy, 1999; Abrahart et al., 1999; Abrahart, 2001, 2003; Abrahart and See, 2000, 2002; Wilby et al., 2003; Anctil et al., 2004), river flow (Imrie et al., 2000; Bruen and Yang, 2005), water quality parameters (Maier and Dandy, 1996; Kneale and Howard, 1997; Zhao et al., 2005), physico-chemical parameters (Moatar et al., 1999; Maier and Dandy, 2002; Huang and Foo, 2002), biological and ecological parameters (Chon et al., 1996; Recknagel at al., 1997; Lek and Guegan, 1999; Schleiter et al., 1999; Karul et al., 2000; Maier et al., 2001; Park et al., 2001, 2003; Wilson and Recknagel, 2001), land use parameters (Haejin and Michael, 2003), ecosystem dynamics (Chon et al., 1996; Hoang et al., 2001; Obach et al., 2001; Park et al., 2003; Levy et al., 2004), fish diversity and management (Lek and Baran, 1997; Guegan et al., 1998; Ibarra et al., 1999, 2003;

Olden and Jackson, 2002; Zhou, 2003), and catchment scale planning and management (Lek et al., 1996, 1999; Wen and Lee, 1998; Shanmuganathan et al., 2005).

The application of ANN in water quality studies was not as rigorous as other water resources studies such as in rainfall-runoff modelling and forecasting. However, several studies have been conducted in search of an appropriate water quality model that relates to point and non-point sources of pollution. In relation to these sources of pollution, the stormwaters and agricultural practices are the major contributions to water quality deterioration in rivers and lakes (Gong et al., 1996; Wong, 1997; Zhao et al., 1997; Loke et al., 1997; Kaluli et al., 1998; Brion and Lingireddy, 1999; Hudak, 2000; Spalding et al., 2001; Harter et al., 2002; Spruill et al., 2002; Johnsson et al., 2002; Mitchell et al., 2003; Lake et al., 2003; Sivertun and Prange, 2003). In the course of the rapid growth in population, physical development has increased tremendously with an increased in impermeable surfaces, which contributed to an increased in the stormwater discharges that significantly affected the water quality of lakes and rivers. This stormwater runoff picks up natural and human-made contaminants that accumulated on the surfaces during the dry days and transports them to the nearest water bodies. The worst scenario is when the runoff flows through the agriculture areas, pick-up the fertilisers, manure application, pesticides, herbicides and leguminous crops and transport them into the nearest water bodies. The types and concentrations of the contaminants from the runoff are closely related to magnitude of the various types and activities of land use. The extensive use of fertilisers may contribute the main source of nitrate leaching to ground water particularly in sandy soils (Hubbard and Sheridan, 1994; Tianhong et al., 2003). In addition, elevated nitrate concentrations in ground water are common around dairy and poultry operations, barnyards, and feedlots (Hii et al., 1999; Carey, 2002). Although pollutants from point sources are manageable, the leachates and spills from these sources are sometime inevitable where many studies have shown that high concentrations of nitrate in areas with septic tanks and dairy lagoons (Erickson, 1992; Arnade, 1999; MacQuarrie et al., 2001). Researches on the application of ANN in water quality modelling are expected to become more vigorous in view of the fact that most of the environmental variables are non-linear in characteristics and this suit well to the properties and the characteristics of ANN.

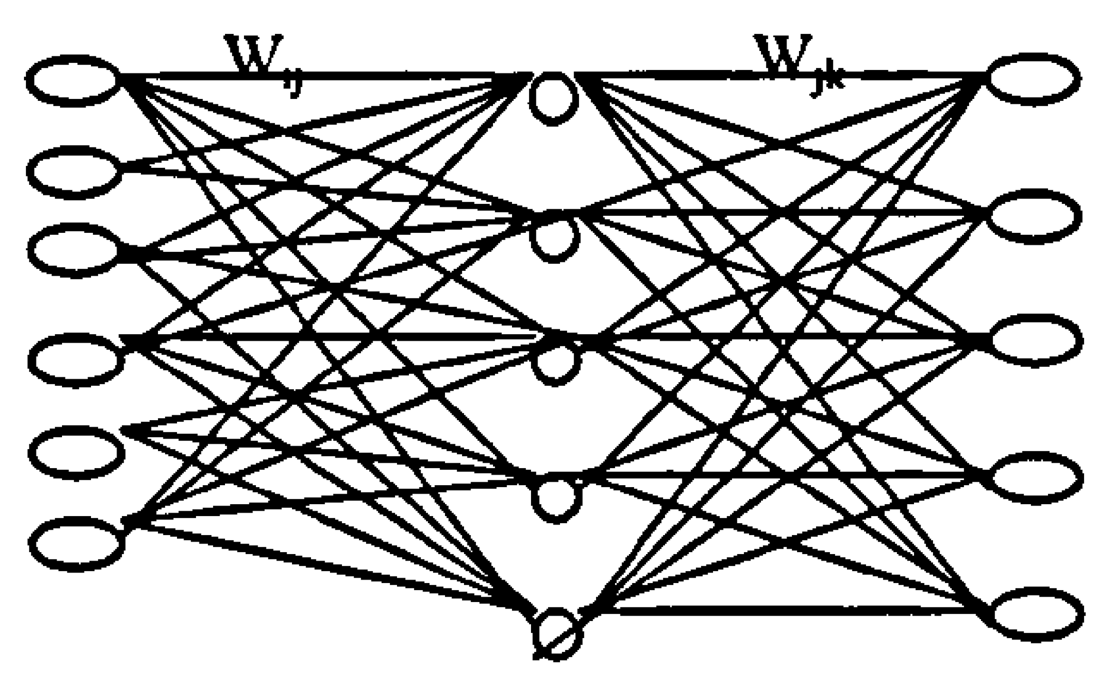
Several successful studies based on the applications of ANN in relation to various water quality variables have been conducted and published. For example, Zhang and Stanley (1997), Ha and Stenstrom (2003), Holmberg et al. (2005) and Sarangi and Bhattacharya (2005) have examined the relationship between water quality variables, sediment loss and various types of land use; Maier et al. (1998), Schleiter et al. (1999), Hoang et al. (2001), Park et al. (2001, 2003), Wilson and Recknagel (2001) have presented the distribution of benthic macroinvertebrates in biological modelling; Lek et al. (1999) and Chaves et al. (2004) have investigated and formulated an integrated management of water resources with respect to quantity and quality; Hong and Rosen (2001) have presented an effective methodology in relating the effect of stormwater infiltration on groundwater quality variables; Huang and Foo (2002) and Bowden et al. (2005) have forecasted salinity and salinity variation in respond to the multiple forcing functions of freshwater input, tide and wind; Brion et al. (2002), Licznar and Nearing (2003), Almasri et al. (2005), Engin et al. (2005) and Sahoo et al. (2006) have investigated and distinguished the impact of pesticide contamination, human sewage and various types of runoff; and Ibarra et al. (2003) have made an assessment of metrics for indices of biotic integrity.

Hydrological modellers have applied different ANN models to assess the water quality. The assessment was based on biological or ecological, physical and chemical variables of the river water quality. Among the most popular ANN models being used for the assessment of water quality are the Multilayer Feedforward with Back-Error-Propagation (BEP) network, Radial Basis Function (RBF), Adaptive-network-based with Fuzzy Inference System (ANFIS) and Self Organising Mapping (SOM).

4.3.4.1 Back-Error-Propagation Neural Network

Generally, the most popular and commonly used is the supervised feedforward BEP, which is a three-layered neural network with sigmoid transfer function (Hsu et al., 1995; Maier and Dandy, 1996, 1998, 2000; Zhang and Stanley, 1997; ASCE Task Committee, 2000; Imrie et al., 2000; Govindaraju and Rao, 2000; Abrahart, 2004; Chaves et al., 2004; Mendez et al., 2004; Sahoo et al., 2006). The schematic of a three-layer feedforward BEP is shown in Box 4.11. The mechanisms involve are; the input signal (stimulus) that comes in at the input layer of the network propagates or feedforward from the input neurons, through the hidden neurons and into the output neurons that received the output response. The strength of the input signals to the hidden neurons was defined as in Equation 4a (Schalkoff, 1992; Haykin, 1999; Friedman and Kandel, 1999; Tsai and Lee, 1999) in Box 4.11. Each hidden neural input was transformed by the transfer function to produce a hidden neural output as defined by Equation 4b. As it feeds forward, these signals produced errors that accumulated in the output layer, thus reducing the accuracy of the network. These signals were propagated backwards from the output neurons into the hidden neurons, and back to the input neurons. As it propagated backward, weights were adjusted and the errors were reduced or entirely eliminated. These errors constitute Means Squares Error (MSE) and are defined as in Box 4.12. In training, this process is repeated over several iterations (epochs) until the lowest MSE value is achieved. Normally, the lowest MSE value constitutes the generalisation capability of the network which determine the effectiveness and the accuracy of the network in discriminating the class membership.

The commonly transfer function being used in BEP is the sigmoid transfer function. It is non-linear in characteristics that help to create a high performance network (Hsu et al., 1995; Raman and Sunilkumar, 1995; Minns and Hall, 1996; Minns and Hall, 1997; Campolo et al., 1999). This algorithm is capable of escaping the local minima in the error surface, provided certain parameters are chosen correctly (Dawson and Wilby, 1998; Maier and Dandy, 1998, 2000; Bowden et al., 2005). Its limitation is the slow convergence rate which is caused by the adjustment of all the weights at the same time within the network. Thus, each unit of the connection weight tries to detect a feature defined by the error signal that propagated backwards. This caused the unit's weights change independently to those of the others, the error signal, which leads to a 'complex dance' amongst the units. Thus, increasing the training time taken to reach a stable condition (Fahlman and Lebiere, 1991).



$$(H_{input})_j = \sum_{i=1}^{m=6} S_i \times W_{ij} - \theta_j, \quad j = 1, 2, 3, \ldots, n = 5 \qquad \text{Equation 4a}$$

where, $(H_{input})_j$ = ith input to the jth hidden neuron;
S_i = value at the ith input neuron;
W_{ij} = connection weight from the ith input neuron to the jth hidden neuron;
θ_j = threshold of the jth hidden neuron;
m and n = number of input neurons and hidden neurons.

$$(O_{input})_k = \sum_{j=1}^{n=5} (H_{output})_j \times W_{jk} - \theta_k, \quad k = 1, 2, 3, \ldots, 5 \qquad \text{Equation 4b}$$

where, W_{jk} = interconnection weight between the jth hidden neuron and each of the kth output neurons;
θ_k = threshold of the kth output neuron;
k = number of the output neurons.

Box 4.11 Theoretical and mathematical concept of the BEP of ANN (Source: Schalkoff, 1992; Haykin, 1999; Friedman and Kandel, 1999; Tsai and Lee, 1999)

$$\text{MSE} = 1/N \sum_{i=1}^{N} (T_i - P_i)^2 \qquad \text{........Equation 4c}$$

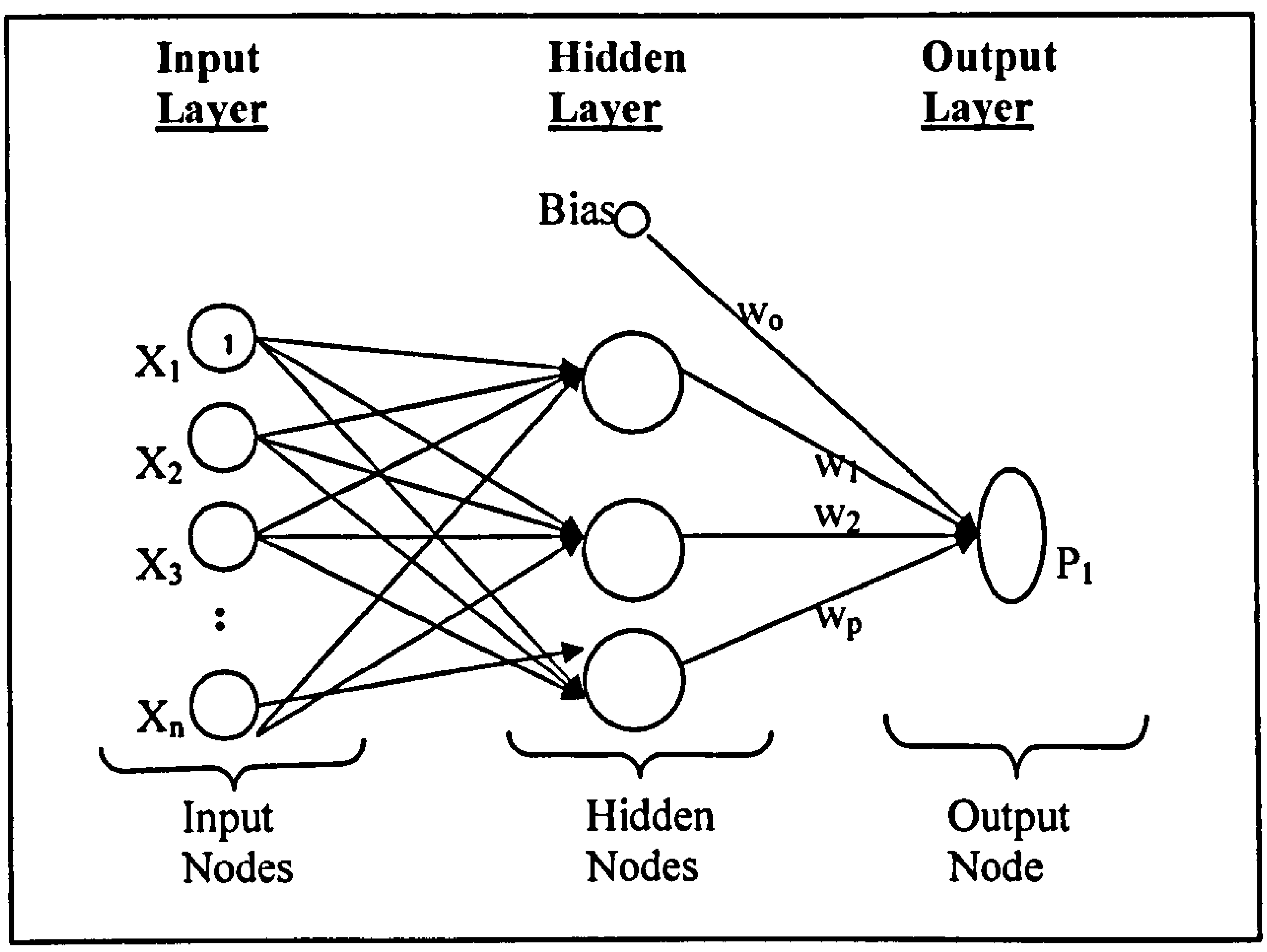
N = number of input samples
Pi = predicted error
Ti = observed (target) error

Box 4.12 Mean Square Error (Source: Hagan et al., 1996; Karul et al., 2000)

When the training phase was completed, the model performance needs to be validated using data set that has not been used in the training phase. This is to ensure that the amount of error obtained using the validation set is not significantly different than that obtained using the training data, thus the two data sets are representative of the same population, or else the network model has been overfitted (Masters, 1993). In addition, poor validation can also be due to the network architecture, lack of data pre-processing and normalisation of training data. Once, the network has been validated, this network will be used to compute test data set or observed data. Details of the BEP application in water quality assessment are discussed in Chapter Five. Other details of the processes in neural network training techniques and backpropagation learning algorithm are explained in Rumelhart et al. (1986), Simpson (1990), Freeman and Skapura (1991), Mathworks (1998), Maier and Dandy (2000) and Abrahart (2004).

4.3.4.2 Radial Basis Function Neural Network

The next popular ANN model being used in water quality assessment is the radial basis function (RBF) neural network. This model consists of an input layer and one hidden layer of basis functions (neurons) with a feed-forward structure output layer. In contrast to BEP, the connections between the input units and the hidden units are not weighted in RBF. Thus, the hidden layer performs a fixed nonlinear transformation with no adjustable parameters (ASCE Task Committee, 2000). This layer comprised of nodes and parameter vector called the center which considered to be the weight vector of the hidden layer. The distance between this center and the input vector is known as the standard Euclidean distance. (Haykin, 1999; ASCE Task Committee, 2000; Chang and Chen, 2003; Haddadnia et al., 2003). The transfer functions in the hidden layer of the RBF possess radial-symmetric properties, whereas the transfer function in BEP is sigmoidal. The input layer is composed of n input nodes. The connections between the input and hidden layer acquired units weights and do not have to be trained (Haddadnia et al., 2003). Thus, the hidden layer neurons do not use the weighted sum of inputs and sigmoid transfer function as in BEP. Instead, the outputs of the hidden layer neurons are determined by the Euclidean distance between the network input and the center of the basis function. When the input signal moves away from a given center, the neuron output drops off rapidly to zero (Hagan et al., 1996). As a result the RBF neural network output is formed by a weighted sum of the hidden layer neuron outputs and the unity bias. The general form of the output of the radial basis function R_j is described in Box 4.13. The weighted sum of the inputs at the output layer is transformed to the network output using a linear activation function. The output y of the RBF is computed using the Equation 4f as in Box 4.14 (Haykin, 1999; Chang and Chen, 2003; Haddadnia et al., 2003). Applications of the RBF neural network are described in Chen et al. (1991), Leonard et al. (1992), Mason et al. (1996), Zheng and Billings (1996), Jayawardena et al. (1997), Fernando and Jayawardena (1998), Haykin (1999), Chang and Chen (2003), Haddadnia et al. (2003) and Abrahart (2004).



Box 4.13 Schematic of the theoretical concept of RBF neural network (Source: Haykin, 1999; Chang and Chen, 2003; Haddadnia et al., 2003)

$$R_j(x) = \varphi\|x - c_j\| \qquad \text{....Equation 4d}$$

$$= - \exp\,[-\|x - c_j\|^2]/2\sigma^2_j \qquad \text{....Equation 4e}$$

$$y = \sum_{j=1}^{N_o} w_j\, R_j(x) + w_o \qquad \text{....Equation 4f}$$

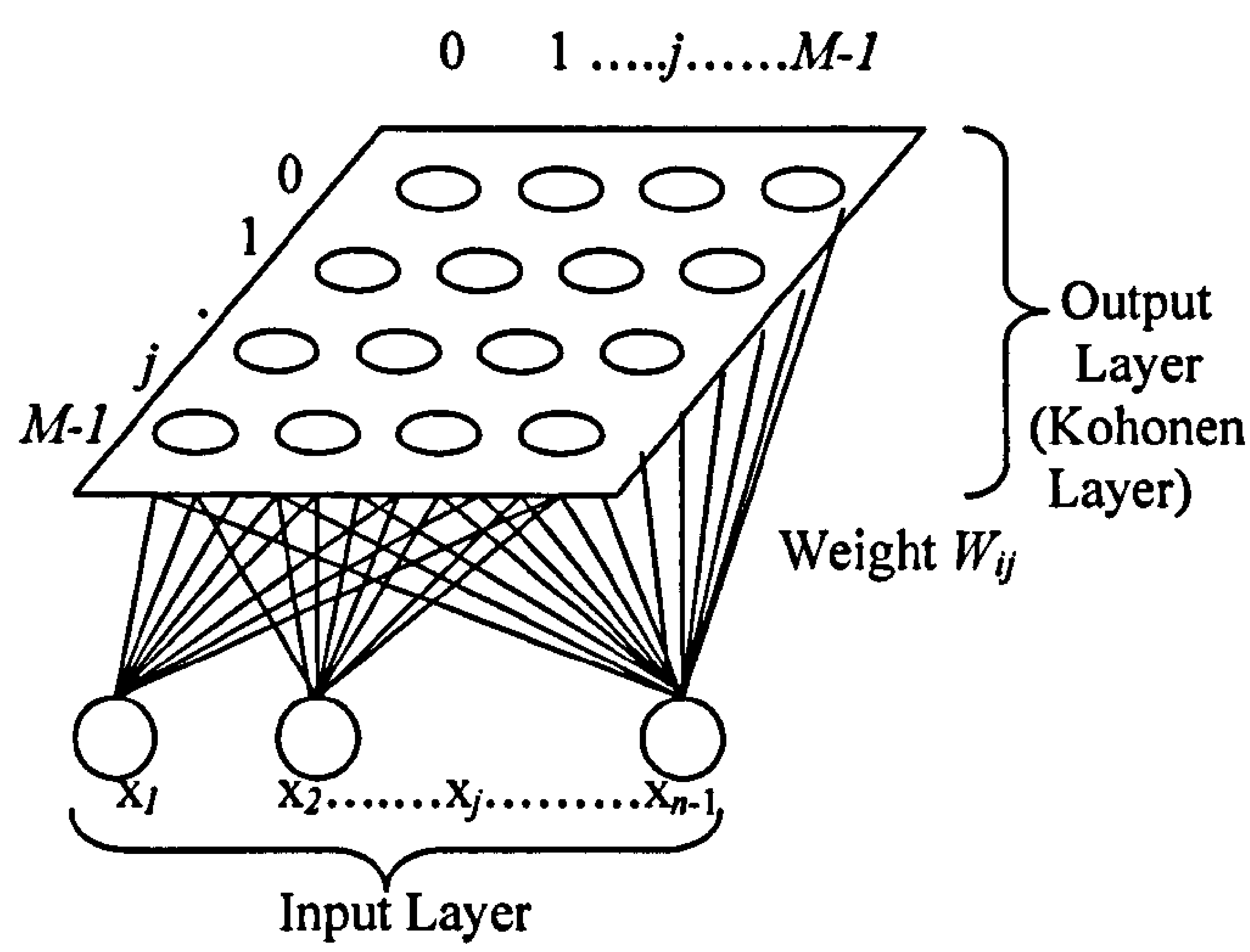
where, c_j = the center of the jth RBF neuron
$\varphi(\cdot)$ = radial symmetric basis function
x = input vector
$\|\cdot\|$ = norm that is the Euclidean distance
σ_j = the spread or the radial distance from the center of the jth RBF neuron
w_o = bias
N_o = total number of RBFNN centers.

Box 4.14 Output of the radial basis function and the activation function (Source: Haykin, 1999; Chang and Chen, 2003; Haddadnia et al., 2003)

4.3.4.3 Self Organising Mapping

The self-organising mapping (SOM) is another popular model which falls into the category of competitive and unsupervised learning methodology (Kohonen, 1995). It is a technique which is capable of ordering multivariate data by similarity, while preserving and maintaining the topological structure of the data. In contrast to BEP, no *a priori* knowledge is needed to assist in the grouping process. The capability of unsupervised learning in SOM is that it allows the investigator to group objects together on the basis of their perceived closeness in *n* dimensional hyperspace, where *n* is the number of variables or observations made on each object. In this way, the cells within the network are able to interact and develop adaptively into detectors of a specific input pattern (Kohonen, 1990).

Kohonen network consists of two layers, an input layer and an output layer (Box 4.15). The input layer is directly connected to the Kohonen layer or output layer. In the Kohonen layer, SOM often consist of a two-dimensional network of neurons arranged in square grid or other geometrical form. Each neuron is connected to its nearest neighbours on the grid. The neurons store a set of weights, each of which corresponds to one of the inputs in the data. None of the processing elements (PEs) in the Kohonen layer are connected to each other. These PEs measure the distance (Euclidean distance) of their weights to the input pattern. The training phase in SOM involves random weight initialisation, presentation of data pattern into the network, the closeness of unit matching and the updating of the winning unit (Abrahart, 2004). This training process is repeated over several iterations (epochs) until a stopping condition is introduced.



Box 4.15 A typical SOM consisting of n inputs in the input layer and a 4 by 4 Kohonen Layer (Source: Kohonen, 1990)

The process of computing the winning PE starts with the determination of weights of each PE in matching the corresponding input pattern. If the input pattern, X have n inputs, then X is denoted as Equation 4g in Box 4.16. Each of the M PEs in the Kohonen layer will have n weight values, where the weight, W is represented as Equation 4h (Box 4.16). This follows with the determination of the Euclidean distance, D_j for each of the Kohonen PEs represented as Equation 4i (Box 4.16).

The processing element, PE with the lowest Euclidean distance value, $\mathbf{D}_j$ is selected as the winner. The lateral interaction of each of this PE with the neighbouring PEs is computed by applying arbitrary network structures called neighbourhood sets, N_b, where the radius can be time variable. All PEs within the winner's neighbourhood set will be updated, except those PEs outside this set are left intact. The updating process is represented as Equation 4j (Box 4.16). When these weights are updated, corresponding inputs are presented into the network and the process continues until convergence is achieved. When all inputs are presented to the SOM, the net effect is the weights which reflect the topological structure or relationship that exists within the input data (Islam and Kothari, 2000). The details of the computation processes of the SOM are described in Kohonen (1982, 1984, 1990, 1995), Lippmann (1987), Hetch-Nielsen (1990), Freeman and Skapura (1992), Lek and Guegan (1999), Chang and Hwang (1999), Islam and Kothari (2000), Aguilera et al. (2001), Hsu et al. (2002), Park et al. (2003), Abrahart (2004) and Bowden et al. (2005).

$$X = \{ x_i;\, i = 1, \ldots\ldots, n\} \qquad \text{....Equation 4g}$$

$$w_{ji} = \{w_{ji};\, j = 1, \ldots\ldots, M\} \qquad \text{....Equation 4h}$$

$$D_j = \|X - W_j\| = \left[\sum_{i=1}^{n}(x_i - w_{ji})^2\right]^{1/2},\ j = 1, \ldots\ldots\ldots M \qquad \text{....Equation 4i}$$

$$W_j(t+1) = \begin{cases} W_j(t) + \alpha(t)[X(t) - W_j(t)] & \text{if } j \in N_b(t) \\ W_j(t) & \text{if } j \notin N_b(t) \end{cases} \qquad \text{....Equation 4j}$$

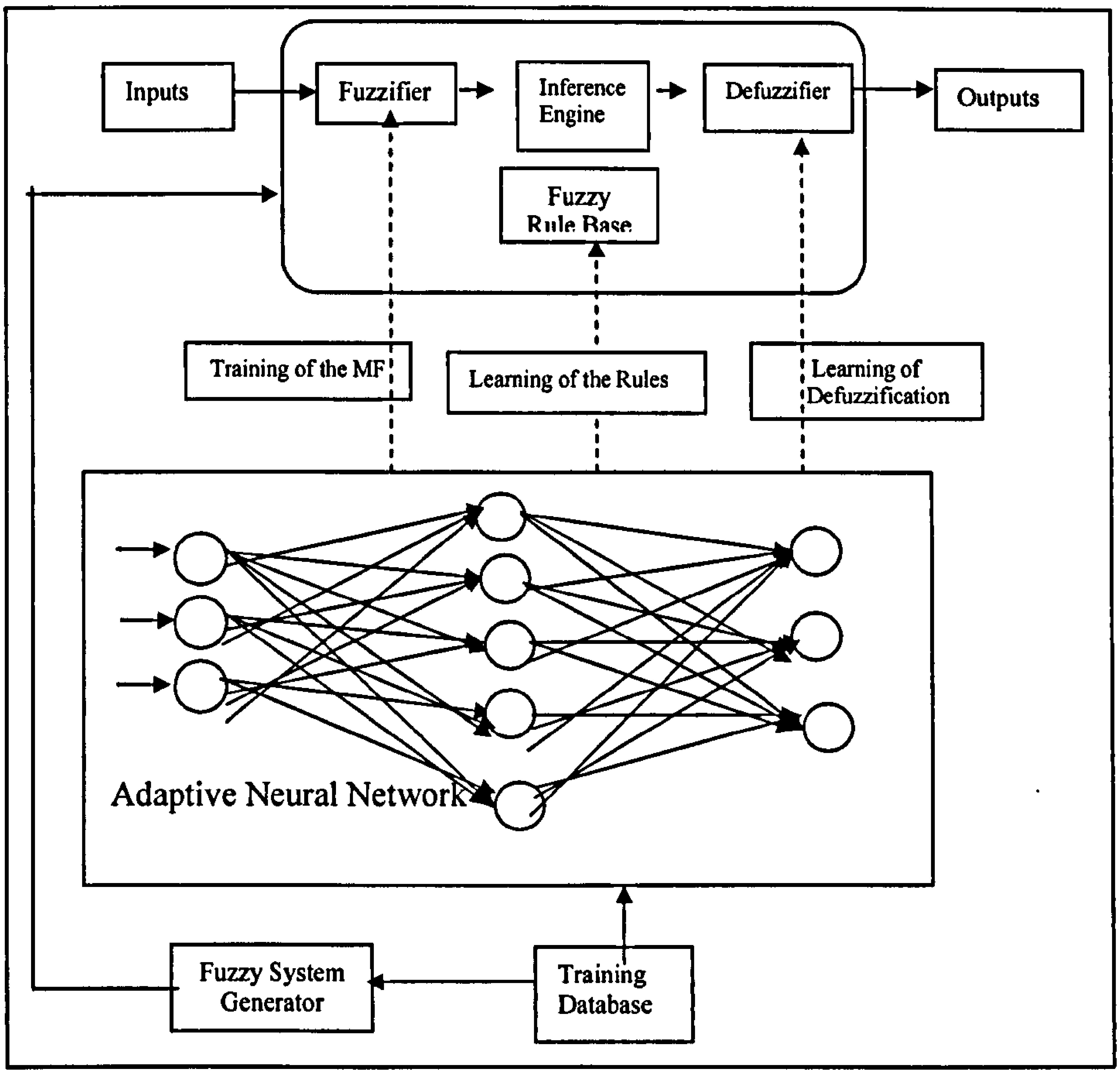
where, α = a scalar valued adaptation gain $0 < \alpha(t) < 1$
N_b = the neighbourhood set.

Box 4.16 Determination of Euclidean distance and the updating process (Source: Kohonen, 1984, 1990)

4.3.4.4 Fuzzy Logic Neural Network

The fuzzy logic neural network is also referred as fuzzy inference system (FIS). Generally, the model application consists of four principal components, which include fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification (Tay and Zhang, 1999, 2000; MathWorks, Inc., Natwick, MA, 2001; Chen et al., 2003). Through fuzzification process, the real world data is transformed into an acceptable form based on the fuzzy membership functions (MF). The output from fuzzification process is used as input for the fuzzy inference engine. This inference engine is to provide appropriate action with respect to a specific condition based on the given rule base (Chen et al., 2003). This fuzzy rule base contains a set of IF-THEN directives that relates to the measured variables to the control variables. For each rule, the antecedent part will classify the behaviour of measured variables by fuzzy MF, while the consequence part will provide the directive for the essential action in terms of a set of control variables. In the final stage, the defuzzification process retranslates the fuzzy action to the non-fuzzy output, which is acceptable by the real world systems. Generally, in a hybrid fuzzy system such as adaptive network-based fuzzy inference system (ANFIS), the system is configured with other neural networks in a parallel fashion based on a competitive or corporative relationship as represented in Box 4.17 (Tay and Zhang, 2000; Chen et al., 2003).

Based on ANFIS's approach, the concept consists of five components, which include; the input and output database, a fuzzy system generator, a FIS, and an adaptive neural network. The application of this hybrid method for the fuzzy inference system is to reduce the poor performance shown by the BEP learning method during the early investigation phase. Usually, this approach follows with the data set checking in order to resolve the problem arise from model over-fitting (Sahoo et al., 2005). The details of the applications of the fuzzy logic neural network are described in Tay and Zhang (1999, 2000), MathWorks, Inc., Natwick, MA (2001), Mujumdar and Sasikumar (2002), Chen, et al. (2003), Haddadnia et al. (2003) and Sahoo et al. (2005).



Box 4.17 The concept of adaptive network-based fuzzy inference system
(Source: Tay and Zhang, 2000; Chen et al., 2003)

4.3.5 Choice for Artificial Neural Networks Model

In hydrological modelling, the choice of ANN's model depends on the problems that need to be resolved. Different model network suit well with different application of hydrological functions and the processes involve. In this case, the systematic approach for the selection of an appropriate ANN's model depends on factors such as data pre-processing, the determination of adequate model inputs and a suitable network architecture, parameter estimation and model validation (Maier and Dandy, 1999).

Various ANN models have been investigated and the multilayer BEP remains the most popular model being used in the research on water resources and management. Based on the studies conducted by Sahoo et al. (2005), the BEP of ANN was found to be relatively more superior then the RBF and ANFIS in terms of prediction and generalisation ability of the network, such as the high performance efficiency (R), the value of root-mean-square error (RMSE) and the 'class' groups. Some models are combined with other techniques in such a manner as to overcome the limitations of an individual technique (Bowden et al., 2005). This case normally applies in the selection of appropriate model that involve multiple inputs. Example is the combination of SOM with a hybrid genetic algorithm and general regression neural network (GAGRNN), where the main emphasis is to determine which inputs have a significant relationship with the output (dependent) variable. Thus, each individual model or technique has specific computational properties that are well suited to a particular problem but not to others.

Comparison was also made between the four-layer and the three-layer BEP of ANN. In terms of performance efficiency (R) and RMSE value, the three-layer supersede the four-layer BEP network, but in terms of the predicted 'class' groups, the four-layer outperform the three-layer BEP network (Sahoo et al., 2005). However, the limitation BEP is the slow convergence rate that occurs during the training phase and the needs to pre-specify the architecture of the ANN that is the number and configuration of its hidden units (Fahlman and Lebiere, 1991). Normally, in speeding up the training process, researchers have applied the second-order algorithm such as the classical Newton and Levenberg-Marquardt, but it was found to be unsuitable for network with more than 100 parameters (Battiti, 1992). In most cases, this second-order algorithm was unable to escape the local minima in the error surface. However, the application of simulated annealing and genetic algorithm, normally used in the global optimization method has the capability to find the near-global optima in the error surface, but again it suffers from slow convergence rate (Hassoun, 1995; Rojas, 1996).

In resolving the long processing time and other limitations, some researchers have used both the feedforward network and recurrent network of ANN, especially in the hydrological prediction and forecasting (Karunanithi et al., 1994; Warner and Misra, 1996; Gencay and Liu, 1997; Krishnapura and Jutan, 1997). In contrast to feedforward network, the capability of the recurrent network is that the processing elements in one layer can be connected to the processing elements in the next layer, the previous layer, the same layer and even to themselves or the same nodes (Warner and Misra, 1996). This makes recurrent network more flexible. In time series applications, the recurrent network has outperformed the feedforward network. This was due to its ability to model time structure implicitly with the aid of the feedforward connections (Gencay and Liu, 1997; Krishnapura and Jutan, 1997). However, it could not model the same time structure explicitly (Hochreiter and Schmidhuber, 1997), and this has encountered a problem of 'remembering' longer term dependencies (Siegelmann et al., 1997; Lin et al., 1998). In addition to this advantages, recurrent network has the ability to model the moving average (MA) as well as autoregressive (AR) elements, whereas, feedforward can only model AR elements (Connor et al., 1994). Both of these models can be used simultaneously in a parsimonious manner. However, in case where processing speed is given due consideration, feedforward network outperform recurrent network (Khotanzad et al., 1997).

Although the feedforward network and recurrent network has produced good results and some have outperformed the conventional models (Imrie et al., 2000), their application is restricted to certain research environment (Crespo and Mora, 1993; Karunanithi et al., 1994; Hsu et al., 1995; Abrahart and Kneale, 1997; Dawson and Wilby, 1998). The main restriction is associated with the capability of the network to generalise effectively when presented with new data (Imrie et al., 2000). This limitation was supported by Minns and Hall (1996), who found that their ANN rainfall-runoff models were unable to estimate synthetically generated flood peaks in excess of those contained within the calibration data. In some of these studies, the application of ANN's model was less effective, where it tends to underestimate the prediction that involves extreme values (Karunanithi et al., 1994; See et al., 1997; Dawson and Wilby, 1998; Campolo et al., 1999). Some researchers agreed that this underestimation was due to a lack of information provided to the network, while others have suggested the used of more high-flow patterns in the training data set;

modelling based on log transformations of flow values; preclassifying the level data into different event types and to give great care when scaling the calibration data prior to ANN training (Hsu et al., 1995; See et al., 1997; Minns and Hall, 1996, 1997).

The generalisation capability of the network is associated with the selected network architecture that depends on the number of input, hidden and output nodes as well as the parameters chosen. The potential input variables to be used may not equally informative, some may correlate, and others are noisy or have no significant relationship with the output variable being modelled. A sensitivity analysis is normally used to determine the relative importance of the input variables (Maier and Dandy, 1996). In this case, input variables that do not have a significant effect on the performance of the network are trimmed out from the input vector, resulting in a more compact network (ASCE Task Committee, 2000). Various methods for ANN input determination have been introduced. For example Abrahart et al. (1999) used a genetic algorithm to optimise the inputs to an ANN model used to forecast runoff from a small catchment. However, this has the major limitation of only capturing the inputs that are linearly correlated with the output. Park et al. (2003) applied the counterpropagation neural network (CPN) to predict species richness and Shannon Diversity Index of benthic macroinvertebrate communities using environmental variables. This CPN is a hybrid neural network applied with SOM and the Grossberg outstar to approximate continuous functional associations between variables that serve as a statistically optimal self-programming look-up table. This method of classifying sampling sites and visualising environmental and biological variables on the trained SOM map, is useful in understanding the complex ecological data. Bowden et al. (2005) applied a hybrid genetic algorithm and general regression neural network (GAGRNN) to determine which inputs have a significant relationship with the output (dependent) variable.

Generally, less consideration are given to the task of selecting appropriate model inputs in the application of ANN in hydrological studies (Maier and Dandy, 2000). This is due to the fact that ANN belongs to the class of data driven approach, which is assumed to be able to determine which model input is critical. In contrast to the conventional statistical approach, which is based on model driven, where the structure of this model is determined *a priori* by using empirical or analytical approaches, before estimating the unknown model parameters (Chakraborty et al., 1992). Thus, there have been great tendencies to use large number of inputs and relied on the selected ANN's network to identify the critical model inputs. The execution of large number of inputs may ended with complex network architecture that incur long training time and create the risk of getting stuck in a local minimum (Bowden et al., 2004). This may induce negative effect on the generalisation capability of the network. According to Cheng and Titterington (1994), generalisation is defined as the ability of the model to perform well on data that were not used to calibrate it and is a function of the ratio of the number of training samples to the number of connection weights. If the network is too small, there will be insufficient degrees of freedom to capture the underlying relationships in the data. However, if it is too large, the network tends to memorise the fluctuations in the training data which did not represent the true system being modelled (Karunanithi et al., 1994, Dawson and Wilby, 1999, 2000). Thus, this will cause poor generalisation and reduce the performance of the network. In handling the uncertainties associated with the selection of initial weights and a stopping criterion, a given neural network is trained several times until the pre-determined epoch sizes with correlation coefficient as the objective function to find the optimal connection weight matrix (Sahoo et al., 2006). Continued training may result in overfitting problem, although the aim of training is to reduce the weights error between the neurons and parameters. This overfitting problem is again exacerbated by the presence of noise in the data (Maier and Dandy, 2000).

Overfitting can be prevented using common methods such as regularisation and early stopping (Karul et al., 2000; Abrahart, 2004). Regularisation involves the modification of the performance function where only a minimum number of hidden layer neurons were assigned to sufficiently trigger the learning process in the system. However, the early stopping involves the stopping of the training process when the error for the validation set begins to increase. Generally, in early stopping method, the data is randomly divided into three categories which include a training data, validation data and testing data (Abrahart, 1998). The error term that is the difference between the measured target values and the calculated values was calculated separately for the training data set, validation data set and the test data set. In the initial part of training, the error on the validation data set will decrease and the network begins to overfit when these data set start to increase. If this increase continues for a certain number of interations, the training is stopped before starting to overfit the data. The network is 'freezed' to keep the captured weight values. The same process is carried out for the test data set. The error term of the validation set is used to compare with the error term of the training data set and test data set and if they exhibit similar behaviour, the training session has produced a well-generalised network (Karul et al., 2000).

Generally, optimum network architecture is selected through trial and error process, which involves a laborious and time-consuming experiment (Karunanithi et al., 1994). Karnin (1990) begins with large number of hidden units and applied pruning approach until an optimal architecture is found. However, Hsu et al. (1995) stated that it is more computationally efficient and more practical to begin with a minimal network and add units one at a time. This can be done either by experimenting with small number of neurons in the input layer, hidden layer and output layer. Various empirical guidelines based on the number of inputs or training patterns have also been suggested (Hecht-Nielsen, 1987; Weigend et al., 1990; Bowden et al., 2004). In search of optimum network architecture, a wide range of algorithms has been developed for training the network to achieve the optimum model performance, while ensuring generalisation and computational efficiency. In hydrological studies, different algorithms have been applied and the successful applications have been reported in studies conducted by Karunanithi et al. (1994), Maier and Dandy (1996), Muttiah et al. (1997), Augusteijn and Warrender (1998), Durucan and Imrie (1998, 1999), Luk et al. (1999), Abrahart and See (2000), Dawson and Wilby (2000) and Abrahart (2004).

4.4 CONCLUSIONS

The review on literature has shown that the ANN's application successfully been applied in handling large-scale physical problems, especially in resolving the non-linearity issues. ANN's application has been widely used in various scientific applications and has gradually gained popularity in hydrological applications (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000). Apart from its unique characteristics, which is not based on the prior knowledge of the statistical distribution of the data or any assumptions of the underlying data distribution (non-Gaussian Distribution), the capability of ANN to resolving the hydrological issues is due to its robustness, ability to learn and generalise from examples to produce meaningful solutions to problems even when input data contain errors or are incomplete.

Among the various types of models being applied, the BEP of ANN remains the most popular model. However, in view of its capability, the network operations and mechanisms were less fully known by most of the hydrological researchers and potential users (Maier and Dandy, 1998). The choice of an appropriate optimisation technique in this model is complicated and is dependent on the model performance criteria. Thus, a thorough understanding of ANN's behaviour is important and the need to develop some kind of guidelines for optimisation of its performance is crucial. These guidelines should assist and not to restrict the hydrological modellers.

In order to produce comprehensive guidelines for the optimisation of the ANN's performance, researchers need to understand the ANN's limitations before these guidelines are produced. Among of these limitations are the lack of a methodology for determining input variables and researchers have raised doubt about the optimality of the inputs obtained. Recently, the importance of input determination has begun to be recognised in the water resources literature, but, only a small number of researchers that treat it as an important step in the modelling process. In some instances, inputs were chosen arbitrarily and in other cases, a *priori* knowledge was employed for input selection (Campolo et al., 1999; Jayawardena et al., 1997;

Thirumalaiah and Deo, 2000). When trial-and-error approaches are used, quite often that the validation data were used together as part of the training process. If important inputs are not included, then some critical information about the system may be lost. On the other hand, if spurious inputs are included, it may tend to confuse the training process that leads to poor network performance. Although a *priori* identification is widely being used, it is very subjective and case dependent, which finally dependent on the researcher's knowledge and approach. The preferred approach for determining appropriate inputs and lags of inputs, involves a combination of a *priori* knowledge and analytical approaches (Maier and Dandy, 1997; Fernando and Jayawardena, 1998; Maier et al., 1998).

When the relationship of the inputs to be modelled is not well understood, an analytical technique, such as cross-correlation, is often employed (Golob et al., 1998; Sajikumar and Thandaveswara, 1999; Luk et al., 2000; Silverman and Dracup, 2000; Huang and Foo, 2002). The major disadvantage of using cross-correlation is that it is only appropriate to detect linear dependence between two variables and is unable to capture any nonlinear dependence that may exist between the inputs and the output (Abrahart, 1998, 2004). This may possibly result in the omission of important inputs that are related to the output in a nonlinear fashion. Inputs may also be selected based on heuristic method, where networks are trained based on different subsets of inputs (Maier, 1998; Jain et al., 1999). The main disadvantage of these approaches is that they are computationally intensive and based on trial-and-error, thus, there is no guarantee that they will find the globally best subsets (Tokar and Johnson, 1999). Significant inputs can also be chosen based on sensitivity analyses from the trained ANN (Maier and Dandy, 1996, 1997; Maier et al., 1998; Schleiter, 1999; Liong et al., 2000). In this approach, the effect that each input has on the error function is examined by removing one input at a time from the trained ANN model (Abrahart et al., 2001). The difficulty is the choosing of the appropriate value to perturb the input by selecting the relevant cut-off point for input significance. However, the main disadvantage of this approach is that it did not retrain the ANN network after removing each input.

Generally, the approach used in the selection of an appropriate optimisation technique in the application of ANN involves large number of inputs and this produced a number of shortcomings (Zheng and Billings, 1996; Maier and Dandy, 1997; Back and Trappenberg, 1999). Among the shortcomings are the increased in input dimensionality, the computational complexity and the increased in the memory requirements of the model. This complex system will create complex networks and with larger data sets will increase the training time of the network. The involvement of irrelevant inputs makes learning becomes more difficult that will increases the number of misconvergence due to increase in number of local minima present in the error surface (Smith, 1994; Tokar and Johnson, 1999). The more complex the network is, the more difficult to understand the model as compare to the simple network model that is easily understood and relatively comparable.

The other least understood and difficult task in the design of the network is the choice of adequate internal network parameters and appropriate algorithms, especially in the design of popular back-propagation networks (Maier and Dandy, 1998). Generally, this network is determined using trial-and-error approach. Review of the literature revealed that the learning rate, momentum, the gain of the transfer function, epoch size and network geometry have a significant impact on training speed, but not on generalisation ability (Rumelhart et al., 1986; Hecht-Nielsen, 1987; Simpson, 1990; Weigend et al., 1990; Freeman and Skapura, 1991; Karunanithi et al.,1994; Maier and Dandy, 1996, 1998; Muttiah et al., 1997; Abrahart, 1998, 2004; Augusteijn and Warrender, 1998; Durucan and Imrie, 1998, 1999; Luk et al., 1999; Abrahart and See, 2000; Dawson and Wilby, 2000; Bowden et al., 2004). The type of transfer and error function used was also found to have a significant impact on learning speed as well as on generalisation ability (Maier and Dandy, 1998; Abrahart, 1998, 2004; Dawson and Wilby, 2000). The aim of training procedure is to adjust the connection weights until the global minimum has been reached, but in practice it is difficult to achieve until certain stopping criteria are met. It should be aware that increase in training may ended the network to memorise the data instead of generalising, thus overfitting the data. The selected network model will imitates the data training set successfully but generates a bad estimation for the data not included in the training. This overfitting can be prevented by regularisation or early stopping approach (Abrahart, 2004).

Based on the literature review, the application of ANN has great potential to be a useful tool in water resources planning and management. The scope of the existing on-going researches covers wide areas of the hydrological prediction and forecasting. However, only a handful of these researches involve classification of water quality, most of it relates to biological and ecological classification that involves benthic organisms. In order to achieve significant advances in these areas, there needs to be a change in the mind-set of hydrological researchers that starts from the application of basic ANN models to an ever-increasing number of case studies, in particular the move towards the development of guidelines for ANN hydrological modellers. At present, there is a tendency among researchers to apply ANN to problems for which other methods have been unsuccessful or less accurate. Research efforts should be directed towards the identification of applications and circumstances in which particular ANN approaches do not perform well in order to define their boundaries of applicability. Based on the current published research materials, the other area that seems to be less considered is the application of the BEP of ANN model in classification of water quality using physico-chemical and land-use parameters. There has been enormous researches done on water quality classification based on physico-chemical and biological parameters, but were based on the traditional approaches and techniques, either statistical or mathematical techniques. Thus, it is timely to explore the capability of the application of ANN to classify several rivers in different catchment areas based on physico-chemical and land use parameters.

In the next chapter, the BEP of ANN model will be used to classify several water quality stations in a selected catchment area in Malaysia. The classification results obtained through this approach will be compared with that of the traditional approaches, the DOE-WQI and Harkins'-WQI. The application of the BEP of ANN model which is based on pattern recognition is to complement and not to emulate the existing assessment systems, the DOE-WQI which is a mathematical formula and the Harkins'-WQI model which is based on non-parametric statistical approach. In view of the rapid land use changes with new forms of pollutants that are being discharges into the river system, the DOE-WQI is too rigid to cater for the inclusion of new and significant variables or for the deletion of obsolete and insignificant variables. The results obtained from Harkin's-WQI model which is based on non-parametric statistical approach should not be used to make comparison with other data set from different catchment areas, thus it is timely to consider and assess the capability and the flexibility of the BEP of ANN in classification of the river water quality in Malaysia. The driving force of this model application is to reduce the operational complexity as portrayed in the DOE-WQI model.

CHAPTER FIVE

PILOT STUDY

5.1 BACKGROUND

In 2001, the water quality monitoring programme in Malaysia covered 980 monitoring stations within 120 designated catchment areas. Such huge areas have made monitoring difficult. After the institutionalisation of the DOE in 1974, some regional offices were set-up at state level, and by 2001, almost all of the 14 states have their own offices. This decentralisation initiative was to ensure that monitoring programme and the related activities run smoothly throughout the country to resolve the issues of water quality and quantity, which were becoming more critical.

In water quality management programmes, methods of monitoring and assessment are standardised throughout all designated water catchment areas. Over the course of time, new methods and techniques have been introduced to achieve greater effectiveness and practicality. Based on this factor, a single catchment area was selected as a representative for this study or as Pilot Study area, in order to explore the effectiveness and practicality of the new technique of assessment of water quality based on the BEP of ANN.

Normally, an application of a new technique of assessment starts with a Pilot Study. It is a form of good management practice so as to avoid unnecessary wasting of resources such as time, man power and fund disbursement. Before the selected classification technique is applied to all designated monitoring stations, this technique will be evaluated and tested through selected samples of monitoring stations within a specific catchment area. The classification results obtained will be evaluated and tested in details, based on the reliability, effectiveness, accuracy and reproducibility of the selected technique. Comparisons are made with the results obtained from the existing assessment models. If classification results are found to be unreliable, ineffective, inaccurate and not reproducibility, then it will not be relevant to proceed using the same technique, otherwise it is acceptable. However, if the results obtained are between fair and moderate, or the results are reliable but not convincing, than subsequent analysis should be carried out with some modifications to ascertain that the selected research technique is acceptable. The determination to whether the research should proceed or stop is based on some statistical evaluation. As such, the objectives of this pilot study were:

(1) To classify rivers within the Langat catchment area, in the State of Selangor, Malaysia, using the DOE-WQI, Harkins'-WQI, BEP of ANN, Maximum-Likelihood Classifier, Mahalanobis Distance Classifier and Decision Tree Classifier, for preliminary assessment of compliance with the standards adopted by the DOE, Malaysia, on the various classes of beneficial uses of water in relation to the physico-chemical variables;

(2) To compare the results of classification based on DOE-WQI, Harkins'-WQI, BEP of ANN, Maximum-Likelihood Classifier, Mahalanobis Distance Classifier and Decision Tree Classifier;

(3) To investigate the reliability and accuracy of the DOE-WQI, Harkins'-WQI, BEP of ANN, Maximum-Likelihood Classifier, Mahalanobis Distance Classifier and Decision Tree Classifier;

(4) To investigate the sensitivity of the network created using BEP of ANN model as compared to that of DOE-WQI mathematical model; and

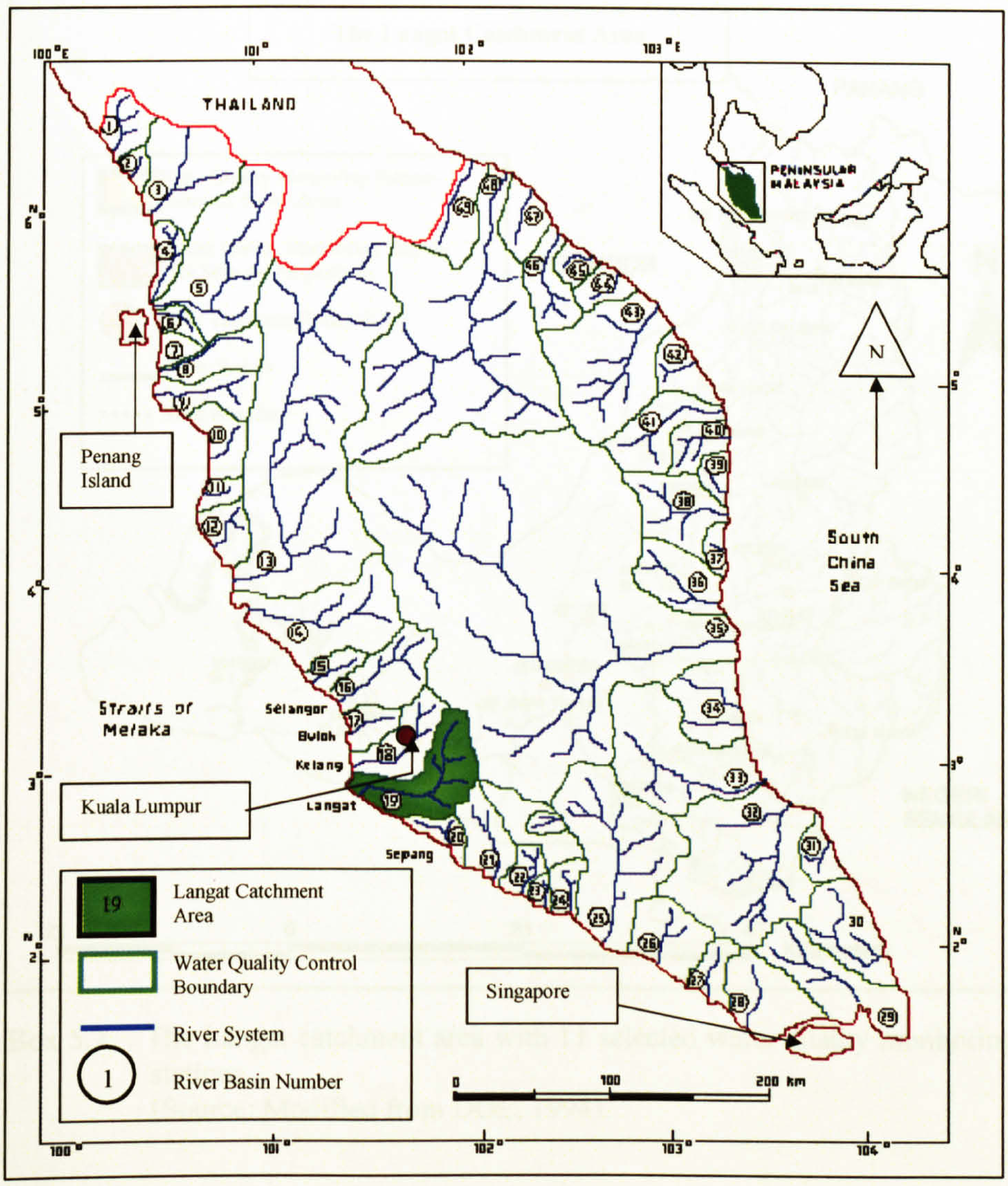
(5) To investigate the reliability and the effectiveness of classification results presentation between the BEP of ANN, DOE-WQI and Harkins'-WQI model.

5.2 STUDY AREA

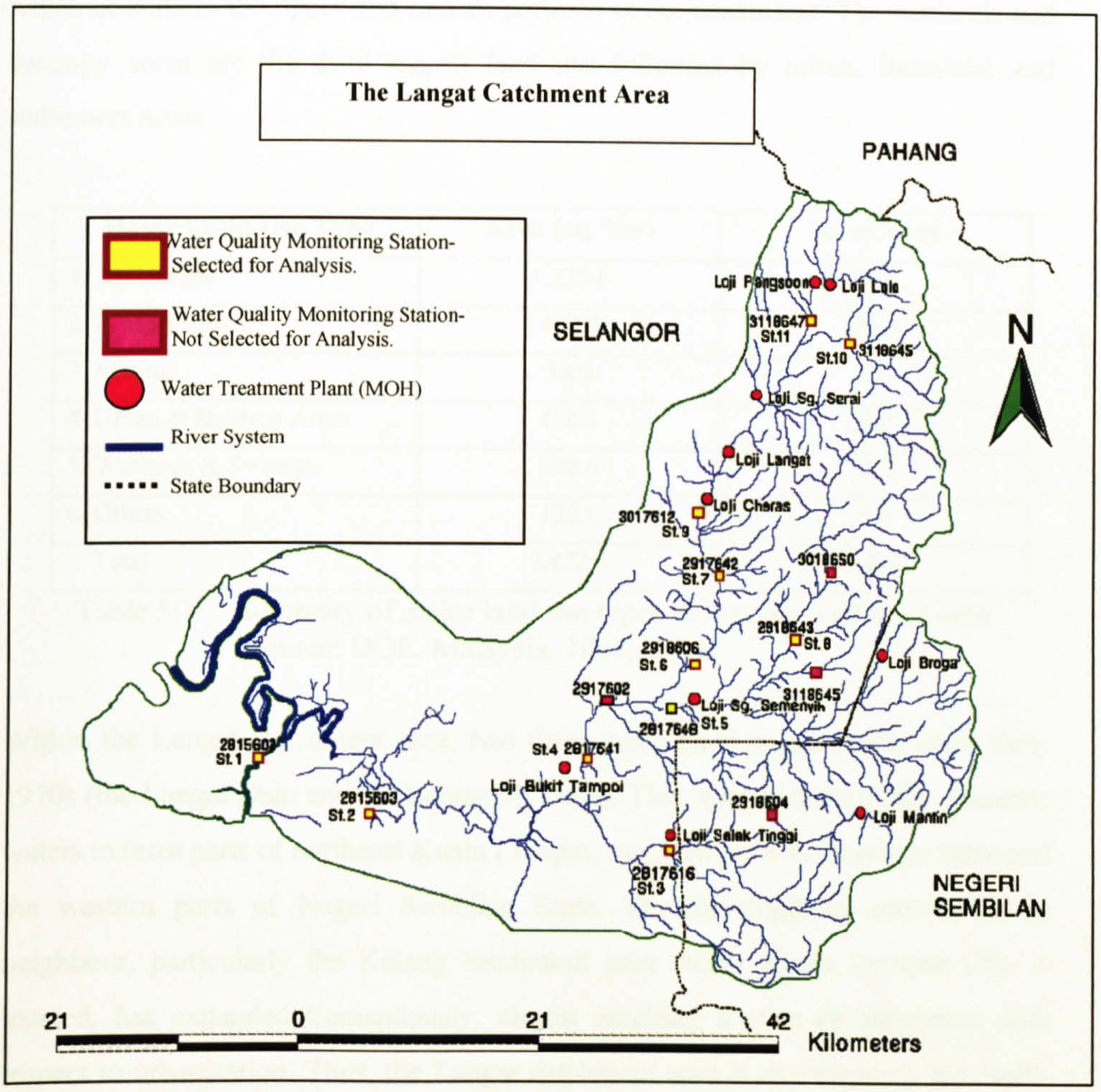
5.2.1 Location and Description

The area chosen is the moderately developed area known as the Langat River Catchment. It is located in the southwest of Peninsular Malaysia (Box 5.1 and Box 5.2). It occupies the south and southeastern part of the state of Selangor, neighbouring the Kelang River Catchment area near to Kuala Lumpur city. The catchment is 78 km in length from 20 km to 52 km wide, and covers an area of 2422.6 sq. km. Langat River is the main river, running from its source at the Pahang-Selangor State border, where the hilly terrain reaches an altitude of 1500 m. Its main tributaries are Semenyih, Labu and Beranang River. The direction of flow of Langat River is towards the south and southwest in the eastern half of the catchment, and westward on the western part of the catchment. It finally drains into the Straits of Malacca on the south-western part of Selangor State.

Based on the morphology of the area, the source of the Langat River begins from the east of the catchment. Thus, the eastern areas receive most of the runoff waters that drain down from the hilly terrain. On the western part is the coastal area from which the Langat River meanders in large curves and bifurcates before draining into the Straits of Malacca. The coastal area is a flat land with swampy forest that dominates most of the area along the estuary. Most of the low-lying areas have been drained for oil palm and rubber plantations (GOM, 1982; DOE, 1986).



Box 5.1 Location of Langat River catchment area in Peninsular Malaysia (Source: Modified from DOE, 1994)



Box 5.2 The Langat catchment area with 11 selected water quality monitoring stations.
(Source: Modified from DOE, 1994).

In terms of geology, the Langat Catchment is underlain by layers of crystalline igneous rocks, belonging to the type of Genting Sempah Microgranite and the Kuala Lumpur Granite. Hilly terrain with sharp ridges dominates the interior parts from which the river source starts to flow. As the river flows into the catchment from the upper reaches, the hilly terrain starts to slope down from 200 m to 50 m above mean sea level and become almost flat towards the coast. In the middle reaches, the underlains geology of the catchment changes to schist and sedimentary rocks. The distribution of land use is summarised in Table 5.1. Agriculture covers most parts of the catchment, especially towards the coast, followed by the primary (natural) forest, which dominates the upper and eastern portions of the catchment. The wetlands and swampy areas are the third largest land use followed by urban, industrial and settlement areas.

Major Land Use Type	Area (sq. km)	% of Area
1. Agriculture	1,335.6	55.1
2. Primary Forest	467.8	19.3
3. Mining	38.9	1.6
4. Urban & Built-up Areas	150.1	6.2
5. Wetlands & Swamps	308.4	12.7
6. Others	121.8	5.0
Total	2,422.6	100.0

Table 5.1 Summary of major land use types in Langat catchment area (Source: DOE, Malaysia, 1994, 1999).

Within the Langat Catchment area, two dams have been in operation since early 1970s (the Langat Dam and the Semenyih Dam). They supply most of the domestic waters to most parts of northeast Kuala Lumpur, northern parts of Selangor State and the western parts of Negeri Sembilan State. The development activity of its neighbour, particularly the Kelang catchment area where Kuala Lumpur City is located, has expanded tremendously, almost reaching a state of saturation with respect to urbanisation. Thus, the Langat catchment area is experiencing the 'spill-over' effects of development. Several major Federal Government projects have already been approved in this area. Among these are the new Federal Administrative and Management Centres that will house all 24 ministries from Kuala Lumpur City centre. Other major projects include: several new universities, industrial development areas for Selangor State and Negeri Sembilan State (Selangor State Government Reports, 1996; Negeri Sembilan State Government Reports, 1996), and the Kuala Lumpur International Airport City.

5.3 SOURCES OF DATA

The main source of water quality data was DOE, Malaysia. The data covers a period of nine years between 1991-1998 (Table 5.2 and Table 5.3). Data were measured *in situ,* using field equipment such as Dissolved Oxygen Meter, and collected samples were sent to laboratories either in the Chemistry Department Headquarters, Petaling Jaya, or to other regional laboratories for immediate analyses. The land use data were obtained from Prime Minister's Department, Mapping and Survey Department, Agriculture Department, Town and Country Planning Headquarters, and State of Selangor and State of Negeri Sembilan District Masters Plan.

Station No.	Station Designation	Name of River/Stream	Distance from Estuary (km)	Strahler Stream Order at Station Point
St1	2815602	Langat	4.2	7
St2	2815603	Langat	33.5	7
St3	2817616	Batang Labu	67.3	4
St4	2817641	Langat	63.4	7
St5	2817648	Semenyih	80.8	6
St6	2917642	Langat	81.1	6
St7	2918606	Langat	86.9	6
St8	2918643	Semenyih	85.6	6
St9	3017612	Langat	93.4	6
St10	3118645	Lui	105.0	5
St11	3118647	Langat	114.0	5

Table 5.2 Station number and the name of rivers in Langat catchment area (Source: DOE, Malaysia, 1994, 1999)

5.4 METHODOLOGY

The DOE in Malaysia is applying a water quality index system to assess the country's water quality that is based on physico-chemical parameters. This assessment involves two techniques; the DOE-WQI and Harkins'-WQI. Subsequently, the index value obtained is transformed into water quality classes. The methodology of these two techniques is firstly discussed before proceeding into the other techniques of assessment.

5.4.1 Interim National Water Quality Standards Table

The INWQS Table (Table 2.2) is used in water quality classification for the Malaysian rivers. This incorporates the water quality criteria and standards, which forms as transitory reference for the establishment of a more practical system of quality standards that can be applied in enforcing compliance. A five-class system was recommended for classification, which correspond to the most sensitive and highest beneficial uses set-up for domestic water supply, fisheries and aquatic life propagation, livestock drinking, recreation and irrigation. Thus, a segment of river can be classified, either in ascending or descending order, according to the most sensitive use and the highest known existing beneficial uses of water.

Station No.	Year of Monitoring/ Number of data collected*								
	1991	1992	1993	1994	1995	1996	1997	1998	Total
St1	5	5	6	5	3	3	4	3	34
St2	5	5	6	5	3	3	4	3	34
St3	5	6	6	5	3	3	4	3	35
St4	5	6	6	5	3	3	4	3	35
St5	5	6	6	5	3	3	4	3	35
St6	5	6	6	4	3	3	4	3	34
St7	5	6	5	3	3	3	4	3	32
St8	5	6	6	4	3	3	4	3	34
St9	5	6	6	4	3	3	4	3	34
St10	5	3	5	4	3	3	4	3	30
St11	5	5	6	4	3	3	4	3	33

Table 5.3 Number of data collected for the six variables, 1991 – 1998.
(Note:* Data were contributed by the DOE, Malaysia)

Based on this INWQS table, all variables are measured in milligrams per litre (mg/l) except the pH, which is unitless. In determination of pH standard values, acidity values are used, since acidic condition contributes more deleterious effect than an alkaline condition (Harkins, 1974, 1977). Classes III, IV and V carry the same standard pH values since the magnitude of the effect on beneficial uses of water and aquatic species for pH 5.0 and below, are the same (DOE, 1994).

5.4.2 Classification Based on DOE-WQI Model

The main water quality index and classification system being used by the DOE, Malaysia is based on the mathematical formula as indicated in Box 3.2. Based on Equation 3.1 (Box 3.2), the weighting for DO is the highest, which implies that it is the most important indicator among the six variables. The effects and impacts of DO and other physico-chemical variables being used in water quality assessment have been discussed in detail by EEC (1981), WHO (1984a, 1984b), Chapman (1992), Dojlido and Best (1993), and Bean and Rovers (1998). Based on the DOE-WQI model, the calculations were performed, not on the parameters themselves, but on their subindices whose values are obtained from series of equations. These are the best-fit equations obtained from rating curves as illustrated in Appendix 2.5. The results of subindex values were transferred into the DOE-WQI formula as in Equation 3.1 to obtain the standard index values for each class. Consequently, using the same formula, the index values from observed data were calculated. These values are transformed into class values by comparing the calculated observed index values to those of standard index values as indicated in Table 3.3. As an example, based on Table 3.3, the calculated observed values are transformed into class grades as indicated in Table 5.4. Table 5.5 illustrate the frequency distribution for 11 stations for the year 1991 to 1998.

Station 1 Year: 1991	Name of River	DOE-WQI (Obs. Val.)	DOE-WQI-Class Value
2814602	Langat	71.5	3
2814602	Langat	73.5	3
2814602	Langat	71.4	3
2814602	Langat	63.4	3
2814602	Langat	75.7	3
Year:1992			
2814602	Langat	71.7	3
2814602	Langat	66.4	3
2814602	Langat	67.7	3
2814602	Langat	45.7	4
2814602	Langat	72.0	3

Table 5.4 Example of calculated observed index values for Station 1, 1991/1992.

Station No.	DOE-WQI				
	Class 1	Class 2	Class 3	Class 4	Class 5
St1	0	0	21	10	3
St2	0	1	12	19	2
St3	0	14	15	5	1
St4	0	0	23	11	1
St5	0	15	18	0	0
St6	0	0	15	15	4
St7	0	0	13	18	1
St8	0	10	22	2	0
St9	0	6	15	13	0
St10	5	25	0	0	0
St11	12	20	1	0	0

Table 5.5 Results based on class frequency distribution using DOE-WQI model for 11 stations from 1991 - 1998.

5.4.3 Classification Based on Harkins'-WQI Model

The other objective of this study is the application of non-parametric statistical approach, which is based on Harkins method of analysis of water quality and the details are discussed in Section 2.3.4. The application of Harkins'-WQI will provide a comparison with the results obtained from DOE-WQI. The calculations were based on ranking procedures as shown by Equation 2.42 and Equation 2.43, Box 2.4. Using these procedures, the observed data, the standard values and a selected set of control values are ranked simultaneously. As an example, computations were performed using Excel of the Microsoft Office for Station 1 data as presented in Table 5.6. The Harkins'-WQI ranked data were presented as in Table 5.7. The standard index values, which correspond to particular classes, were obtained simultaneously with the observed index values from the data sets. Based on Table 5.7, the calculated observed values as displayed in row 8 and below were referred to the standard values that correspond to a specific class grade as shown in rows 3 to 7. This determines the class grade for a particular water quality sample. Finally, the class frequencies for the 11 stations using Harkins'-WQI model are presented in Table 5.8.

Station 1		AN	BOD	COD	DO	PH	SS
	Control	0.00	0.0	0.0	8.0	7.0	0.0
	Class I	0.10	1.0	10.0	7.0	7.0	25.0
	Class II	0.30	3.0	25.0	5.0	6.0	50.0
	Class III	0.90	6.0	50.0	3.0	5.0	150.0
	Class IV	2.70	12.0	100.0	1.0	5.0	300.0
	Class V	3.00	13.0	130.0	0.0	5.0	310.0
	Name of River						
Year: 1991	Langat	0.44	1.1	82.7	4.5	6.4	45.0
2814602	Langat	0.32	3.6	66.8	4.4	6.0	14.0
	Langat	0.35	1.2	17.7	2.6	5.0	22.0
	Langat	0.05	7.5	89.5	3.8	6.9	95.0
	Langat	0.40	1.5	22.6	4.0	5.0	10.0
Year: 1992	Langat	0.20	1.3	45.5	3.5	6.5	40.0
	Langat	0.20	0.8	27.6	2.8	5.0	102.0
	Langat	0.10	0.0	95.7	2.7	7.2	38.0
	Langat	0.90	1.0	70.8	2.4	4.7	2152.0
	Langat	0.60	0.0	3.6	3.4	4.1	34.0

Table 5.6 Example of data set-up for ranking process in Harkins'-WQI model.

St 1		Day,J	RANj	RBODj	RCODj	RDOj	RpH	RSSj	Harkins Index	Harkins Class
	Control	1	1	2	1	1	1.5	1	0	0
	Class I	2	4.5	12.5	3	2	1.5	6	1.15	1
	Class II	3	15.5	28	6	3	27	12	12.69	2
	Class III	4	32	31	13	4	34	23	26.28	3
	Class IV	5	36	33	32	5	34	28	37.20	4
	Class V	6	39	35.5	33	6	39	29	43.64	5
SNO(91)	Langat	7	22.5	14.5	27	7	24	11	14.56	3
2814602	Langat	8	18	29	18	8	27	3	15.12	3
	Langat	9	19.5	16.5	4	9	34	4.5	12.74	3
	Langat	10	2	32	29	10	12.5	15	15.65	3
	Langat	11	22	19.5	5	11.5	34	2	14.52	3
SNO(92)	Langat	12	14	18	11	11.5	21.5	9	8.27	2
	Langat	13	7	11	7	13	34	16	11.87	2
	Langat	14	6	2	31	14	8	8	8.90	2
	Langat	15	33	12.5	19	16	37	40	33.55	4
	Langat	16	28	2	2	16	38	7	17.48	3

Table 5.7 Example of Harkins'-WQI values transformed into classes for Station 1.

Station No.	Harkins'-WQI				
	Class 1	Class 2	Class 3	Class 4	Class 5
St1	0	6	15	10	3
St2	0	2	10	21	1
St3	0	18	16	1	0
St4	0	5	25	4	1
St5	0	24	11	0	0
St6	0	1	23	9	1
St7	0	0	18	14	0
St8	0	15	19	0	0
St9	0	13	15	6	0
St10	5	25	0	0	0
St11	13	20	0	0	0

Table 5.8 Results based on class frequency distribution using the Harkins'-WQI model for Langat catchment area, 1991-1998.

5.4.4 Artificial Neural Networks Application in Water Quality Classification

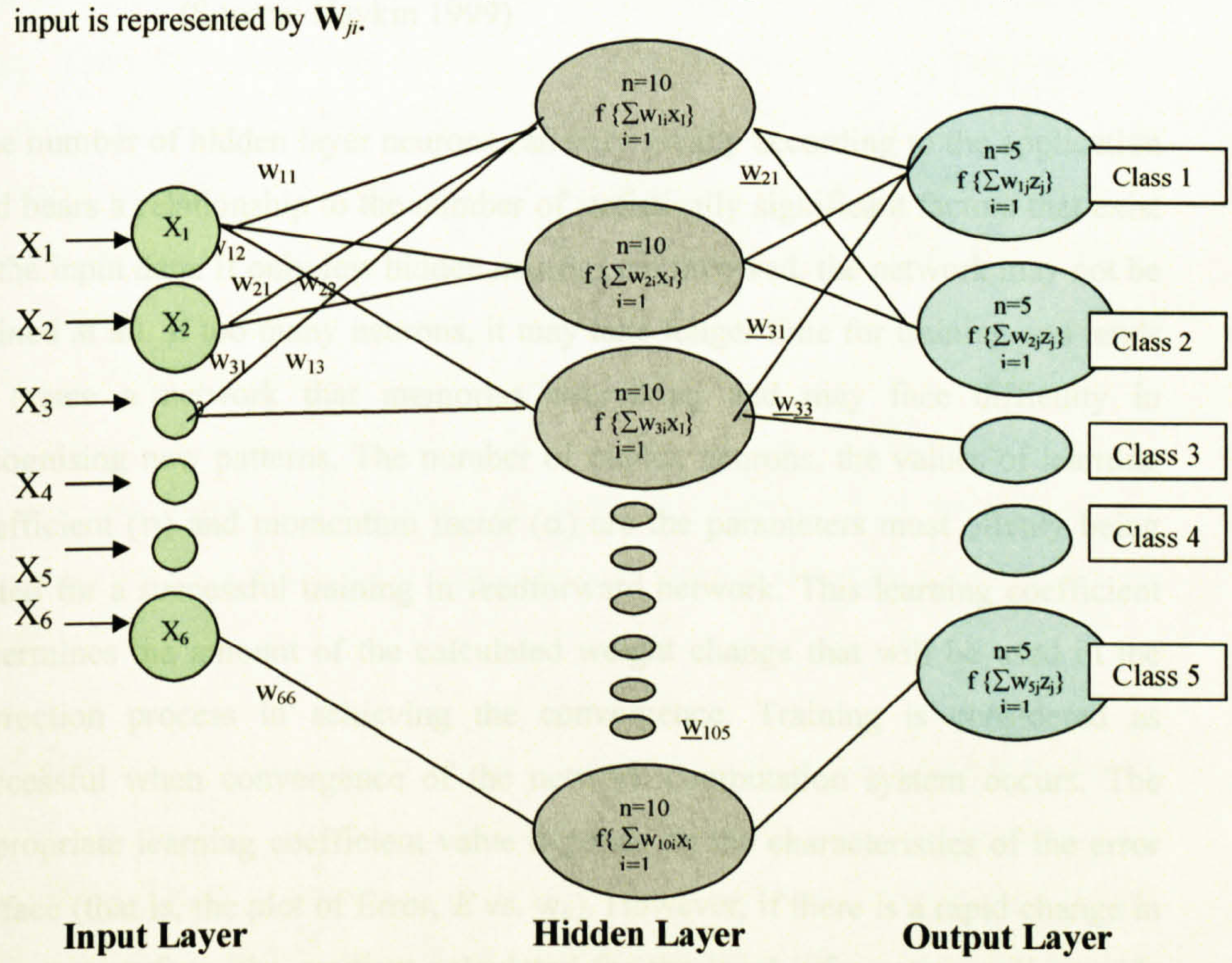
The ANN approach can be applied differently through many techniques and the most common is the feedforward based on supervised learning (or backpropagation training). An example of three-layer feedforward network model that can be applied for water quality classification is shown in Box 5.3. This network consists of input neurons, which constitutes the input layer (on the left of Box 5.3), where the input variables or patterns are first assigned into the networks. The input patterns are presented to the networks and processed simultaneously in parallel-distributed manner. In feedforward, each input can take on any value (between 0 and 1) where the input values are continuous and normalised between the values of 0 and 1. This continuous value inputs provides significant flexibility to ANN.

Normalising of input patterns may act as a tool for preprocessing data in different ways. The data can be normalised by considering either all of the inputs together, or each input channel can be normalised separately, or normalise in groups of channels. An input channel means running a set of inputs into one input neuron. In certain cases, the way in which normalisation of inputs is performed can affect the performance of the networks. Where all inputs consist of raw data points, it is more appropriate to normalise all of the channels together simultaneously. If the inputs consist of parameters, normalising of each channel can be done separately, or normalising the channels that represent similar kinds of parameters together as indicated by the five classes of INWQS (Table 2.2).

In the input layer, when input patterns or signals are introduced, the input neurons simply distribute the signals along the multiple paths to the hidden layer neurons. The output of each input layer neuron is exactly equal to the input of the hidden layer neuron and is in the range of 0 to 1. A weight is associated with each connection to a hidden neuron. As illustrated in Box 5.3, each neuron of the input layer is connected to every neuron of the hidden layer. Similarly, each neuron of the hidden layer is connected to every neuron of the output layer. The flow of these pattern signals move from left to right (constitutes feedforward network) and in this situation there are no feedback loops, even within neuron unit itself.

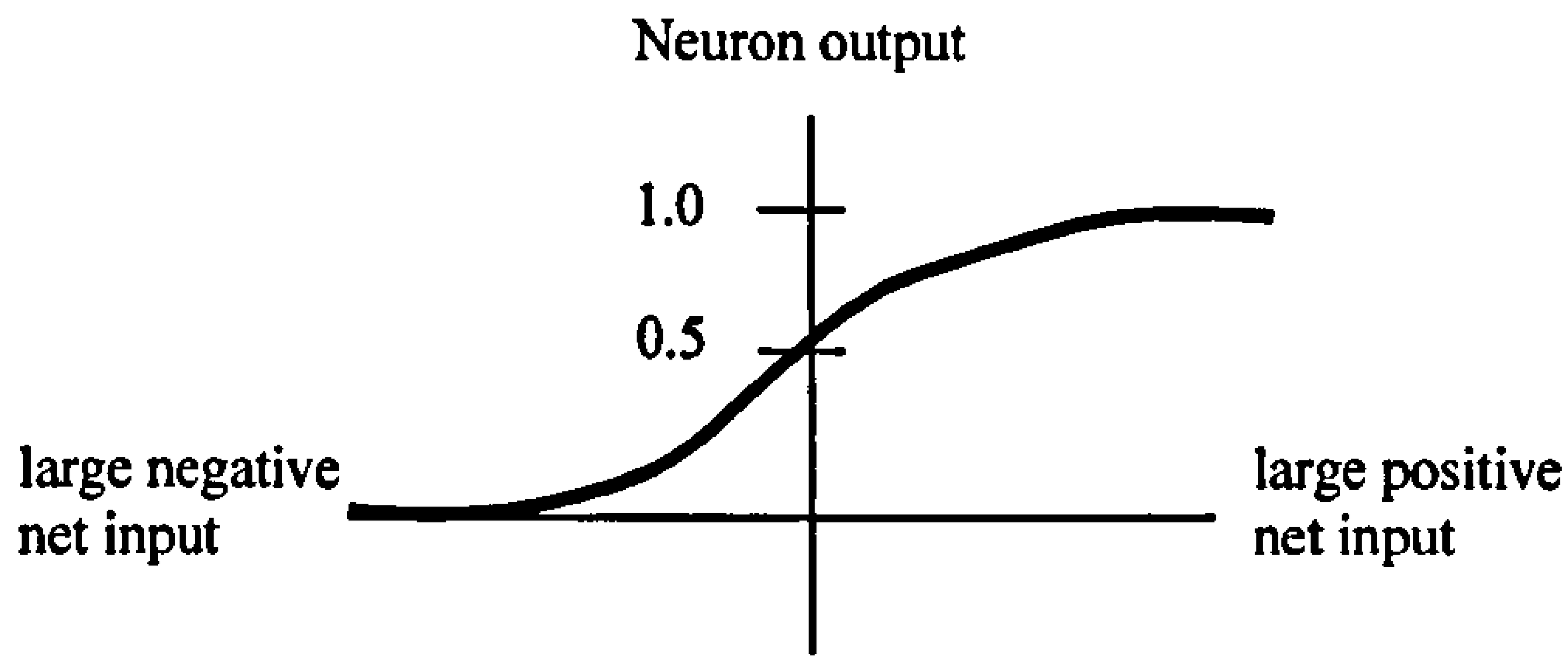
Most of the feedforward networks use the sigmoid neurons with an additive characteristic. When a signal is transmitted into a hidden layer neuron, the output value of the input node multiplies the value of the connection weight. The net input to a hidden neuron is calculated as the sum of the values for all connections presented into the neuron as in Equation 5.1, Box 5.4 (Haykin, 1999). In many applications of ANN, the neural unit characteristics can be modified by introducing a bias that helps to speed up the convergence rate as in Equation 5.2. The output of a hidden neuron as a function of its net input is expressed as in Equation 5.3, which is the sigmoid function, also known as 'squashing' function. This sigmoid function is non-linear in characteristic that helps to create a high performance network. The graphical shape of this sigmoid function is illustrated in Box 5.4, which carries the value between 0 and 1.

In the diagram below, a circle represents each neuron or node and each interconnection with its associated weight is represented by an arrow. The attributes of individual neurons or connections are represented by lowercase letters with subscripts. The letter *i* denotes an input, output *j*, a connection weight *w*, and *n* is the number of neurons or nodes of a particular layer. The input vector to the input layer consisting of all individual inputs, $\mathbf{i}_i$ and $\mathbf{j}_l$ is the output vector of the output layer. The combination of the input and output constitute a pattern vector, **p**, such that $\mathbf{p}_r$ can represents a training pattern, and testing pattern, $\mathbf{p}_s$. The connection weights, w_{ji}, is the weight of the connection from an input neuron to a hidden neuron. The receiving neuron is the first subscript and the second is the sending layer. Normally, the matrix of weights to the hidden layer from the input is represented by $\mathbf{W}_{ji}$.



Box 5.3 Example of the three layer Feedforward Neural Network that can be applied for water quality classification.
(Source: Modified from Schalkoff, 1992; Tsai and Lee, 1999; Haykin, 1999; Friedman and Kandel, 1999)

$\text{Net-input}_j = i_j = \sum_i W_{ji}O_i$	Equation 5.1
$\text{Net-input}_j = i_j = \sum_i W_{ji}O_i + \text{bias}_j$	Equation 5.2
$\text{Output}_j = O_j = 1/[1+\exp(-i_j)]$	Equation 5.3



Box 5.4 Input, output signals and sigmoid transfer function used in feedforward network.
(Source: Haykin 1999)

The number of hidden layer neurons can vary greatly according to the application and bears a relationship to the number of statistically significant factors that exist in the input data. If only few hidden neurons are involved, the network may not be trained at all. If too many neurons, it may take longer time for training and tends to create a network that memorise everything and may face difficulty in recognising new patterns. The number of hidden neurons, the values of learning coefficient (η) and momentum factor (α) are the parameters most oftenly being tested for a successful training in feedforward network. This learning coefficient determines the amount of the calculated weight change that will be used in the correction process in achieving the convergence. Training is considered as successful when convergence of the network computation system occurs. The appropriate learning coefficient value depends on the characteristics of the error surface (that is, the plot of Error, E vs. w_{ij}). However, if there is a rapid change in this error surface, the gradient calculated for the local information will provide poor indication of the right path. Thus, it needs a smaller learning coefficient value. If this surface is relatively smooth, a larger learning coefficient value will speed up convergence. But this is not always the case; larger coefficient value may also result with rapid oscillations that prevent the convergence of the network. This oscillation can be prevented or reduced when the momentum factor (α) is added to the system that help to escape the local minima of the error function. However, if this momentum factor is greater than the learning coefficient, the system may become less sensitive to local changes. If it enters local minima during this converging process, the momentum factor that is introduced during entry into the minima may acquire enough momentum (energy) to push it back. Once the outputs of all hidden layer neurons have been calculated, the net input to each output layer neuron is calculated in an analogous manner as expressed in Equation 5.1 and Equation 5.2, which form the expressions for the output of each output layer neuron.

A local minima is analogous to a downward slope of a hill characterised with several bowl-shaped surfaces or ridges. When a ball is rolled from the hilltop, the ball may either get stuck halfway down the hill slope or it may reach the lowest ridge. The ball that got stuck halfway is equivalent to local energy minima where the error could not be achieved at the most minimum level. Whereas, the ball that managed to settle at the lowest ridge is termed as global minima or globally optimal solution. This will depends on how strong the ball can be pushed and in this situation, it is most likely acquired a small limits on each individual movement and this should correspond to a small value of learning coefficient, η. The strength of ball movement to which it can reach the global minima can be resolved by assigning the momentum factor. It is achieved by multiplying the previous (previous movement) weight change by a momentum factor, α (values between 0 and 1).

In the training or learning phase, the feedforward output calculation process run simultaneously with the back propagation calculation and weight adjustment calculation. The error reduction is performed on the basis of an individual neuron for the entire set of patterns and not on each individual pattern. The error can be expressed as in Equation 5.4 in Box 5.5 (where t_l is the target value, o_l is the actual value acquired as a result of feedforward calculation, and subscript p represents the value for a given pattern). Normally, the Delta rule (either the Generalised Delta rule) is used in this approach, by comparing the actual result at the output with the desired result and then either strengthening or weakening the weights which have firing inputs, by some amount proportional to the size of the error (Schalkoff, 1992). These weights are computed so that the output becomes closer and closer to the actual solution until convergence is achieved. For all neurons, these errors are summed up giving a grand total for all neurons and all patterns. This grand total of errors is then divided by the total number of patterns to give an average sum-squared error value. Since the factor of 0.5 in Equation 5.4 is a constant, it is deleted from the calculations process. Thus, **the goal of the training process is to minimise this average sum-squared error over all training patterns.** This process is also known as Least Mean Squares, where errors are reduced based on gradient descent approach (Rumelhart and McClelland, 1986; Hertz et al., 1991; Zurada, 1992; Schalkoff, 1992). Arbitrarily, this error for the whole patterns in a multi-dimensional space can be represented in the form of an error surface.

$E_p =$	$0.5 \sum_{l=1}^{n_l} (t_{pl} - o_{pl})^2$	Equation 5.4
$\delta_l =$	$f'(i_l)\,(t_l - o_l)$	Equation 5.5
$\delta_l =$	$(t_l - o_l)\,o_l\,(1 - o_l)$	Equation 5.6

Box 5.5 Error produced from individual neuron during learning process and the sigmoid function for each output neuron.
(Source: Eberhart and Dobbins, 1990; Haykin, 1999)

In the output layer, the output of a neuron is a function of its input (either $O_l = f(i_l)$) as represented in Equation 5.3 of the sigmoid function. This function is transformed into its first derivative ($f'(i_l)$) and finally the error signal (δ_l) for each output neuron of the output layer is expressed as in Equation 5.5 in Box 5.5. In case of sigmoid function, its first derivative is represented as $o_l\,(1 - o_l)$ and the expression for the output layer error signal calculated for each output neuron is given by Equation 5.6.

In reducing the average sum-squared error, the error value as in Equation 5.6 is propagated back (back-propagation) into the network, which then perform weight adjustment. Back propagation is carried out in two ways; the first involves propagating the error back and weights adjustment is carried out after each training pattern (on-line or single-pattern training); and the second is to accumulate and sum-up all the error signal values (δ_l's) for each neuron for the entire training set, and propagate back the error based on the grand total error value (δ) (batch or epoch training). Generally, the batch training of backpropagation is applied since it can speed up the training process. However, before the weights are updated, each weight is initialised to some value. If all the weights are equal to zero or saturated with large values, it will face the difficulty in training process or the network may not learn due to the presence of homogenous weight values. Therefore, it is typical to assign relatively small random numbers to speed up the training process (Eberhart and Dobbins, 1990).

In updating the new weight (W_{lj}), error (δ_l) produced is used to feed into the output layer as represented in Equation 5.7 in Box 5.6, where η is the learning coefficient. However, this weight assignment may get caught or stuck in local minima. This can be resolved by multiplying the previous (previous movement) weight change by a momentum factor (α). The updated weights feeding a neuron of an output layer is represented as in Equation 5.8 (Box 5.6). Thus, the new weight is the result of addition of the old weight and the weight change (ΔW_{lj}). This weight change consists of error signal term (δ) and the momentum factor term (α). Therefore, the previous movement of the weight provides momentum to the ball, pushing it much more likely to reach the global minimum.

The convergence rate can be sped up by introducing the bias as in Equation 5.2. The bias neurons, (always with an output value of 1) serve as threshold units for the layers to which they are connected. The weights from this bias to each of the neuron in the following layer are adjusted exactly like the other weights. Based on Equation 5.8, for each of the output neuron, the subscript *j* takes on values from 0 to n_j, which represents the number of hidden neurons and the n_jth value is associated with the bias value.

$$W_{lj}(\text{new}) = W_{lj}(\text{Old}) + \eta\delta_l O_j \qquad \text{Equation 5.7}$$

$$W_{lj}(\text{new}) = W_{lj}(\text{Old}) + \eta\delta_l O_j + \alpha[\Delta W_{lj}(\text{Old})] \qquad \text{Equation 5.8}$$

$$\delta_h = f'(i_h) \sum_{l=0}^{n_j} W_{lh}\delta_l \qquad \text{Equation 5.9}$$

$$\delta_h = O_h(1 - O_h) \sum_{l=0}^{n_j} W_{lh}\delta_l \qquad \text{Equation 5.10}$$

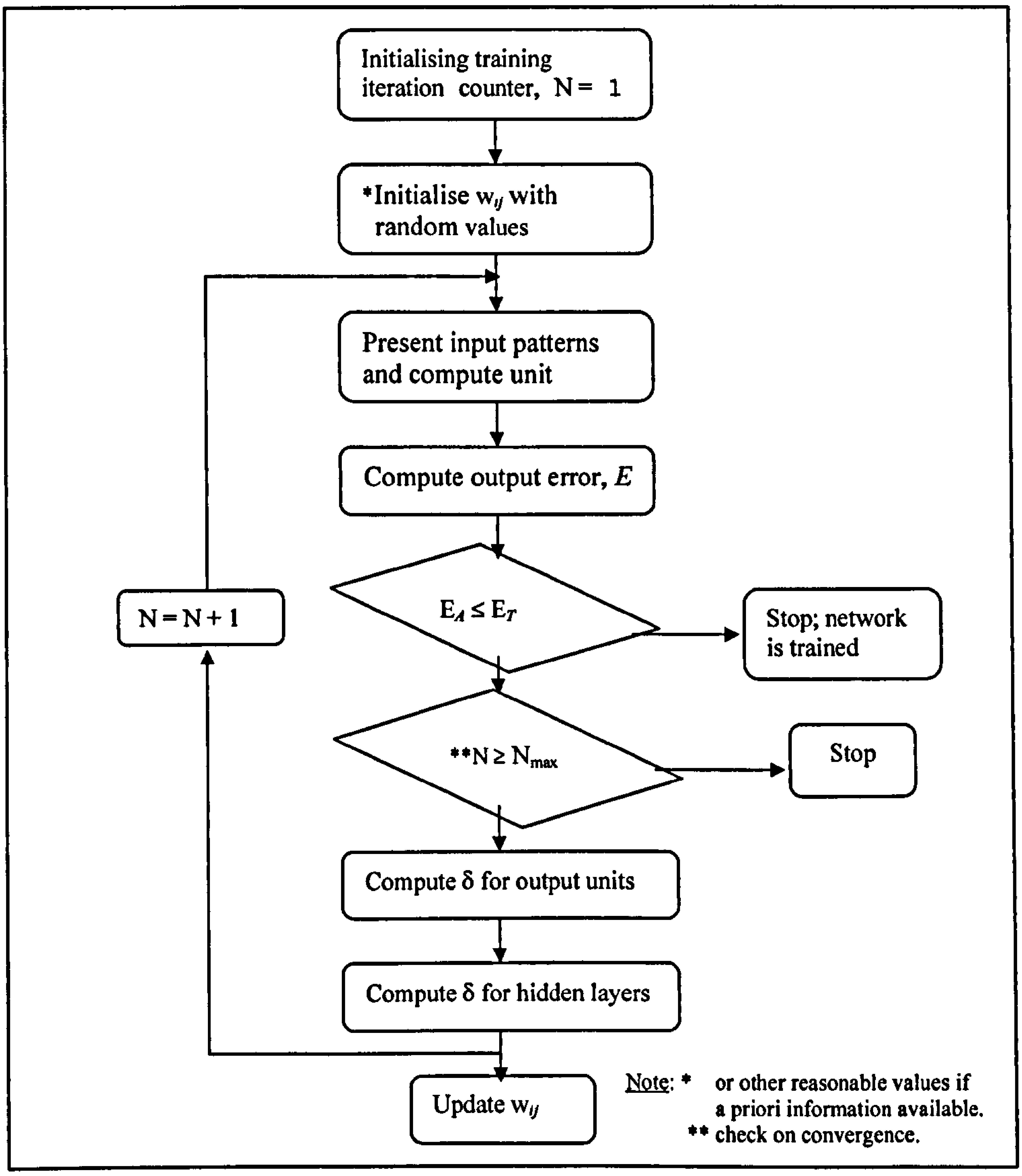
$$W_{ji}(\text{new}) = W_{ji}(\text{Old}) + \eta\delta_j O_i + \alpha[\Delta W_{ji}(\text{Old})] \qquad \text{Equation 5.11}$$

Box 5.6 Weights adjustment and errors in hidden and output layers. (Source: Eberhart and Dobbins, 1990)

The next step is to view the assignment of weights for the hidden layer neurons where the error for hidden neuron is expressed as in Equation 5.9. As noted earlier, the output of a neuron in the hidden layer is a function of its input (written as $O_h = f'(i_h)$). When represented with sigmoid transfer function, this derivative becomes O_h (1 - O_h) and represented as Equation 5.10. The calculations of the weight changes for the connections feeding into the hidden layer from the input layer is similar to those feeding the output layer from the hidden layer as represented in Equation 5.11 (where each hidden node, the subscript i take the values between 0 to n_i, the number of input neurons). As in output layer, the weight of the bias is represented in the calculation by the n_ith value. The error is calculated using Equation 5.6 for each output neuron, then for each hidden neuron using Equation 5.10 for each pattern in the training set.

Since the updating of training is based on batch (epoch) mode, the errors (δ) as in Equation 5.8 and 5.11 are the grand totals for each neuron for the entire training set, whereas errors calculated in Equation 5.6 and 5.10 are error calculated pattern by pattern and is summed up after one epoch. Generally, only one value of learning coefficient (η) and momentum factor (α) is selected for each of the given implementation, although the values of $\eta$and α can be assigned on a single layer basis or even by a single neuron basis. The weight is adjusted using the Equation

5.8 and Equation 5.11 and the process proceed based on the selected number of cycles (iterations) as indicated in Box 5.7. Finally, the computation stops when it has reached convergence level (either the Actual Error value is less or equal to Target Error value, $E_A \leq E_T$) and at this stage the number of iteration is at optimum or maximum level ($N \geq N_{max}$). In this way, the error is reduced significantly.



Box 5.7 Back-propagation learning procedure
(Source: Schalkoff, 1992)

In successful training where the trained set is chosen, these values are adjusted and left alone within the network. When the errors are calculated using Equation 5.10, the old (existing) weights (not the new weights as calculated in Equation 5.8) from the hidden to the output layer are used in the equation. This is one of the potential problems in updating the weights after each training pattern is presented. But when using epoch training, weights will not be updated until all patterns have been presented to the networks. Finally, the trained data set can be used on the test data for the purposes of generalisation. Quite often that when a network is trained, it create a critical region in the training cycle where the trained networks generalise better. Beyond this point, error generalisation decreases and this situation is termed as overtraining or overfitting. Overtraining create a situation where the networks tend to memorise the training patterns, thus produce unsatisfactory output test patterns. This network becomes a specialist in data training. Thus, the effectiveness of this learning process provides ANN to be a powerful pattern recognition technique. The details of the backpropagation processes are described in Rumelhart and McClelland (1986), Eberhart and Dobbins, 1990; Carling, 1992; Schalkoff, 1992; Ripley, 1996; Friedman and Kandel, 1999; and Haykin, 1999.

5.4.5 Methodology Applied for BEP of ANN Model

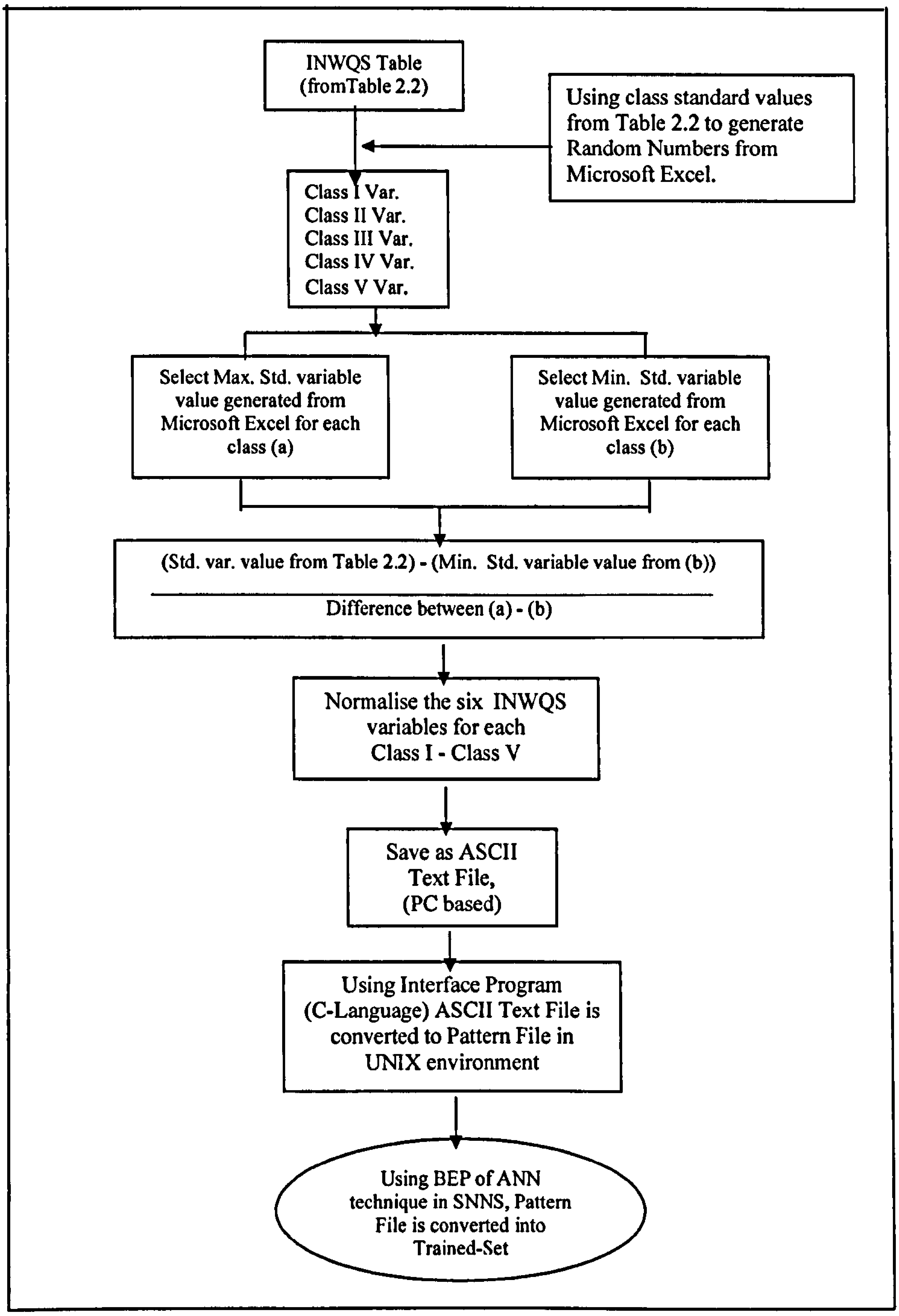
In this research, the application of BEP is to classify water quality based on the most beneficial uses of water. The numbers of input variables for the input layer were fixed to six variables as they were selected by the water quality experts. These variables were the AN, BOD, COD, DO, pH and SS. The same variables were computed for DOE-WQI and Harkins'-WQI in classification of water quality as indicated in Section 5.4.2 and Section 5.4.3. The methodology used on the application of BEP of ANN was divided into three phases; the training phase, validation phase and the testing phase.

(a) Training Phase

Data selected for training were acquired from the standard variable values indicated in INWQS, as illustrated in Table 2.2. Using this table, data were created using random numbers of the Microsoft Excel for each of the five classes. These standard random variable values were significance values in determining the status of water quality, which emphasis on the highest safety for human health and the survival of aquatic species. Therefore, the values generated act as *a priori* knowledge that were used for training in order to obtain an appropriate trained-set. Training was performed to aggregate these standard variable values into a desired generalised trained-set, based on their respective standard classes. This represented the standard water quality training-set, where classification can be performed in the proceeding processes.

In preparation for training data set in supervised learning, the standard random values selected were normalised in Excel of Microsoft Office. Normalising in ANN refers to rescaling by the minimum and range of the vector, to make all the elements lie between 0 and 1 (Sarle, 1994). The process in data normalising is illustrated in Box 5.8. Normalising of these values was based on Equation 5.12 in Box 5.9 for each variable from the INWQS Table 2.2. Normalisation was first carried out for the Class 1 standard values. This first step in data normalizing was referred to as the First Segment for Class I, then it followed with Second Segment for Class II, until all five segments were normalised.

The five segments were then transformed into a single ASCII Text File. Example of the format set-up for the first two patterns in this Text File is shown in Table 5.9. The six columns represent the six variables to be used as inputs. In the first column of second row, the value 795 is the total number of patterns used in the training process. The value [21 1 6] means that the total number of patterns created for Class I using six variables input was 21, in the fifth row was the number of patterns created for Class II using the same number of variables was 42 and so forth. Using an interface program, this ASCII Text was converted into a Pattern File in Stuttgart Neural Network Simulator (SNNS) format (Zell et al., 1999). This interface program was developed by Dr. Carlos Vieira, School of Geography, University of Nottingham. Consequently, this Pattern File was ready for training and simultaneously creating the neural networks structure in the supervised mode.



Box 5.8 Data normalising and conversion to Pattern File

$$X_{(P)} = \{ X_{(Std)} - X_{(MinStd)} \} / \{ X_{(MaxStd)} - X_{(MinStd)} \quad \text{........ Equation 5.12}$$

where, $X_{(P)}$ = normalised variable value for trained data set

$X_{(Std)}$ = standard value from INWQS Table

$X_{(Max)}$ = maximum std. variable value from Random Numbers

$X_{(Min)}$ = minimum std. variable value from Random Numbers

Box 5.9 Normalisation for trained data set

As indicated earlier, the algorithm selected to operate in the SNNS program (Zell et al., 1999) is the BEP (Rumelhart et al., 1986). The approach being used was Standard Back-Propagation with randomised weights. This simulator runs on UNIX system and is capable of performing training in supervised and unsupervised learning, visualising of networks connection and presenting of errors, 'freezing' of trained data set, computing the validation and test data that activated into the trained set for results determination. The UNIX system used was the Sun Enterprise 450 Server, configured with dual 400 Mhz UltraSPARC2 CPU processors with 256 Mb RAM.

Norm AN	Norm BOD	Norm COD	Norm DO	Norm pH	Norm SS
795 21 1 6					
0.007609	0.004391	0.002597	0.500000	0.687500	0.002502
0.008608	0.005372	0.002618	0.510120	0.700000	0.003422
42 2 6					
0.014825	0.015368	0.006494	0.357143	0.625000	0.005108
0.015827	0.015266	0.007193	0.456121	0.73710	0.006182
126 3 6					
0.047471	0.031833	0.012987	0.214286	0.500000	0.015532
0.042487	0.032851	0.021871	0.223776	0.522501	0.026511
120 4 6					
0.123524	0.064764	0.025974	0.007143	0.500003	0.031169
0.127429	0.075713	0.029877	0.008125	0.612501	0.041271
486 5 6					
0.134426	0.064764	0.025974	0.007143	0.000034	0.041169
0.134127	0.071735	0.036862	0.008362	0.001230	0.589836

Table 5.9 Example of data format in ASCII Text File

In anticipation of the long computation time, and to obtain the most reliable trained network structure, the experimentation was performed based on trial and error; firstly is the selection of the number of patterns and the creation of pattern file (Box 5.8), then it follows with the selection of the number of hidden nodes. Since there are too many options for patterns and different numbers of hidden nodes to be experimented, a quick and robust estimation was firstly conducted. The robust estimation of the number of hidden nodes was based on Garson (1998) using the expression in Equation 5.13 in Box 5.10. As soon as the pattern file and the number of hidden nodes were selected, training was performed simultaneously, with first iteration (epoch) numbers set to 10,000 cycles, initialised weight set to [1.0,-1.0] and with a first constant learning rate set to 0.2. This experiment was repeated in search for the lowest MSE using different number of patterns and different parameters as indicated in Table 5.10. The number of patterns and parameters tested were tabulated as in Table 5.11. Example one of the trained patterns created is illustrated in Table 5.12, which displayed the input patterns with six decimal numerical values of (for the six variables) and the output patterns (for five classes) for each class with values designated as 1 0 0 0 0 and so forth. The lowest achievable values of MSE were selected as the stopping criteria and through observations of the graphical displayed several patterns that seem to fit this criterion were listed and tabulated accordingly. The experiments were laborious with long training time, where some trainings got stuck in the local minima, while some have achieved partial local minima.

No. of Hidden Nodes = N_p / r [N_i + N_o] .... Equation 5.13

where N_p = Total Number of Patterns
r = a value between 5 and 10
N_i = number of input nodes
N_o = number of output nodes

Box 5.10 Determination for the number of hidden nodes.
(Source: Garson, 1998)

Number of Iterations (Epoch)	Initialised Weights	Learning Rate	Approach Selected
10,000 – 30,000	[1.0, -1.0] – [0.8, -0.8] for every changes of 0.1.	a) 0.2 b) 0.1	1. Standard Backpropagation 2. Topological Order 3. Randomised Weights

Table 5.10 The range of selected network parameters.

No.	No. Training Patterns	Class 1	Class 2	Class 3	Class 4	Class 5
1	205	41	41	41	41	41
2	394	7	42	42	60	243
3	450	90	90	90	90	90
4	632	2	42	42	60	486
5	650	130	130	130	130	130
6	651	21	42	42	60	486
7	706	4	63	63	90	486
8	795	21	42	126	120	486
9	841	4	105	126	120	486
10	852	15	105	126	120	486
11	1174	226	226	239	240	243
12	1180	28	105	231	330	486
13	1243	7	189	231	330	486
14	1486	7	189	231	330	729
15	2151	12	339	441	630	729

Table 5.11 The number of training patterns used in searching for the most reliable network.

(b) Validation Phase

The network models with lowest MSE values were captured and tabulated as in Table 5.13. These results reveal that the networks with 450 total numbers of patterns (90 samples for each class) with five hidden nodes, which acquired MSE values between 0.64000 to 0.67000, have partially escaped the local minima. The performance of these selected networks model needs to be validated using data that have not been used in the training phase. In this case the same amount of data (450 data with 90 samples for each class as indicated in Table 5.14) was generated from random numbers using Excel of Microsoft Office. This same amount of data used was to ensure that the influence of the magnitude of data was the same as in training phase and also to provide an indication of when to cease training.

SNNS	pattern	definition	file	V3.2		
generated	at	Thu	Jun	21	21:22:30	1997
No.	of	patterns	:	450		
No.	of	input	units	:	6	
No.	of	output	units	:	5	
#	Input	pattern	01:00			
0.000018	0.000019	0.00001	0.001961	0.002696	0.00001	
#	output	pattern	01:00			
1	0	0	0	0		
#	Input	pattern	02:00			
0.000018	0.000019	0.00001	0.001961	0.002702	0.00001	
#	output	pattern	02:00			
1	0	0	0	0		
#	Input	pattern	91:00:00			
0.000054	0.00006	0.000025	0.001401	0.001961	0.00002	
#	output	pattern	91:00:00			
0	1	0	0	0		
#	Input	pattern	92.00:00			
0.000054	0.00006	0.000025	0.001401	0.001973	0.00002	
#	output	pattern	92:00.00			
0	1	0	0	0		

Table 5.12 Format of trained pattern file created in BEP model of ANN

Selected Network Pattern	No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learning Rate	MSE
450	5	20,000	0.93, -0.93	0.2	0.65338
450	5	20,000	0.92, -0.92	0.2	0.65517
450	5	20,000	0.91, -0.91	0.2	0.65716
450	5	20,000	0.90, -0.90	0.2	0.65934
450	5	20,000	0.95, -0.95	0.2	0.65020
450	5	20,000	0.95,-0.95	0.1	0.67747
450	5	20,100	0.95,-0.95	0.2	0.64364

Table 5.13 The refined selected network parameters.

In validity testing, a total of 450 randomised data (each 90 samples represent Class I, Class II, Class III, Class IV and Class V) were computed consecutively, into each of the seven network models as indicated in Table 5.13. All parameters such as the number of iterations, initialised weights and learning rate, were tested simultaneously for each network models. The results were tabulated as in Table 5.15. Based on the lowest MSE value, the network model with MSE of 0.65020 was selected and the structure was captured to be used in testing of the real data sets.

Class	No. of Patterns	No. of Variables
I	90	6
II	90	6
III	90	6
IV	90	6
V	90	6
Total	450	6

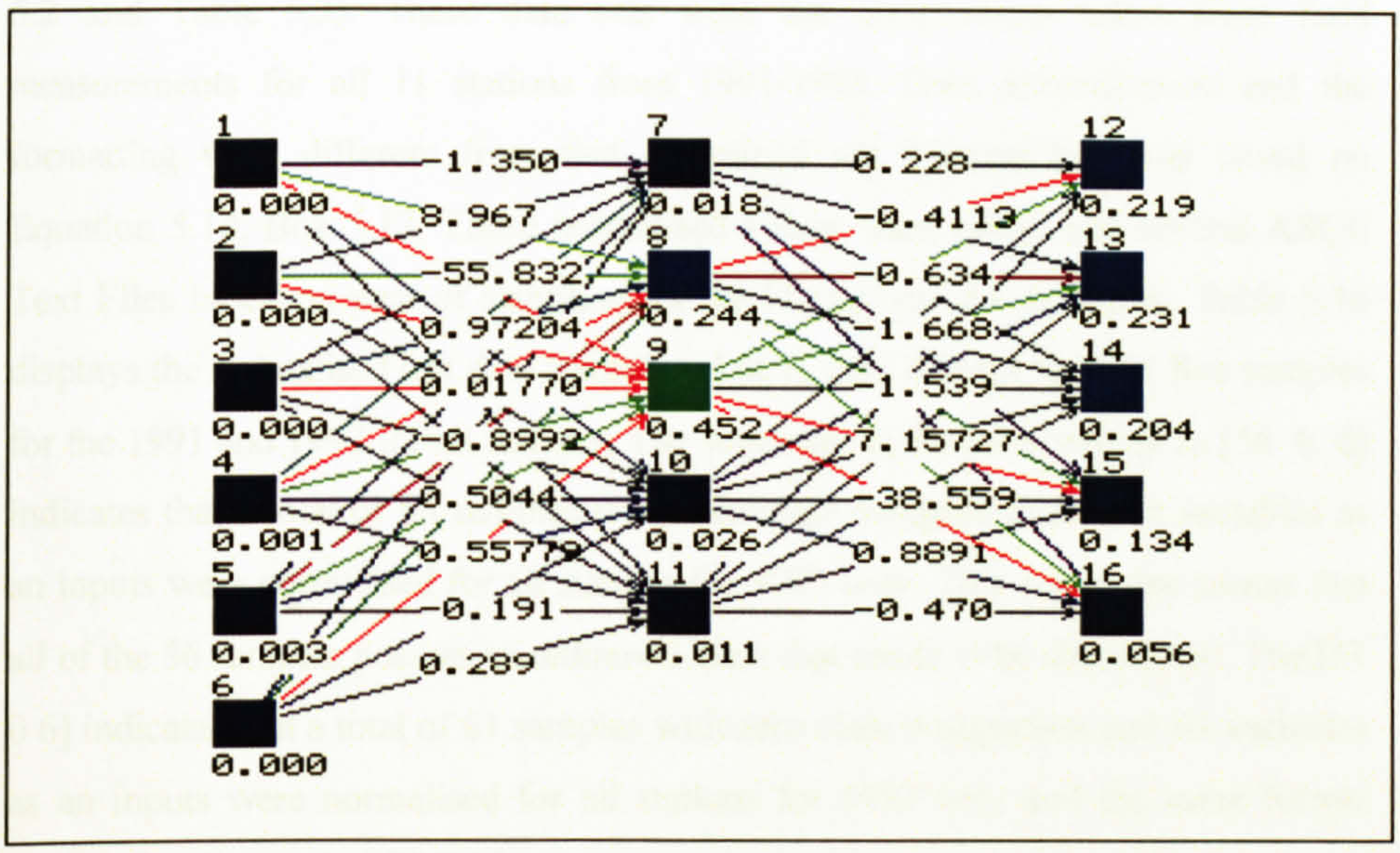
Table 5.14 Number of patterns for each class segment

Selected Network Pattern	No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learning Rate	MSE	No. of sample falls within this class.				
						Cl. I	Cl. II	Cl. III	Cl. IV	Cl. V
450	5	20,000	0.93, -0.93	0.2	0.65338	100	71	78	-	100
450	5	20,000	0 92, -0.92	0.2	0 65517	100	66	81	-	100
450	5	20,000	0.91, -0.91	0.2	0.65716	100	57	84	-	100
450	5	20,000	0.90, -0.90	0.2	0 65934	100	47	89	-	100
450	5	20,000	0.95, -0.95	0.2	0.65020	100	77	74	-	100
450	5	20,000	0.95,-0 95	0.1	0.67747	100	-	44	-	100
450	5	20,100	0.95,-0.95	0.2	0 64364	100	100	-	-	100

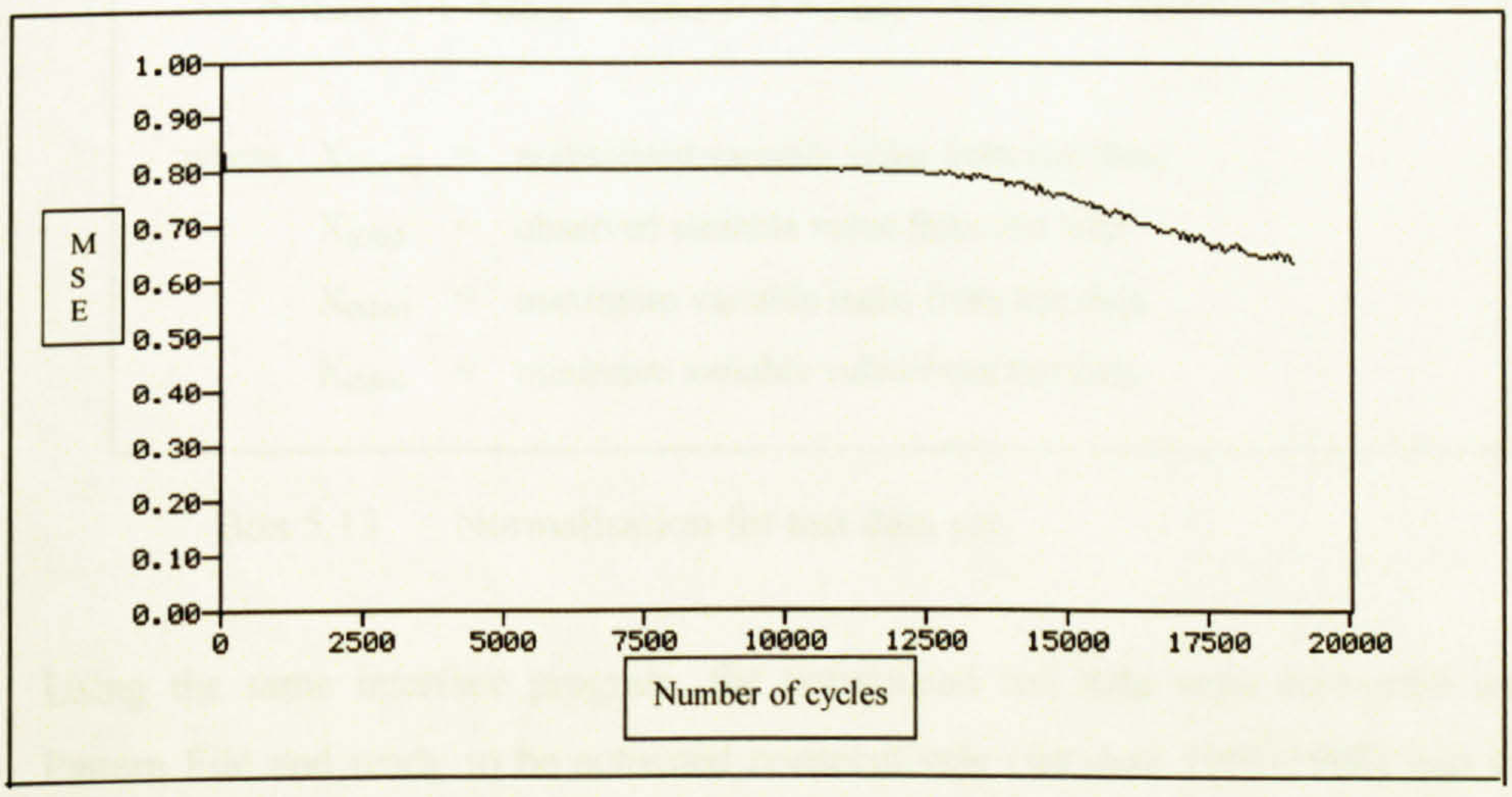
Table 5.15 The results of network validation.

The captured network structure obtained from this experiment is illustrated as in Box 5.11, which shows the weights of the connection links between the six input nodes, the five hidden nodes and the five output nodes. Notice that the highest weight assigned is 8.967 and the lowest is –55.832. Based on this structure the selected network parameter values are the number of iterations of 20,000 cycles, initialised weights of [0.95, -0.95], learning rate of 0.2 and mean square error (MSE) of 0.65020. The graphical display of MSE is shown in Box 5.12 where at 13,000 cycles, the network started to possess the local minima and finally ended at 20,000 cycles. Based on this structure, this network is designated as $I_6H_5O_5$, which consists of six input neurons (m = 6), five hidden neurons (n = 5) and five output neurons (p = 5). The validation results show that none of the 90 samples of

Class IV was classified for all of the seven network models. The unclassified samples may relate to the poor generalisation capability of the networks and this will be discussed in the next section.



Box 5.11 The trained network structure, $I_6H_5O_5$ obtained from the experiment



Box 5.12 Mean Square Error (MSE) graph for the selected network, $I_6H_5O_5$

(c) Testing Phase

Testing set was carried out using independent water quality data (real data) taken from Langat catchment area for a period of nine years between 1991-1998 (Table 5.2 and Table 5.3). These data sets were the observations taken from field measurements for all 11 stations from 1991-1998. Data normalisation and the formatting were different from that of trained set. Normalising was based on Equation 5.14, Box 5.13. These normalised values were saved into several ASCII Text Files based on year of sampling for all 11 stations. As examples, Table 5.16 displays the normalised test data format in ASCII Text File for the first five samples for the 1991 and 1992 for all stations. The statement in the table written as [56 0 6] indicates that a total of 56 samples with zero class designation and six variables as an inputs were normalised for all stations for 1991 only. This zero value means that all of the 56 samples possess an unknown class that needs to be determined. The [61 0 6] indicates that a total of 61 samples with zero class designation and six variables as an inputs were normalised for all stations for 1992 only and the same format applies for all samples till 1998.

$$X_{(Norm)} = \{ X_{(Obs)} - X_{(Min)} \} / \{ X_{(Max)} - X_{(Min)} \} \quad \text{...Equation 5.14}$$

where, $X_{(Norm)}$ = normalised variable value from test data

$X_{(Obs)}$ = observed variable value from test data

$X_{(Max)}$ = maximum variable value from test data

$X_{(Min)}$ = minimum variable value from test data

Box 5.13 Normalisation for test data set

Using the same interface program, the normalised test data were converted into Pattern File and ready to be activated consecutively (for data 1991-1998) into the selected trained set (Box 5.11) using the same SNNS software program. Example of the format of test pattern created is shown as in Table 5.17, which displayed the first six input patterns without the five output pattern that needs to be computed.

56 0 6					
Norm-AN	Norm-BOD	Norm-COD	Norm-DO	Norm-PH	Norm-SS
0.140097	0.006740	0.021481	0.053571	0.600000	0.004587
0.101449	0.027801	0.017351	0.052381	0.555556	0.001355
0.111111	0.007582	0.004597	0.030952	0.444444	0.002189
0.014493	0.060657	0.023247	0.045238	0.655556	0.009799
0.127214	0.010110	0.005870	0.047619	0.444444	0.000938
61 0 6					
0.011060	0.006037	0.011818	0.250000	0.687500	0.004065
0.007834	0.003293	0.007169	0.200000	0.500000	0.010529
0.005530	0.000000	0.024857	0.192857	0.775000	0.003857
0.041935	0.004391	0.018390	0.171429	0.462500	0.224226
0.028111	0.000000	0.000935	0.242857	0.387500	0.003440

Table 5.16 Normalised test data for the first five samples for 1991 (total sample is 56) and 1992 (total samples is 61).

SNNS	pattern	definition	file	V3.2		
generated	at	Thu	Jun	21	21:22:30	1997
No.	of	patterns	:	56		
No.	of	input	units	:	6	
#	Input	pattern	01:00			
0.00008	0.000019	0.000084	0.001261	0.002647	0.000018	
#	Input	pattern	02:00			
0.000058	0.000073	0.000068	0.001232	0.002451	0.000005	
#	Input	pattern	03:00			
0.000063	0.000022	0.000018	0.000728	0.001961	0.000009	
#	Input	pattern	04:00			
0.000009	0.000157	0.000091	0.001064	0.002892	0.000038	
#	Input	pattern	05:00			
0.000072	0.000028	0.000023	0.00112	0.001961	0.000004	

Table 5.17 Format of Input Pattern for Test Data

The output classification values from SNNS are given in terms of probability density, as illustrated in Table 5.18. From this Table, the first column row 10, represents the probability density for Class I, the second column is the probability density for Class II and so forth. This Table illustrates the examples taken from the first five output results for Station 1 for the 1991 test data set. These values were converted into probability distribution based on Equation 5.15 in Box 5.14, and the highest distribution was selected as the respective class value as shown in the last column of Table 5.19. The probability density from all the eight output results files were transformed into probability distribution and finally, the class frequencies for all of the 11 stations for the period of 1991 to 1998 were tabulated as in Table 5.20.

SNNS	result	file	V1.4-3D				
generated	at	Sun	Apr	15	10:33:25	2001
No.	of	patterns	:	56		
No.	of	input	units	:	6	
No.	of	output	units	:	5	
startpattern	:	1				
endpattern	:	56				
#1.1						
0.19243	0.22786	0.20318	0.14289	0.07003		
#2.1						
0.17737	0.22354	0.20341	0.1482	0.07588		
#3.1						
0.06571	0.17916	0.20597	0.21921	0.17812		
#4.1						
0.14294	0.21271	0.20399	0.16259	0.09303		
#5.1						
0.13496	0.20997	0.20415	0.16651	0.09803		

Table 5.18 Example of the probability density obtained from the output results of the BEP of ANN model

$$CxPD_i = CxDen_i / \{ \sum_{i=1}^{5} CxDen_i \} \qquad \text{......Equation 5.15}$$

where, $CxPD_i$ = probability distribution of ith Class

$CxDen_i$ = probability density of ith Class

Box 5.14 Conversion from probability density to probability distribution

Station	Class 1	Class 2	Class 3	Class 4	Class 5	Class Designation
St1(2814602)	0.2301	0.2724	0.2429	0.1708	0.0837	2
St1(2814602)	0.2141	0.2698	0.2455	0.1789	0.0916	2
St1(2814602)	0.0775	0.2112	0.2428	0.2585	0.2100	4
St1(2814602)	0.1753	0.2609	0.2502	0.1994	0.1141	2
St1(2814602)	0.1659	0.2581	0.2509	0.2047	0.1205	2

Table 5.19 Example of class designation after converted into probability distribution using Equation 5.15 based on Table 5.18.

Station	Class 1	Class 2	Class 3	Class 4	Class 5
St1	0	2	20	8	4
St2	0	1	14	16	3
St3	0	21	10	3	1
St4	0	4	24	5	2
St5	0	29	6	0	0
St6	0	5	17	10	2
St7	0	2	17	11	2
St8	0	21	12	0	1
St9	0	13	18	3	0
St10	1	28	1	0	0
St11	9	24	0	0	0

Table 5.20 Class frequency distribution using the BEP of ANN model for the 11 stations of Langat catchment area, 1991-1998.

5.4.6 Methodology Based on Maximum Likelihood Distance Classifier, Mahalanobis Distance Classifier and the Decision Tree Classifier

The results obtained from the DOE-WQI, Harkins,-WQI and BEP of ANN will be compared to some of the other type of models. The models selected in these studies were the Maximum Likelihood Classifier, Mahalanobis Distance Classifier and the Decision Tree Classifier. Based on the results of these three models, the validity of the BEP of ANN can be evaluated in details in the next section.

5.4.6.1 Classification Based on the Maximum Likelihood Distance Classifier and the Mahalanobis Distance Classifier

The Maximum Likelihood Distance Classifier (MLDC) and the Mahalanobis Distance Classifier (MDC) are the statistical classifiers which operate under supervised learning mode. These two classifiers use specific rules based on Swain (1978), as described in Box 5.15. Using these models, the classification process involves two phases; the training of data set and the classification of the test data.

In creating a supervised training set, the range of the lowest and highest values for each variable for every class of the INWQS (Table 2.2) was utilised. Within this range, values were generated from random numbers in Excel of Microsoft Office.

These values were used to obtain the respective training patterns. An example of the pattern format created is illustrated as in Table 5.21. A total of 500 patterns were created, with each class pattern based on 100 patterns. In contrast to the BEP of ANN method, the values for the data set created were firstly normalised in the range of 0 to 1, then converted into Text and ASCII File, and subsequently run into the Pattern File before training was performed in supervised mode within SNNS environment. Whereas in MLDC and MDC, the original concentration values were retained and normalisation of data set was not performed. Data were then saved into a Text File, and converted into Pattern File before training was performed within the MATLAB environment. MATLAB (version 5) is a comprehensive software and easy-to-use environment, which integrates computation, data analysis, visualisation and programming in a flexible, open environment.

Since the MLDC and the MDC acquire the same statistical characteristics, the same Pattern Files were used in this analysis. In the training process, these two classifiers were activated simultaneously to obtain two different trained sets using an interface sub-program developed in MATLAB by Dr. Taskin Kavzoglu, School of Geography, University of Nottingham. For MLDC, the trained set was the *a priori* probabilities (Equation 5c, Box 5.15) that were assumed to be equal.

The test data sets that were converted into Text Files for Langat catchment area (years 1991 to 1998) for the 11 stations. These were activated into the trained set and computations were performed by the ML classifier within the same MATLAB environment. In the process of evaluation, the highest discriminant value was selected. This value, designated as $g_i(X)$, was based on the third term of Equation 5h in Box 5.15, which indicated how close this value was to all defined class boundaries. This was the output class value that represents the status of water quality for a particular station as illustrated in Table 5.22. As compared to the BEP of ANN method, a threshold can be used to eliminate those patterns that do not fall easily into any of class boundaries. The same test data sets were activated into the trained set created for MDC. The results of these two models of classifications are illustrated as in Table 5.22.

The maximum-likelihood decision rule based on Swain (1978)

It stated that for a set of m classes, w_j, the maximum-likelihood decision rule is represented as in Equation 5c. For simplicity purpose, the *a priori* probabilities of the classes, $p(w_i)$, are assumed to be equal to 1/m. When X belongs to class i, the input vector X is the probability density function, $p(X|w_i)$. The discrimination function for each class in an assumed multivariate normal density function is expressed as Equation 5d or can be represented in matrix form as in Equation 5e.

Decide input vector $X \in w_i$ if and only if

$p(X|w_i)p(w_i) \geq p(X|w_j)p(w_j)$ for all $j = 1,2,\ldots,m$ Equation 5c

The values in the mean vector, U_i, and the covariance, Σ_i are the estimated from the training data by the unbaised estimators as represented in Equation 5f and Equation 5g, where P_i is the number of training patterns in class i. Equation 5d is simplified into Equation 5h by introducing natural logarithm and discarding the constant π term.

$$g_i(X) = p(X|w_i)p(w_i) = \frac{p(w_i)\,\mathrm{Exp}.[-1/2(X-U_i)^T\Sigma^{-1}_i(X-U_i)]}{(2\pi)^{n/2}|\Sigma_i|^{1/2}} \quad \text{Equation 5d}$$

where n = number of variables

X = data vector

U_i= mean vector of class i

Σ_i= covariance matrix class i.

$$X = \begin{bmatrix} X_i \\ X_i \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ X_n \end{bmatrix} \quad U_i = \begin{bmatrix} U_{i1} \\ U_{i2} \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ U_{in} \end{bmatrix} \quad \Sigma_i = \begin{bmatrix} 6_{i11} & 6_{i12} & \ldots & 6_{i1n} \\ 6_{i21} & 6_{i22} & \ldots & 6_{i2n} \\ \cdot & \cdot & & \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ 6_{i11} & 6_{i12} & \ldots & 6_{i1n} \end{bmatrix} \quad \text{Equation 5e}$$

$$0_{ij} = (1/P_i)\sum_{l=1}^{Pi} X_{jl} \qquad j = 1,2,\ldots,n \qquad \text{Equation 5f}$$

$$0_{ij} = (1/P_i - 1)\sum_{l=1}^{Pi}(X_{jl}-0_{ij})(X_{kl}-0_{ij}) \quad j = 1,2,\ldots,n;\ k = 1,2,\ldots,n. \qquad \text{Equation 5g}$$

$$g_i(X) = [\log_e p(w_i)]-[1/2\log_e|\Sigma_i|]-[1/2(X-U_i)^T\Sigma^{-1}_i(X-U_i)] \qquad \text{Equation 5h}$$

Box 5.15 The Maximum Likelihood rules based on Swain (1978)

AN	BOD	COD	DO	PH	SS	Class
0.005	0.285	3.636	5.729	7.815	2.437	1
0.009	0.545	9.261	5.512	8.468	21.418	1
0.017	0.153	2.333	6.085	6.768	17.483	1
0.288	2.464	19.429	5.181	6.513	33.844	2
0.164	1.462	20.262	5.905	8.656	49.420	2
0.174	1.244	13.565	6.471	7.968	29.755	2
0.454	4.929	33.651	3.618	7.204	53.361	3
0.328	3.177	35.797	4.107	6.629	83.701	3
0.502	5.805	48.243	4.710	7.072	139.589	3
2.421	7.901	83.312	2.609	7.299	209.991	4
1.116	11.451	79.943	2.964	7.010	162.047	4
1.099	10.300	56.793	2.014	6.044	287.026	4
4.192	15.617	160.061	0.643	4.763	3168.604	5
21.560	24.277	111.302	0.377	2.151	3473.891	5
9.928	32.370	124.719	0.572	1.875	3503.628	5

Table 5.21. Example of the format of "pattern data set" converted into Text File.

Station No.	Maximum Likelihood Distance Classifier (MLDC)					Mahalanobis Distance Classifier (MDC)				
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 1	Class 2	Class 3	Class 4	Class 5
St1	0	0	12	12	10	0	0	10	10	14
St2	0	0	11	10	14	0	0	11	6	18
St3	0	10	15	5	4	0	7	18	5	4
St4	0	0	9	17	8	0	0	8	18	8
St5	0	3	29	2	1	0	2	30	2	1
St6	0	0	13	13	8	0	0	12	14	8
St7	0	0	6	21	5	0	0	6	19	7
St8	0	6	16	9	2	0	7	15	9	2
St9	0	0	16	13	5	0	0	16	13	5
St10	7	12	10	1	0	7	11	11	1	0
St11	14	15	4	0	0	15	14	4	0	0

Table 5.22 The results of class frequency using the MLDC and the MDC for all stations, Langat catchment area, 1991 – 1998.

5.4.6.2 Classification Based on the Decision Tree Classifier

Another type of classification model, based on the nearest neighbour rule, is the Decision Tree (DT) model. DT can be applied to classify a case where computation seems to start at the root of the tree and moving through it until a leaf is encountered (Swain and Hauska, 1977; Chou and Gray, 1986; Quinlan, 1986, 1987). At each non-leaf decision node, the sample for the test at the node is determined and attention shifts to the root of the sub-tree corresponding to this sample. When this process finally leads to a leaf, the class of the sample is recorded at the leaf.

The DT is non-parametric in nature, thus it does not requires any assumptions about the underlying data distributions (Swain and Hauska, 1977; Breiman et al., 1984; Friedl and Brodley, 1997). It is flexible and robust with respect to nonlinear and noisy relations among input data and class labels (Swain and Hauska, 1977; Quinlan, 1986). Having these similarities with that of neural classifier and Harkins'-WQI model, it is therefore timely to investigate its capabilities in classification of water quality. A decision tree program known as C4.5 developed by J. Ross Quinlan (1993), University of Sydney was used in view of its compatibility to the existing UNIX system that operates on Sun Enterprise 450 Server. The same data type in supervised mode was evaluated using the C4.5.

Data pre-processing was similar to that performed for the BEP of ANN model, as illustrated in Box 5.8. These data sets were converted from ASCII Text File into Pattern File, using the same Interface Program as performed for the BEP of ANN model. Thus, to speed-up computation process, the same Pattern File for creating trained set and test data set were utilised. This Pattern File was activated into DT classifier in UNIX environment using the C4.5 Decision Tree Programs (Quinlan, 1993). Examples of the results format for 1991, Langat catchment area are illustrated in Table 5.23.

Based on the results shown in Table 5.23, the upper portion shows the format of the trained Pattern Set, and the lower portion, the class grading. The six bands correspond to the six variables used. Using this format, a flowchart of the Decision Tree is drawn as shown in Box 5.16, which indicates that Class 3, with 239 patterns, was firstly classified. The overall results for all stations in Langat catchment area (years 1991 to 1998) are presented as in Table 5.24.

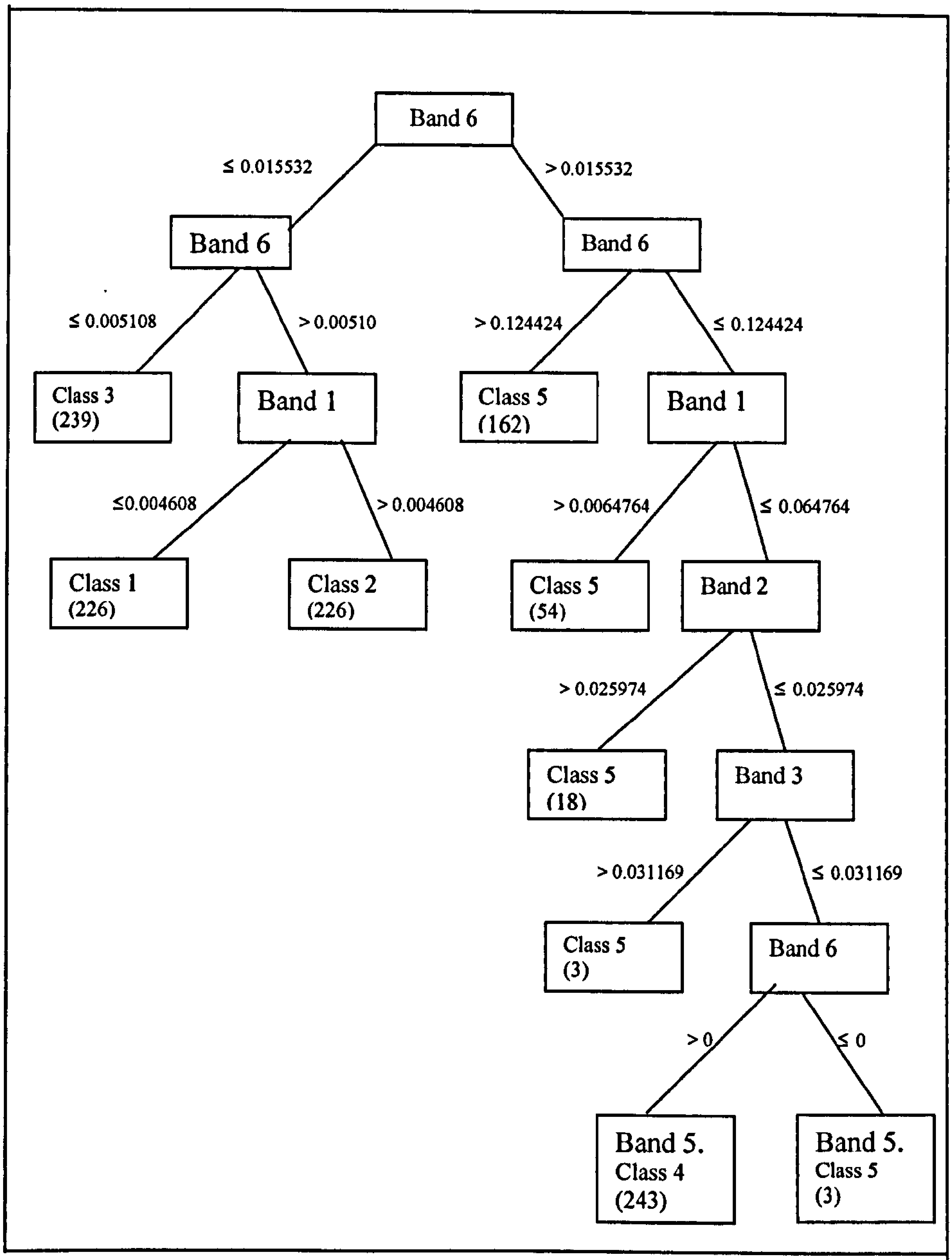
band6 <= 0.015532:					
:...band6 > 0.005108: 3 (239)					
: band6 <= 0.005108:					
: :...band1 <= 0.004608: 1 (226)					
: band1 > 0.004608: 2 (226)					
band6 > 0.015532:					
:...band1 > 0.124424: 5 (162)					
band1 <= 0.124424:					
:...band2 > 0.064764: 5 (54)					
band2 <= 0.064764:					
:...band3 > 0.025974: 5 (18)					
band3 <= 0.025974:					
:...band6 > 0.031169: 5 (3)					
band6 <= 0.031169:					
:...band5 <= 0: 5 (3)					
band5 > 0: 4 (243/3)					

1991					
Case Class [Predicted]					
#1 ? [2]					
#2 ? [2]					
#3 ? [2]					
#4 ? [3]					
#5 ? [2]					

Table 5.23 Example of the format of the results obtained using the DTC model, Langat catchment area for the year 1991.

Station Number	Class 1	Class 2	Class 3	Class 4	Class 5
St1 (4.2 km)	0	6	24	2	2
St2 (33.5 km)	0	6	17	8	3
St3 (67.3 km)*	0	10	24	0	1
St4 (63.4 km)	0	0	28	6	1
St5 (80.8 km)*	0	3	32	0	0
St6 (81.1 km)	0	0	28	4	2
St7 (86.9 km)	0	0	22	8	2
St8 (85.6 km)*	0	5	26	3	0
St9 (93.4 km)	0	1	31	2	0
St10 (10.5.0 km)*	12	12	5	1	0
St11 (114.0 km)	9	22	2	0	0

Table 5.24 The overall classification results using the DTC model for all stations, Langat catchment area, 1991-1998.
Note: * - Tributaries of Langat River.



Box 5.16 Flowchart of classification process based on the Decision Tree model (From Table 5.23)

5.5 RESULTS AND EVALUATION

The results and evaluation of the pilot study for Langat catchment area were based on the general findings, statistical analysis, trend analysis, estimation of accuracy and sensitivity testing. However, the sensitivity analysis was carried only for the BEP of ANN model. This is to justify one of the main objectives of this research that is to investigate the advantages and limitations of the BEP of ANN that represent the neural classifier which is the new approach in water quality assessment.

5.5.1 General Findings

A general evaluation of the results was based on the frequency distribution of classes obtained from all of the six models as shown in Table 5.25. These class frequencies were the average class for each station, evaluated for the years 1991 to 1998. The DOE-WQI is a mathematical model and Harkins'-WQI is the non-parametric statistical model, thus both are non-classifiers. Other models are based on classifier approach such that the neural classifier is non-statistical, mathematically designed and sometime considered as 'black-box', whereas, the MLDC, and MDC are statistical, and DT is the non-parametric statistical model.

Based on Table 5.25, almost all models possess high frequency for Class 3, except the BEP of ANN model with high frequencies for Class 1 and Class 2. Using the results obtained for all models evaluated for 1991 to 1998, the class values for all five classes were averaged to obtain a Reference Class value. For example, for Station 1 and for each model for the period from 1991 to 1998, the number of frequency for Class I, was added and divided by six (the total number of model used) and the average number of frequency for Class I was recorded. The same averaging processes were carried out for the same station for Class II, Class III, Class IV and Class V. Then, the average class value for Station 1 was calculated

St. No.	DOE-WQI					Harkins'-WQI					BEP of ANN				
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 1	Class 2	Class 3	Class 4	Class 5	Class 1	Class 2	Class 3	Class 4	Class 5
St1	0	0	21	10	3	0	6	15	10	3	2	5	8	11	8
St2	0	1	12	19	2	0	2	10	21	1	0	3	7	10	14
St3	0	14	15	5	1	0	18	16	1	0	15	15	1	1	3
St4	0	0	23	11	1	0	5	25	4	1	1	19	9	3	3
St5	0	16	18	1	0	0	24	11	0	0	23	11	0	1	0
St6	0	0	15	15	4	0	1	23	9	1	3	13	6	4	8
St7	0	0	13	18	1	0	0	18	14	0	2	9	8	6	7
St8	0	10	22	2	0	0	15	19	0	0	27	7	0	0	0
St9	0	6	15	13	0	0	13	15	6	0	23	7	3	1	0
St10	5	25	0	0	0	5	25	0	0	0	29	1	0	0	0
St11	12	20	1	0	0	13	20	0	0	0	33	0	0	0	0

St. No.	MLDC					MDC					DT				
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 1	Class 2	Class 3	Class 4	Class 5	Class 1	Class 2	Class 3	Class 4	Class 5
St1	0	0	12	12	10	0	0	10	10	14	0	6	24	2	2
St2	0	0	11	9	14	0	0	11	6	17	0	6	17	8	3
St3	0	10	16	5	4	0	8	18	5	4	0	10	24	0	1
St4	0	0	10	17	8	0	0	8	19	8	0	0	28	6	1
St5	0	3	29	2	1	0	2	30	2	1	0	3	32	0	0
St6	0	0	13	13	8	0	0	12	14	8	0	0	28	4	2
St7	0	0	6	21	5	0	0	6	19	7	0	0	22	8	2
St8	0	7	16	9	2	0	7	15	10	2	0	5	26	3	0
St9	0	0	16	13	5	0	0	16	13	5	0	1	31	2	0
St10	7	12	10	1	0	7	11	11	1	0	12	12	5	1	0
St11	14	15	4	0	0	15	14	4	0	0	9	22	2	0	0

Table 5.25 Summary of the classification results based on the six models

and this represents the average class for Station 1 (for the period of 1991-1998) of the Reference Class. The same averaging processes were carried out for other stations and classes. Finally, the average class frequency for each station designated as Reference Class was tabulated as shown in the last column in Table 5.26. The frequency of class similarity for each model as compared to that of Reference Class was tabulated as in Table 5.27. Based on these results (Table 5.27), the frequency of similarity of class value shows that the DOE-WQI possess the highest score of similarity, follows by the MLDC, MDC, DT and the least are the Harkins'- WQI and the BEP of ANN models. This reveals that statistical and neural classifiers tend to be relatively less accurate as compared to mathematical model. This general findings can be justified that mathematical model is parametric in characteristic (Gaussian distribution), thus it can be more accurate.

5.5.2 Statistical Analysis

The results from Table 5.25 were further analysed using several statistical approaches. These analyses were to determine whether there exist a relationship between the frequency of classification and the station's location, the evaluation of the degree of correlation between models and to investigate whether the distributions of the class frequency of the six models were the same.

(a) Chi-square Test of Independence

Chi-square is a non-parametric test hypothesis and requires no assumption about the exact shape of the population distribution. The frequency of occurrence is used to test the independence that relate to two variables. Hence, it is applicable in this type of analysis based on the frequency data of Table 5.25. The null hypothesis for a chi-square test of independence is that the station's location and the frequency of classification are independent. Thus, the assumption drawn was, no relationship between these two variables. Statistical analysis at significant level, α of 0.05 revealed that there was a significant relationship between the station's location and frequency classification of water quality. Table 5.28 shows the statistical results based on Chi-square test of independence. These results revealed that the MDC acquires the highest chi-square calculated value and the least was the DTC.

Station No.	Strahler Stream Order at Station Point	Distance from Estuary (km)	Average Class						Reference Class
			DOE-WQI	Harkins'-WQI	BEP of ANN	Maximum Likelihood	Mahala-nobis	Decision Tree	
St1	7	4.2	3	3	4	4	5	3	4
St2	7	33.5	4	4	4	3	5	3	4
St3*	4	67.3	3	2	2	3	3	3	3
St4	7	63.4	3	3	3	4	4	3	3
St5*	6	80.8	3	2	2	3	3	3	3
St6	6	81.1	4	3	4	4	4	3	4
St7	6	86.9	4	3	4	4	4	3	4
St8*	6	85.6	3	3	3	3	3	3	3
St9	6	93.4	3	3	2	3	3	3	3
St10*	5	105.0	2	2	1	2	2	2	2
St11	5	114.0	2	2	1	2	2	2	2
Frequency of Similarity To Reference Class			10	6	6	9	8	7	

Table 5.26 Average class value for the six models
(Note: * Tributaries of the main river, Langat River)

Model	Frequency of Similarity to Reference Class	Percentage of Similarity to Reference Class
DOE-WQI	10	22
Harkins'-WQI	6	13
BEP of ANN	6	13
Maximum Likelihood Distance Classifier	9	20
Mahalanobis Distance Classifier	8	17
Decision Tree Classifier	7	15

Table 5.27 Percentage of result similarity to Reference Class from Table 5.25

(b) Spearman's Rank Correlation Coefficient Analysis

Spearman's rank correlation coefficient evaluates the degree of correlation between two models. Hence, it was used to test the degree of relationship between each model applied. Spearman's rank correlation coefficient procedure is a simple ranking technique. The application of this procedure is to evaluate the strength of correlation between each model based on the class frequency (Table 5.25), using two-tailed significant test at a selected significant level, α of 0.05 and 0.01. Using the SPSS Version 12.0, the results from these analyses are shown in Table 5.29, which revealed that the BEP of ANN correlated well with all of the models. The highest correlation is between the BEP of ANN and Mahalanobis Distance Classifier, follows with the BEP of ANN and DOE-WQI, BEP of ANN and Maximum Likelihood Classifier, and BEP of ANN with Harkins'-WQI.

Model	Chi-square (Calculated Value)	No. of Station, N	Degree of Freedom, df
1. DOE-WQI	321.49	11	40
2. Harkins'-WQI	326.36	11	40
3. BEP of ANN	304.45	11	40
4. MLDC	310.16	11	40
5. MDC	333.33	11	40
6. DTC	270.04	11	40

Table 5.28 Chi-square Test of Independence

Note: Signif. Level α = 0.05. Chi-square critical value from Chi-square Table is 55.759. Hence, there is a relationship between the class frequency value and the station's location.

(c) Friedman's Rank Test

Another statistical analysis applied was the Friedman's Rank Test, which was used to evaluate whether the distributions of the class frequency of the six models were the same. Using the same SPSS Version 12.0, the results obtained were tabulated as in Table 5.30. These results revealed that the distribution of class frequency of all models were statistically significant with calculated rank value of less then 17.289. Friedman's Chi-square Table indicated a value of 17.289 at p-value of 0.004 (Table 5.31). Hence, there was evidence that the distributions of the class frequency of the six models were different. Based on these ranked values, Mahalanobis Distance Classifier acquired the highest rank while BEP of ANN was the lowest.

Model	DOE-WQI	Harkins'-WQI	BEP of ANN	Maximum Likelihood	Mahalanobis	Decision Tree
DOE-WQI	1.0000	0.7210 (*)	0.8690 (**)	0.6830 (*)	0.7750 (**)	0.7420 (**)
Harkins'-WQI	0.7210 (*)	1.0000	0.8180 (**)	0.5660 (*)	0.8020 (**)	0.5850 (*)
BEP of ANN	0.8690 (**)	0.8180 (**)	1.0000	0.8250 (**)	0.9340 (**)	0.6970 (*)
Maximum Likelihood	0.6830 (*)	0.5660 (*)	0.8250 (**)	1.0000	0.8020 (**)	0.7240 (*)
Mahalanobis	0.7750 (**)	0.8020 (**)	0.9340 (**)	0.8020 (**)	1.0000	0.6970 (*)
Decision Tree	0.7420 (**)	0.5850 (*)	0.6970 (*)	0.7240 (*)	0.6970 (*)	1.0000

Table 5.29 Spearman's Rank Correlation Coefficient

Note: * Correlation is significant at the 0.05 level (2-tailed)

** Correlation is significant at the 0.01 level (2-tailed)

Model	Ranks
Mahalanobis	4.6400
Maximum Likelihood	4.0900
DOE-WQI	3.8200
Decision Tree	3.0500
Harkins'-WQI	2.7300
BEP of ANN	2.6800

Table 5.30 Friedman's Rank Test

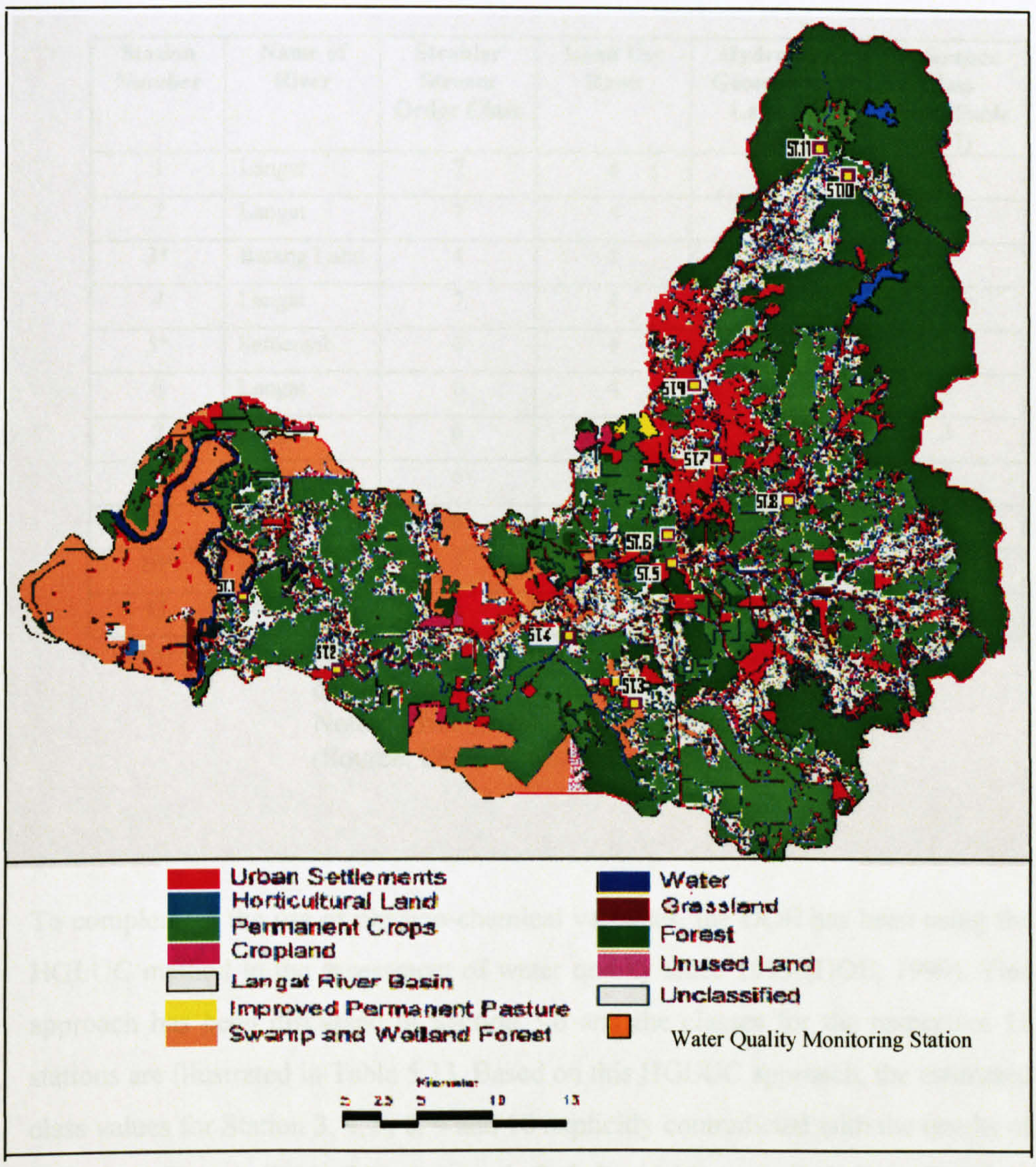
N	11
Chi-square	17.2890
Degree of freedom (df)	5.0000
Asymp. Sig.	0.0040

Table 5.31 Friedman's Rank Test Statistics

5.5.3 Hydrology-Geomorphic and Land Use Classification

In the preceding section the classification evaluation was based on physico-chemical variables. Other then these variables, classification can also be based on the different set of variables such as the hydrological features, geomorphological features of the river and the type of land use activities within a particular catchment area. These features are classified accordingly either as Strahler Stream Order Class, Land Use Rank and Hydrology-Geomorphic Land Use Class, and are based on specific criteria set by the related agencies as indicated in Table 5.32 (DOE, 1999). Using these features, the next step is to investigate the classification based on the Hydrology-Geomorphic and Land Use Classification (HGLUC), and subsequently to compare the results similarity for DOE-WQI, Harkins'-WQI and BEP of ANN. Box 5.17 displays the spatial distribution of the various types of land use activities within the Langat catchment, for the year 1995 (DOE, 1999). The impact of these activities upstream will be monitored by the downstream stations, as presented in Box 5.18.

Normally, the impact from land use upstream is described into a general statement, often referred as descriptor as indicated in the Descriptor Table 2.3. This descriptor has been shown elsewhere to correlate quite well between the water quality index and classification scheme (Ott, 1978; and House, 1986). Using this descriptor's approach, the estimated water quality class for Station 1, 2, 4, 6, 7 and 9 of Box 5.17 are expected to be 'slightly polluted' to 'very polluted' (DOE, 1986). In particular, Station 6 and 7 are situated in highly congested urban and industrial areas, thus these stations are estimated to be 'hardly' or 'rarely' in a situation of 'high water quality'. Station 3, 5, 8 and 10 are stations, which monitor the tributaries of the main Langat River. However, Station 3 and 5 are also situated in highly congested areas. These stations are expected to posses a condition in the range of 'good' to 'slightly polluted'. Station 8, 10 and 11 are situated in the interior parts of the catchment area and are expected that these stations should always in a state of 'excellent' water quality.

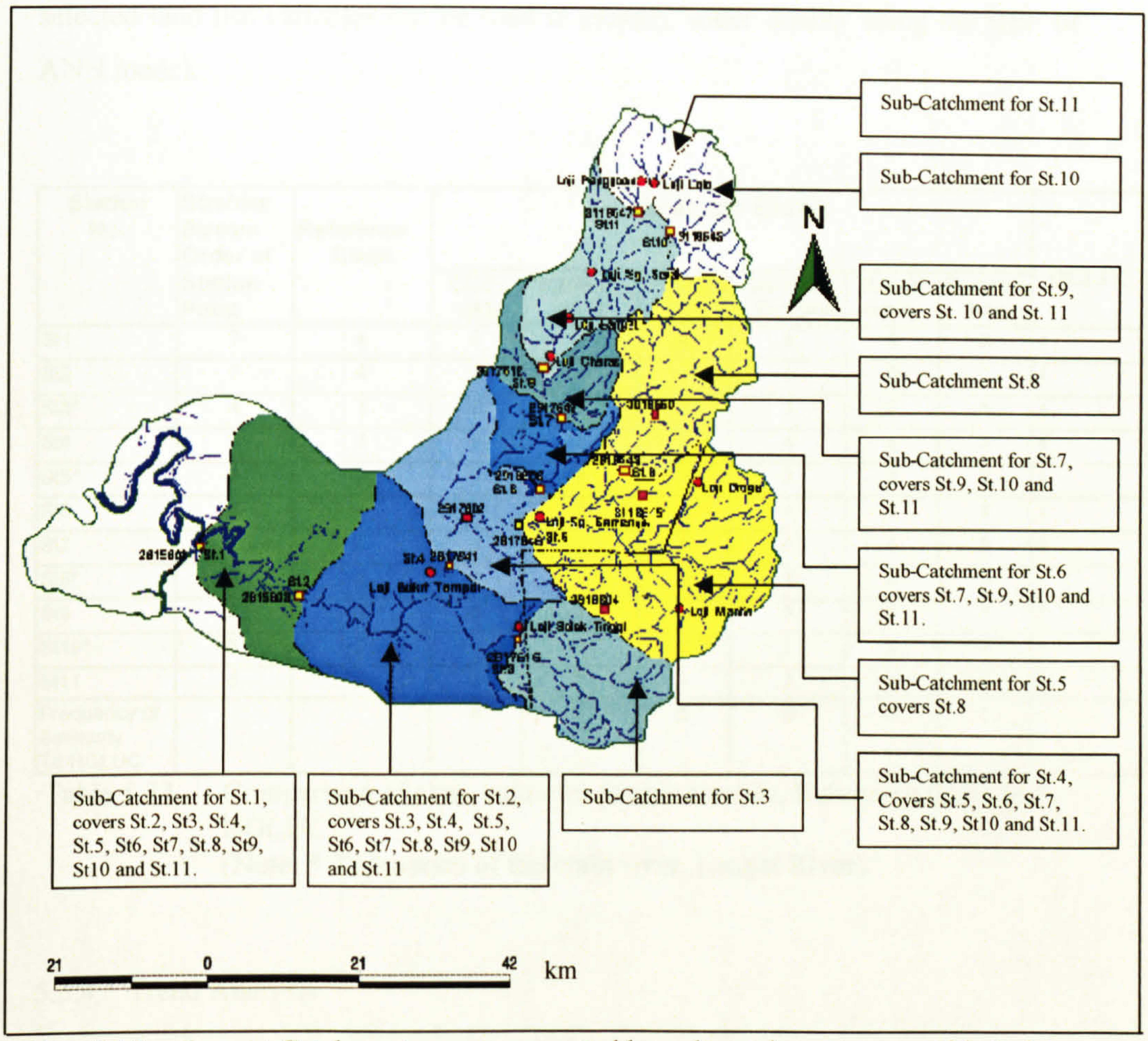


Box 5.17 Land use map of Langat catchment area, 1995
(Source: DOE, Malaysia, 1999)

Station Number	Name of River	Strahler Stream Order Class	Land Use Rank	Hydrology-Geomorphic/ Land Use Class	Reference Class (from Table 5.27)
1	Langat	7	4	4	4
2	Langat	7	4	4	4
3*	Batang Labu	4	4	4	3
4	Langat	7	4	4	3
5*	Semenyih	6	4	4	3
6	Langat	6	4	4	4
7	Langat	6	4	4	4
8*	Semenyih	6	4	4	3
9	Langat	6	3	2	3
10*	Lui	5	1	1	2
11	Langat	5	2	2	2

Table 5.32. Hydrology-Geomorphic and Land Use classes of Langat catchment area.
Note:* Tributaries of Langat River.
(Source: DOE, Malaysia, 1999)

To complement the use of physico-chemical variables, the DOE has been using the HGLUC method in the assessment of water quality since 1999 (DOE, 1999). This approach has been discussed in Section 3.6 and the classes for the respective 11 stations are illustrated in Table 5.33. Based on this HGLUC approach, the estimated class values for Station 3, 4, 5, 8, 9 and 10 explicitly contradicted with the results of Reference Class in Table 5.26. Station 1, 2, 6, 7 and 11 were all similar. Based on Box 5.17 and Box 5.18, Station 9, which monitors the heavily populated areas, is rated as Class 2 ('good' quality) based on HGLUC method. This result seems to be ambiguous due to the fact that the water quality within a heavily populated subcatchment area would 'hardly' exist between the range of 'good' to 'excellent' water quality (Class 2 to Class 1). However, all the five models classified it as Class 3, except the BEP of ANN model which also rated Station 9 as 'good' quality (Table 5.26). Class 3 should be a good estimated class for Station 9.



Box 5.18 Langat Catchment area represented by sub-catchment areas with their respective stations.
(Source: modified from DOE, Malaysia Reports, 1994, 1999)

Stations which contradicted the results from the Reference Class as indicated in Table 5.32 are; Station 3, 4 and 5 rated as Class 4 using HGLUC method, whereas all six models rated it as between Class 2 and Class 3, and Station 10 rated as Class 1 using HGLUC method similar to that of BEP of ANN, whereas the other five models rated it as Class 2. The class rated for all stations (Station 3, 5, 8 and 10) located along the tributaries of Langat River contradicted the class grade rated by the HGLUC method. This evaluation shows that the results of classification based on the HGLUC approach were 45 % similar to that of Reference Class. Although HGLUC is a robust and less accurate method in classification of water quality, the selected land use variables can be used to classify water quality using the BEP of ANN model.

Station No.	Strahler Stream Order at Station Point	Reference Class	Average Class						HGLUC
			DOE-WQI	Harkins-WQI	BEP of ANN	Maximum Likelihood	Mahala-nobis	Decision Tree	
St1	7	4	3	3	4	4	5	3	4
St2	7	4	4	4	4	3	5	3	4
St3*	4	3	3	2	2	3	3	3	4
St4	7	3	3	3	3	4	4	3	4
St5*	6	3	3	2	2	3	3	3	4
St6	6	4	4	3	4	4	4	3	4
St7	6	4	4	3	4	4	4	3	4
St8*	6	3	3	3	3	3	3	3	4
St9	6	3	3	3	2	3	3	3	2
St10*	5	2	2	2	1	2	2	2	1
St11	5	2	2	2	1	2	2	2	2
Frequency of Similarity To HGLUC			4	2	5	5	4	1	

Table 5.33 Comparison of class value for the six models, Reference Class and HGLUC
(Note: * Tributaries of the main river, Langat River)

5.5.4 Trend Analysis

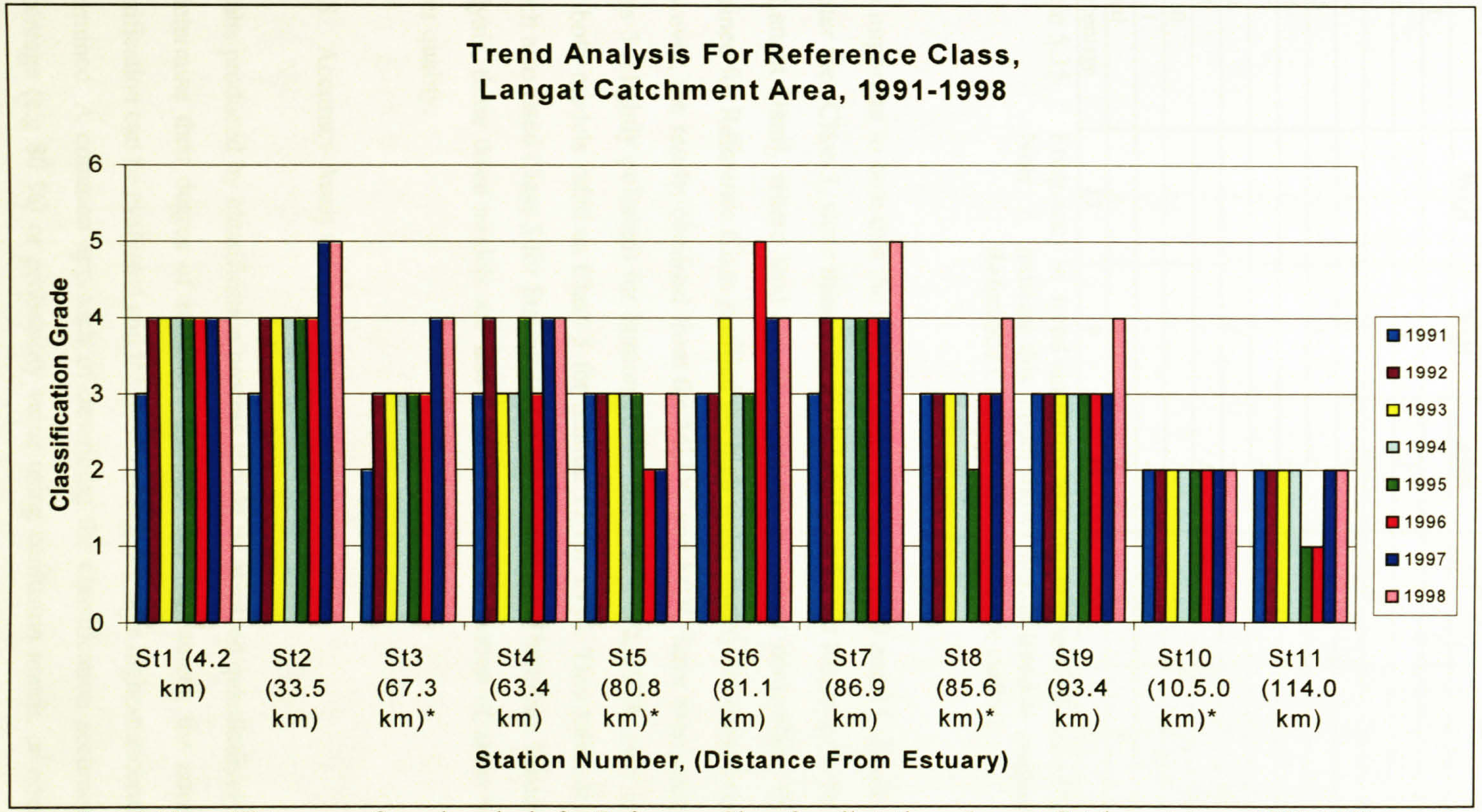
The next evaluation involved comparing the reliability of each model using trend analysis. As described in Section 5.5.1 (para 2), the average class frequency obtained from all of the six models for each station and for each consecutive year (1991-1998) were averaged and tabulated as shown in Table 5.34. This represents the average class frequency distribution for the Reference Class and shown as histogram (from 1991 to 1998) in Box 5.19. Based on this histogram, Stations 1, 2, 3, 4, 6, 7, 8 and 9 shows a gradual increase in pollution level (either increased in frequency of low water quality) from 1991 to 1998. Stations 4 and 6 shows a fluctuation of water quality between Class 2 and Class 3, and between Class 3 and Class 5 respectively.

Station No.	1991	1992	1993	1994	1995	1996	1997	1998
St1 (4.2 km)	3	4	4	4	4	4	4	4
St2 (33.5 km)	3	4	4	4	4	4	5	5
St3 (67.3 km)*	2	3	3	3	3	3	4	4
St4 (63.4 km)	3	4	3	3	4	3	4	4
St5 (80.8 km)*	3	3	3	3	3	2	2	3
St6 (81.1 km)	3	3	4	3	3	5	4	4
St7 (86.9 km)	3	4	4	4	4	4	4	5
St8 (85.6 km)*	3	3	3	3	2	3	3	4
St9 (93.4 km)	3	3	3	3	3	3	3	4
St10 (10.5.0 km)*	2	2	2	2	2	2	2	2
St11 (114.0 km)	2	2	2	2	1	1	2	2

Table 5.34 Results of water quality classification based on Reference Class for all stations, Langat Catchment Area, 1991-1998.

Histograms were drawn for all six models as shown in Appendix 5.1 and short summaries were tabulated as in Appendix 5.2. The frequency of trend similarities in water quality for each model against the trend as indicated by the Reference Class is presented as in Table 5.35. The results show that the BEP of ANN model possess highest trend similarity of 45 % for Station 2, 4, 7, 9 and 10 as compared to Reference Class histogram. The DOE-WQI possesses 27 % in trend similarity for Station 1, 6 and 8. Both MLDC and MDC also possess 27 % similarity for Station 2, 3 and 7 respectively. The Harkins'-WQI possesses only 9 % similarity for Station 8 and no occurrence of similarity for DTC model.

The similarity in trends was also evaluated between each pair of models. The results are shown in Table 5.36, which reveals that the DOE-WQI and Harkins-WQI scores with the highest frequency of trend similarity for Stations 2, 8, 10 and 11. These are followed by the Harkins-WQI and BEP of ANN for Stations 1, 3 and 6, and BEP of ANN and MLDC, and MDC for Stations 2 and 7. The MLDC and MDC had the same water quality trend for almost all stations, except Station 1, as might be expected given the similarity of their theoretical basis.



Box 5.19 Histogram of trend analysis for Reference Class for all stations, Langat Catchment Area, 1991-1998

Station No.	DOE-WQI	Harkins-WQI	BEP of ANN	MLDC	MDC	DT
St. 1	/	-	-	-	-	-
St.2	-	-	/	/	/	-
St.3	-	-	-	/	/	-
St.4	-	-	/	-	-	-
St.5	-	-	-	-	-	-
St.6	/	-	-	-	-	-
St.7	-	-	/	/	/	-
St.8	/	/	-	-	-	-
St.9	-	-	/	-	-	-
St.10	-	-	/	-	-	-
St.11	-	-	-	-	-	-
Total	3	1	5	3	3	0
Percentage	27	9	45	27	27	0

Table 5.35 Frequency in trend similarity as compared to Reference Class.
Note: /, indicate this model shows similar trend as acquired by the Reference Class for that respective station.

It is important to note that the water quality for Stations 10 and 11 should never be greater then Class 3, since these two are located in a Forest Reserve (in the vicinity of Langat Dam), where land use development is tightly controlled. The results obtained for Reference Class justified the high water quality for these two stations. However, the results obtained from the MLDC and MDC have then rated them as Class 3 (slightly polluted) for Station 10 for the year 1992, 1993, 1997 and 1998, and both models rated as Class 3 for Station 11 for 1998. This follows with DT, which also rated Class 3 for Station 10 for the year 1992. Therefore, based on trend analysis, these three models are less reliable for classification of areas with high water quality.

5.5.5 Accuracy Analysis

Results produced by classification process should be assessed quantitatively in order to determine their degree of accuracy. Through this assessment, the error or mis-classification can be evaluated and the model which acquires highest accuracy can be determined. A common approach of describing the classification accuracy is by a percentage (e.g 80 %) or probability value using confusion matrix or error matrix.

This matrix displays the confusion of water quality samples through mis-classifications of each model being applied. It is a square matrix containing the number of rows and columns where the number of frequency of class value falls into the respective classes. The correctly classified samples for each class are located along the principal diagonal of the confusion matrix.

Model	DOE-WQI	Harkins-WQI	BEP of ANN	MLDC	MDC	DT
DOE-WQI	-	St. 2, 8, 10 & 11	St.7	St.7	St.7	St.2
Harkins-WQI	St. 2, 8, 10 & 11	-	St.1, 3 & 6	-	-	St.2 & 7
BEP of ANN	St.7	St.1, 3 & 6	-	St.2 & 7	St.2 & 7	-
MLDC	St.7	-	St.2 & 7	-	All stations, except St.1	St.5
MDC	St.7	-	St.2 & 7	All stations, except St.1	-	St.5
DT	St.2	St.2 & 7	-	St.5	St.5	-

Table 5.36 Station similarity in trend analysis for each pair of different model, Langat Catchment area, 1991 – 1998.

The accuracy of each class is described along with both the errors of inclusion (commission error) and errors of exclusion (omission error) presented in the classification. A commission error, represented by off-diagonal row elements of the confusion matrix occurs when a classified water quality sample is included in a category to which it does not belong. However, an omission error, represented by off-diagonal column elements of the confusion matrix, is the error that a classified water quality sample is excluded from the category that the grid belongs to. Every error is an omission from the correct category and a commission to a wrong category (Congalton and Green, 1999). In addition, not all of the tested samples are able to be evaluated, some samples are lost within the system model, thus cannot be classified in any of the five classes.

The overall accuracy can be computed by dividing the total number of correctly classified water quality samples (i.e. the sum of the diagonal elements of the confusion matrix) by the total number of water quality sample evaluated by the system model. Thus, the unclassified water quality is the loss classes within the system model. The overall accuracy can be viewed as an average of individual class accuracies. It can only show the overall effectiveness of a particular model.

(a) Confusion Matrix

The evaluation of accuracy was based on Rândom Numbers selected from Excel of Microsoft Office. Based on the experiment to generate the most reliable network as described in Section 5.4.5, a total of 450 Random Numbers, each class acquired 90 Random Numbers were selected. For this purpose, the same amount of Random Numbers was generated so as to avoid the effect of different amount of data used on the accuracy of the results. Thus, Class 1 was represented by 90 Random Numbers that acquired Class 1 classification values generated from Excel of Microsoft Office, the same 90 Random Numbers were generated from Excel of Microsoft Office that acquired Class 2 classification values, another 90 Random Numbers generated for Class 3, Class 4 and Class 5. Thus, a total of 450 Random Numbers were generated for the evaluation of the accuracy of each model. These Random Numbers were classified using each of the models. For example, a good water quality model will classify all 90 Random Numbers of Class 1 values to Class 1 correctly, 90 Random Numbers of Class 2 values to Class 2 correctly and so forth. However, a poor model will mis-classify or will not classify at all of the respective Random Numbers.

The evaluation of accuracy based on confusion matrix for each model is shown in Table 5.37(a) and 5.37(b) for DOE-WQI, Table 5.38(a) and Table 5.38(b) for Harkins'-WQI, Table 5.39(a) and Table 5.39(b) for BEP of ANN, Table 5.40(a) and Table 5.40(b) for MLDC, Table 5.41(a) and Table 5.41(b) for MDC and Table 5.42(a) and Table 5.42(b) for DTC. The overall accuracy based on confusion matrix for the six models is shown in Table 5.43. These analyses revealed that DOE-WQI scores the highest percentage of accuracy (96.2%), follows by the

Harkins'-WQI and DTC (90.2%), MDC (89.5%), MLDC (88.6%), and the least accurate is the BEP of ANN (86.9%). The number of commission errors is highest in BEP of ANN model, follows by DOE-WQI and no commission error for the Harkins-WQI, MLDC, MDC and DTC. All models acquired some omission errors and the model with the highest omission errors is the MLDC, follows by MDC, Harkins'-WQI, DTC, BEP of ANN and the least is the DOE-WQI. The highest total number of mis-classified sample is the MLDC, follows by the BEP of ANN, MDC, Harkins'-WQI, DTC and DOE-WQI respectively. Some random samples were lost or unclassified within the system model and the analysis shows that the BEP of ANN has the highest number of lost or unclassified sample follows by the DTC, Harkins-WQI, MDC and MLDC. Based on the results in Table 5.39(b) of the Confusion Matrix for BEP of ANN, there was no random sample classified into Class 4, most of these random samples were lost (69 samples lost) in the system model, with 20 samples designated as commission errors and 30 samples as omission errors. The DOE-WQI was the only model where all of the 450 samples were evaluated, but has mis-classified 17 random samples of which 12 samples designated as commission errors and 5 samples as omission errors.

(i) Confusion Matrix for DOE-WQI Model

Class	No. of Random Sample Tested	Number of Random Sample falls into this class
1	90	97
2	90	89
3	90	85
4	90	79
5	90	95
Total	450	445

Table 5.37(a) Number of random sample correctly classified for DOE-WQI model

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	97	0	0	0	0	97
Class 2	1	89	0	0	0	90
Class 3	0	1	85	1	0	87
Class 4	0	0	1	79	0	80
Class 5	0	0	1	0	95	96
Column Total	98	90	87	80	95	450

Table 5.37(b) Confusion Matrix for DOE-WQI model

No. of sample lost in the DOE-WQI system model = 0
Commission error = 7 + 5 (Class 1 and Class 5) = 12
Omission error = 1+1+2+1+0 = 5
Total no. of sample mis-classified = 12+5 = 17
Overall Accuracy for DOE-WQI model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (90+89+85+79+90)/450 = 433/450 = 96.2 %.

(ii) Confusion Matrix for Harkins'-WQI Model

Class	No. of Random Sample Tested	Number of Random Sample falls into this class
1	90	97
2	90	89
3	90	85
4	90	79
5	90	95
Total	450	445

Table 5.38(a) Number of random sample correctly classified for Harkins'-WQI model

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	81	0	2	0	1	84
Class 2	3	79	3	3	2	90
Class 3	2	3	71	3	2	81
Class 4	2	2	3	81	3	91
Class 5	1	2	3	2	75	83
Column Total	89	86	82	89	83	429

Table 5.38(b) Confusion Matrix for Harkins'-WQI model

No. of sample lost in the Harkins'-WQI system model = 450-429 = 21
Commission error = 0
Omission error = 8+7+11+8+8 = 42
Total no. of sample mis-classified = 8+7+11+8+8 = 42
Overall Accuracy for Harkins'-WQI model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (81+79+71+81+75)/429 = 387/429 = 90.2 %.

(iii) Confusion Matrix for the BEP of ANN Model

Class	**No. of Random Sample Tested**	**Number of Random Sample falls into this class**
I	90	100
II	90	77
III	90	74
IV	90	-
V	90	100
Total	450	351

Table 5.39(a) Number of random sample correctly classified for BEP of ANN model

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	80	3	2	2	2	89
Class 2	3	78	3	3	2	89
Class 3	2	3	82	3	3	93
Class 4	2	3	3	79	4	91
Class 5	2	2	2	2	79	87
Column Total	89	89	92	89	90	449

Table 5.40(b) Confusion Matrix for MLDC model

No. of sample lost in the MLDC system model = 450-449 = 1
Commission error = 0
Omission error = 9+11+10+10+11 = 51
Total of sample mis-classified = 9+11+10+10+11 = 51
Overall Accuracy for MLDC model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (80+78+82+79+79)/449 = 398/449 = 88.6 %.

(v) Confusion Matrix for Mahalanobis Distance Classifier Model

Class	No. of Random Sample Tested	Number of Random Sample falls into this class
I	90	82
II	90	81
III	90	75
IV	90	79
V	90	83
Total	450	400

Table 5.41(a) Number of random sample correctly classified for MDC model

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	**82**	3	2	2	2	91
Class 2	3	**81**	3	2	3	92
Class 3	2	3	**75**	3	3	86
Class 4	2	2	3	**79**	3	89
Class 5	1	2	1	2	**83**	89
Column Total	90	91	84	88	94	**447**

Table 5.41(b) Confusion Matrix for MDC model

No. of sample lost in the MDC system model = 450-447 = 3
Commission error = 0
Omission error = 8+10+9+9+11 = 47
Total of sample mis-classified = 8+10+9+9+11 = 47
Overall Accuracy for MDC model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (82+81+75+79+83)/447 = 400/447 = 89.5 %.

(vi) Confusion Matrix for Decision Tree Classifier Model

Class	**No. of Random Sample Tested**	**Number of Random Sample falls into this class**
I	90	72
II	90	71
III	90	75
IV	90	73
V	90	77
Total	450	368

Table 5.42(a) Number of random sample correctly classified for DTC model

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	72	2	2	1	0	77
Class 2	3	71	3	2	2	81
Class 3	3	3	75	3	2	86
Class 4	2	2	3	73	3	83
Class 5	0	1	1	2	77	81
Column Total	80	79	84	81	84	408

Table 5.42(b) Confusion Matrix for DTC model

No. of sample lost in the DTC system model = 450-408 = 42
Commission error = 0
Omission error = 8+8+9+8+7 = 40
Total of sample mis-classified = 8+8+9+8+7 = 40
Overall Accuracy for the DTC model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (72+71+75+73+77)/408 = 368/408 = 90.2 %.

	Commission Error	**Omission Error**	**Total of Sample Mis-classified**	**Total Sample Lost in System Model**	**Percentage Accuracy**
DOE-WQI	12	5	17	0	96.2
Harkins'-WQI	0	42	42	21	90.2
BEP of ANN	20	30	50	69	86.9
MLDC	0	51	51	1	88.6
MDC	0	47	47	3	89.5
DTC	0	40	40	42	90.2

Table 5.43 Overall accuracy based on Confusion Matrix for the six models

5.5.6 Sensitivity Test for the BEP of ANN Model

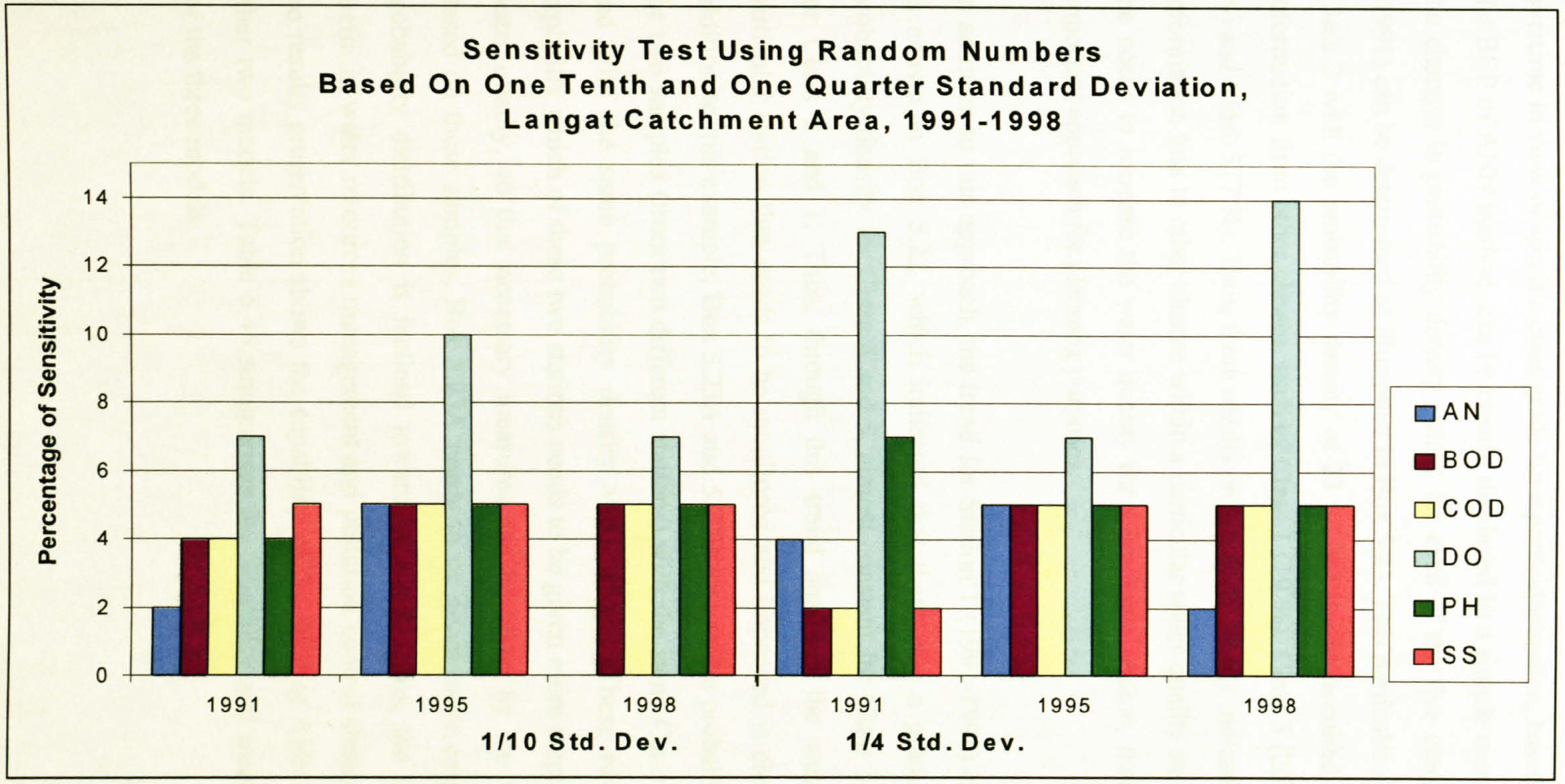
A sensitivity analysis was performed only for the BEP of ANN model, and not for the other two models. This is due to the fact that both DOE-WQI and Harkins'-WQI have shown stable results in the evaluation of accuracy as displayed in Table 5.43. The purpose of this analysis is to evaluate which of the six variables is the most sensitive based on the analysis of data using different standard deviation. The approach used for sensitivity analysis is based on the random numbers generated for Normal Distribution type of data using Excel of Microsoft Office. The data generated are such that they remain within one standard deviation from the mean, and are subsequently divided into several parts. When a specific water quality variable was subjected to changes, the other five variables were kept constant. Data preparation follows the normal procedures as in Box 5.8 and was activated into the selected network using the same SNNS program. The results obtained for three selected years (1991, 1995 and 1998) were compared with that of original results and the percentage of changes in classification results were tabulated as in Table 5.44. The selected standard deviation of one tenth and one quarter of the random numbers were found to be very sensitive to DO as shown by the histograms in Box 5.20. In particular, the standard deviation of one quarter was the most sensitive to DO. These results are in accordance with the DOE-WQI mathematical formula (Equation 3.1, Box 3.2), which assigned the highest weightage to DO (0.22). Thus, both models exhibit the importance of DO in classification of water quality. The BEP of ANN model also shows that after DO, the next sensitive variables, in descending order, are the pH, SS, BOD, COD and least sensitive is AN. Thus, other than DO, the result contradicted that of DOE-WQI formula, where AN (0.15), BOD (0.19), COD (0.16), pH (0.12) and SS (0.16) are considered as the order of important variable selected by the DOE's water quality experts. However, the SS position as rated by BEP of ANN model (second sensitive variable) was reasonably close when compared to DOE-WQI model (third important variable). Therefore, based on sensitivity analysis, the BEP of ANN model perform reasonably quite well in classification of water quality although some variables have shown contradiction in results particularly for pH and AN.

Water Quality Variable	Standard Deviation Selected						Average
	1/10			1/4			
	1991	1995	1998	1991	1995	1998	
AN	2	5	0	4	5	2	3
BOD	4	5	5	2	5	5	4
COD	4	5	5	2	5	5	4
DO	7	10	7	13	7	14	10
pH	4	5	5	7	5	5	5
SS	5	5	5	2	5	5	5
Average	4	6	5	5	5	6	

Table 5.44 Percentage of sensitivity for the two types of standard deviation

5.5.7 Reliability of Classification Result Presentation

The description of the status of water quality as discussed in Chapter 2 and 3 is based on a numeric index value, classification grade or sometime in a relatively general (descriptor) statement. The main idea is to provide the simplest method of describing the status of water quality that can be easily interpreted by the layman and consequently, can be utilised effectively by the technical person. Based on the methods of calculation discussed in Section 5.4.2 and 5.4.3, the DOE-WQI and Harkins'-WQI model are capable of providing a single index value that can be transformed into a classification grade. However, based on the BEP of ANN method, the results of classification for a single sample are displayed promptly in dual presentations either as probability density values for each class of the five classes and also as classification grade as shown in Table 5.19. Although it may need a simple computer program to transform into classification grade from probability density, the computation operation in activating the test data into the network seems to be much simpler for the BEP of ANN method compared to the other two models. Inspection of the results for probability densities (Table 5.19) shows the user which class the sample belongs to, based on probability density.

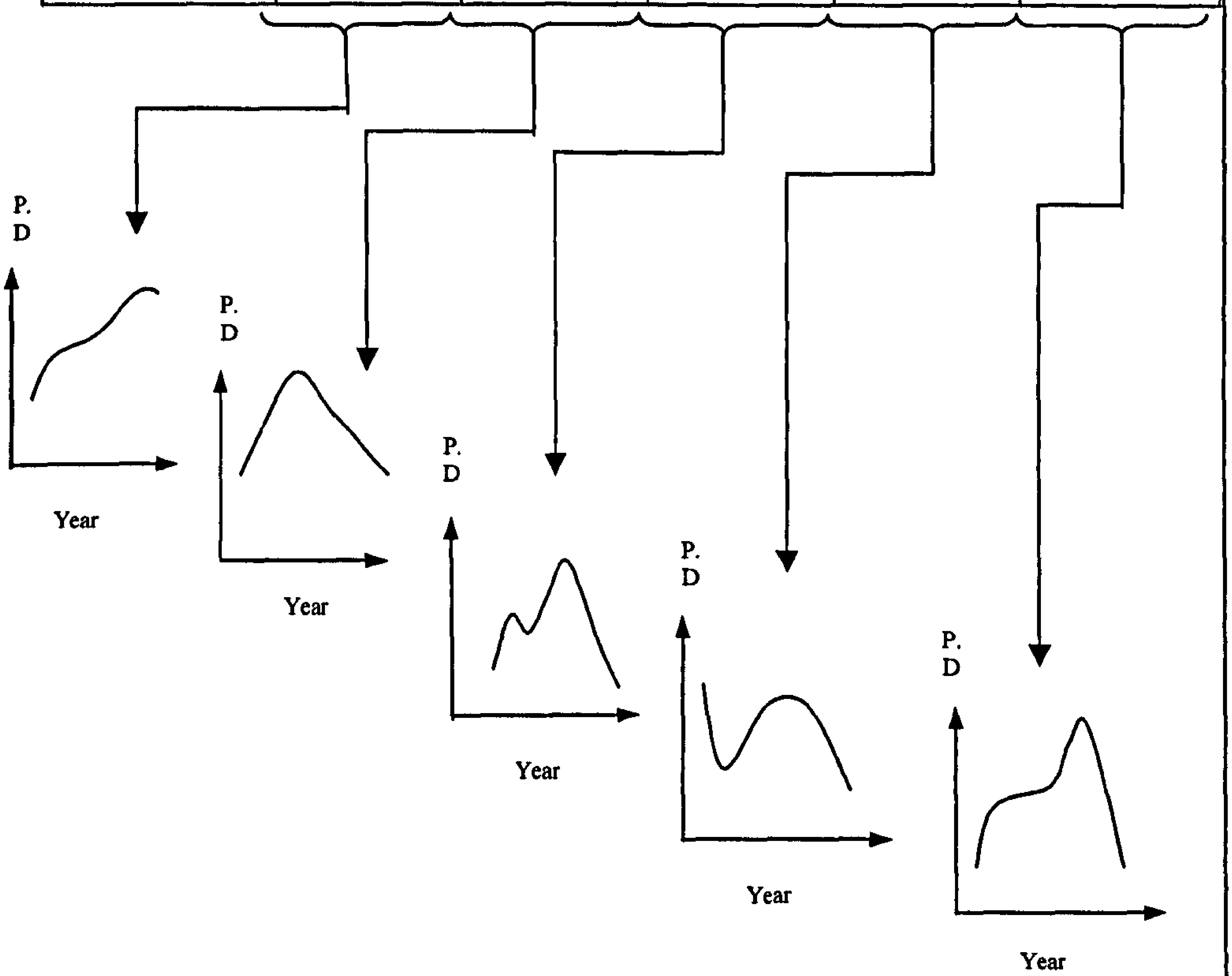


Box 5.20 Histograms of sensitivity using one tenth and one quarter standard deviation

The other advantage of this approach is that the changes of probability density overtime in view of specific class grade for a particular station, based on the results of the BEP of ANN method, can be clearly displayed in a simple manner. In this case, the changes in probability density values for each of the five classes for Station 1 (1991) can be determined as illustrated in Box 5.21. This particular sample is rated as Class 2 with the probability density of 23 %, but it also acquired some portion of information from other classes, such as Class 1 (19 %), Class 3 (20 %), Class 4 (14 %) and Class 5 (7 %). Thus, these results presentation clearly indicated the amount of information loss to other classes within a particular water quality sample. If there are the needs to increase the water quality for a particular station, then this is another important approach for planning purposes.

In addition to this approach, the trend for Station 1 (1991-1998) can be explained as shown in Box 5.22, which indicated that there was a gradual increased in probability density for Class 4 and 5, almost constant for Class 3, and a dropped for Class 2 and 1. Thus, through this trend analysis, the water quality of a particular station that needs to be monitored and improved is clearly defined. In addition to this example, Box 5.23A and 5.23B, shows the probability distribution for two samples (from two different stations) with the same Class 3 water quality and with the same probability density value of 0.5. These two figures show explicitly which of these two stations needs to be given more emphasis to improve water quality, so that necessary measures can be taken by the water authority. Based on these samples, Box 5.23A needs to be given more emphasis since the probability distribution is inclined towards Class 4. Thus, the analysis is very useful in water resources management and pollution control strategy. The form of the results presentation shows the capability of the BEP of ANN model over the other two models. Table 5.45 summarises the reliability and ease of presentation for the three models.

	Class 1	Class 2	Class 3	Class 4	Class 5
Probability Density	0.1924	0.2279	0.2032	0.1429	0.0700

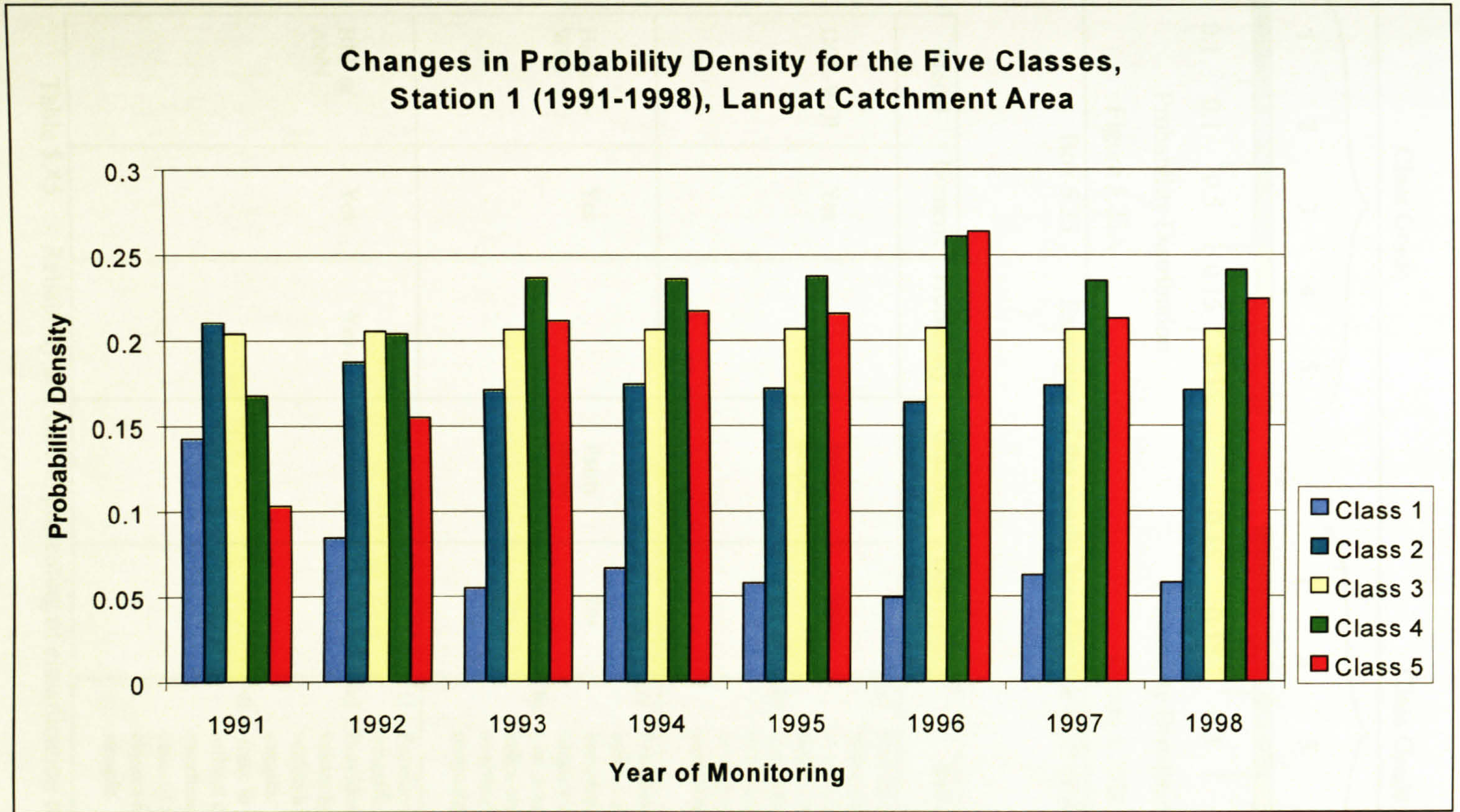


Box 5.21 Examples of the advantages using the probability values for each of the five classes for each sample (Example Station 1, 1991).

5.6 SUMMARY OF THE RESULTS AND EVALUATION

The results and evaluation were initially presented in the form of class frequency distribution, and comparisons were made for the six models. The trend of changes in classification patterns for each station were examined temporally, and displayed as histograms (Appendix 5.1). Average class values were obtained for all stations and a Reference Class was created. This Reference Class reflects the results from the combination of the six different models comprising of three different theoretical bases, which include mathematical, statistical and classifier methods. Classification results obtained from each of the six models were compared to the Reference Class. On the basis of evaluations using the general land use features and stations location, the results of Reference Class were reasonably acceptable.

Based on this Reference Class, the water quality assigned for most stations falls within the range of Class 2 and Class 4. Among the five classes, Class 3 scores the most number of occurrences for the period 1991 to 1998. Although individual sample frequently rated as Class 1 and Class 5, when averaging was performed, no station seems to possess an average Class 1 ('excellent' condition) or average Class 5 ('heavily' polluted). However, the evaluations from each model shows that only the BEP of ANN model rated Station 10 and 11 as an average Class 1 ('excellent' water quality) and only the MDC model rated Station 1 and 2 as an average Class 5 ('heavily' polluted). These results contradicted that of Reference Class approach. In case of the BEP of ANN model, the selected network structure may not reach its optimal level during the training process although several experiments were performed to generate the best network structure. This has affected the generalisation capability of the network structure and the results displayed some unexpected errors which tend to dominate the Class 1. In case of MDC model, the relatively small amount of data created for Class 5 (from standard values of INWQS) used in training, may have generated a patterns that tends to dominate this class. Thus, most of the low water quality samples tend to falls into Class 5.



Box 5.22 The changes in probability density for each of the five classes for Station 1, Langat catchment area (1991-1998)

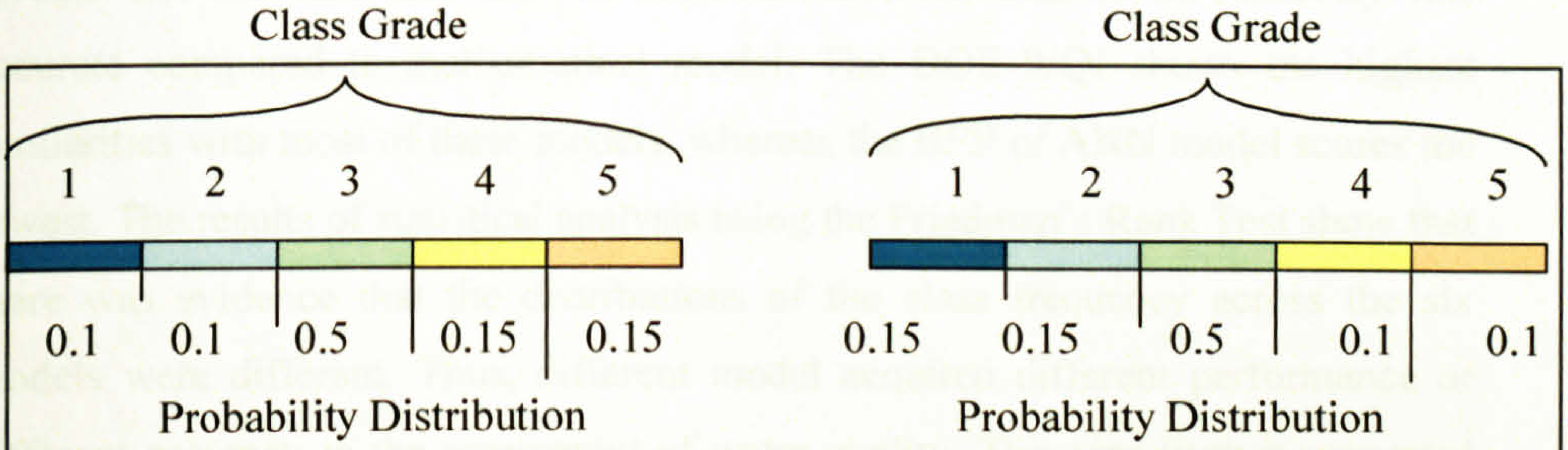


Figure 5.23A Figure 5.23B

Box 5.23 Examples of the results based on the BEP of ANN model

Model	Numeric	Probability	Grading Process	Descriptor	Remarks
DOE-WQI	Yes	-	Fairly simple	Yes	a) Provides single index value, needs to transform into a single class grade. b) Can detect refined index changes overtime for a particular sample
Harkin's-WQI	Yes	-	Fairly simple	Yes	a) Provides single index value, need to transform into a single class grade. b) Can detect refined index changes overtime for a particular sample.
BEP of ANN	Yes	Yes	Most simple	Yes	a) Provides a direct classification grade. c) Provides probability values for all classes within a single sample. d) Easy to detect refined changes overtime in each class of the five classes for each sample.

Table 5.45 Reliability and ease in presenting of classification results.

Comparison on the scores for the results of similarities against the Reference Class reveals that the statistical and the classifier methods tend to be relatively less accurate compared to mathematical model. The DOE-WQI shows the highest similarities with most of these models, whereas the BEP of ANN model scores the lowest. The results of statistical analysis using the Friedman's Rank Test show that there was evidence that the distributions of the class frequency across the six models were different. Thus, different model acquired different performance or different accuracy in the assessment of water quality. This was further supported by the Chi-square Test of Independence which revealed that there was a significant relationship between the station's location and the frequency of class value of water quality. This concluded that the frequency of polluted or slightly polluted waters measured at heavily populated areas was high and vice versa for those water quality measured in the interior parts or forested areas. Since different model acquires different classification performance, the Spearman's Rank Correlation Coefficient was applied to evaluate the correlation strength between the six models. Based on this analysis, the BEP of ANN correlated well with all of the models, the highest correlation is between the BEP of ANN and Mahalanobis Distance Classifier and the BEP of ANN with DOE-WQI. Thus, in statiscal analysis, BEP of ANN was found to be relevant model for classification of river water quality.

The accuracy of classification of the six models was further evaluated based on the Confusion Matrix approach. The overall results revealed that DOE-WQI remains as the most accurate model and the least accurate was the BEP of ANN, where the total number of lost samples in the system model was the highest. Although BEP of ANN acquired the highest commission errors, in terms of omission errors are almost the same as the other four models and the number of sample mis-classified was relatively low as compared with other four models. In view of the mis-classified samples, the problem of low generalisation capability has reduced the performance of the network. This can also relate to the allocation of the fix number of input (six variables) and fix number of output (five classes) imposed by the water quality experts. If the allocation of the number of input and output variables to be investigated is more flexible, it is expected that the performance of the network will be more generalise or may achieve the performance as portrayed by the DOE-WQI model. Thus, the achievement of 86.9 % of accuracy, the BEP of ANN model can be used in the assessment of river water quality.

The HGLUC approach is being used by the DOE, Malaysia, for estimation of water quality class based on the principles of hydrology-geomorphic and land use classification scheme. Comparisons of results were made between the HGLUC method and Reference Class. The similarity result of 45% between HGLUC method and the Reference Class is quite low. This justifies that the HGLUC method was a robust estimation of water quality, where the class grade assigned for the selected parameters were based on qualitative criteria. Therefore, it can be concluded that the HGLUC method is relevant for qualitative assessment of water quality.

The evaluation on the trends of water quality for each model against the Reference Class reveals that the BEP of ANN scores showed the highest similarity, followed by the DOE-WQI, MLDC, MDC, Harkins-WQI and DTC respectively. Comparisons of trend similarity between each model shows that DOE-WQI is relatively similar to Harkins'-WQI, whereas, Harkin's-WQI was also similar to BEP of ANN. Models that possess the highest similarity are the MLDC and MDC. However, the results obtained from MLDC, MDC and DTC models, which rated Class 3 for Station 10 and 11, contradicted the results of Reference Class, which rated it as Class 2. Since these stations are located in Forest Reserve areas which act as water catchment area in the vicinity of Langat and Semenyih Dams, changes to lower than Class 2 is 'unacceptable'. Therefore, based on trend analysis, MLDC, MDC and DTC are less reliable models for stations of high water quality.

Sensitivity analysis was only performed on the BEP of ANN model. This is due to the fact that both DOE-WQI and Harkins'-WQI have shown good results for the evaluation of estimate of accuracy. The results of sensitivity analyses for BEP of

ANN using data generated from random numbers with standard deviation of one quarter is the most sensitive to DO. These results are in accordance with the DOE-WQI mathematical formula, which has assigned the highest weightage to DO. Thus, both models demonstrate the importance of DO in classification of water quality. However, the other five variables have also shown some sensitivity such that the pH and SS (similar percentage in sensitivity), follows by the BOD and COD (similar percentage in sensitivity) and the least is AN respectively. The order of importance of these five variables based on BEP of ANN contradicts to the order as indicated in DOE-WQI model.

The evaluation on classification results presentation shows that the BEP of ANN surpasses the other two models (DOE-WQI and Harkins'-WQI). The results were displayed for a single sample either as probability density (or probability distribution) for each class of the five classes, or in the form of classification grading. The refined changes in probability density of these classes overtime can be determined effectively. Based on the results of statistical and the accuracy analysis, it can be concluded that the BEP of ANN model is capable to be used as another method in classification of water quality. Although, the results of similarity evaluations when compared to Reference Class were not so convincing, however in the trend analyses, the BEP of ANN model performed relatively much better. One of the reasons of not performing very well as compared to the DOE-WQI was due to the selected neural network. Numerous trainings were performed to obtain the network structure with the lowest MSE value and the expectation of global minima to occur. However, only one network structure was selected with the lowest MSE value as indicated in Box 5.11 and Box 5.12. This MSE value of 0.65020 was quite high and the global minima started to achieve at 13,000 cycles and ended at 20,000 cycles. The high MSE value affects the generalisation capability of the network, which rendered the BEP of ANN to be less accurate.

In addition to DOE-WQI and Harkins-WQI assessment systems, the new models, which were based on the concept of PR were capable of classifying water quality. The findings concluded that the statistical and neural classifiers based on the concept of PR tend to be relatively less accurate as compared to mathematical model. As discussed in Chapter Four, these PR models acquire specific technique of their own and their performance can be improved further towards the performance of the DOE-WQI model through further research. Although, the DOE-WQI model performed better than the other five models, its main limitation as discussed in Chapter Two and Three, is the rigidity of the model for the inclusion of new variables or exclusion of the obsolete variables. In view of the main aim of the research, the BEP of ANN has revealed some remarkable findings when its performance was compared with DOE-WQI and Harkins'-WQI, but the results obtained were not convincing as that of DOE-WQI. In the statistical analysis of the class frequency distribution, the BEP of ANN performance has surpassed other models. Thus, it is summarised that the BEP of ANN model tends to be less accurate for evaluating waters in areas of high water quality and heavily polluted waters of downstream areas. The advantage of this model as discussed in Chapter Four is the flexibility of the approach that needs to be explored in greater detail.

Water quality classification was also made based on the HGLUC method and compared to the Reference Class, but the results were not convincing due to the qualititative mode of the selected parameters. In view of this, the flexibility and the reproducibility of the BEP of ANN model will be investigated further in the next chapter using the physico-chemical water quality data from eight catchment areas, land use variables and hydrological features. These investigations need to go through some modifications where two new network structures will be developed for classification; one for physico-chemical variables for the eigth-catchment area, and the other for the land use variables and hydrological features. The results obtained will be compared with the results based on physico-chemical variables of the DOE-WQI model and the BEP of ANN model for the Langat catchment area. The reliability and sensitivity analysis of the new neural networks will be carried out accordingly.

CHAPTER SIX

APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR WATER QUALITY CLASSIFICATION BASED ON LAND USE VARIABLES

6.1 BACKGROUND

The severity of water quality deterioration is closely related to the land use activity, particularly from uncontrolled land use management within a particular catchment area. This activity can be associated with urbanisation, industrialisation, agriculture, forestry or any other human activities that arise out of the economic growth (Singh, 1995; Newson, 1997). Some of these activities may render greater impacts on water quality than others. Usually the form and magnitude of water pollutant discharges into the receiving water reflect the type or nature of land use activity of the respective area. Therefore, in water pollution control and management, it is critically important to pinpoint exactly the location of different activities. Once the sources of the pollutant discharge have been determined, appropriate control measures can be taken to reduce and contain the pollutant outfalls.

Most of the existing water quality assessment systems are based on physico-chemical variables (House, 1986; Dojlido et al., 1994). The severity of the discharge of these variables into the water bodies may relate to the characteristic and magnitude of the land use activities and also the influence of the hydrological features of the particular catchment area. Based on the characteristics of a catchment area, assessment can also be investigated using the corresponding land use activity and the hydrological features. This approach is being used by the DOE, Malaysia based on HGLUC method as discussed in Chapter Three and Chapter Five. The result and evaluation reported in Chapter Five (the Pilot Study) shows that the

HGLUC method was less accurate as compared to other models. However, it can be used as a robust assessment of water quality. The approach of using the land use variables and hydrological features can further be evaluated based on the concept of pattern recognition, through the application of BEP of ANN. The process of evaluation was similar as described in Section 5.4.5. Prior to this evaluation, the reproducibility of the selected neural network structure needs to be tested with other data sets. In addition to this, the approach can be modified so as to develop a new network structure based on the land use variables and hydrological features, without the use of water quality variables. Thus, through this new approach, the water quality can be classified based on land use variables and hydrological features. In view of this thesis and the results of the earlier analysis, the following objectives are set-up for this chapter;

(1) To classify 29 sub-catchment areas using the BEP of ANN and the DOE-WQI model based on physico-chemical variables;

(2) To investigate the performance of classification results of the BEP of ANN model as compared to the DOE-WQI model;

(3) To investigate the accuracy, sensitivity and reproducibility of the selected network as compared to the network selected for classification of water quality for the Langat catchment area based on the BEP of ANN model;

(4) To determine the common land use variables and hydrological features that contribute significantly to the changes in water quality for the selected 29 sub-catchment areas;

(5) To obtain a trained network structure based on the BEP of ANN model created from data of common land use variables and hydrological features;

(6) To classify the water quality based on the common land use variables and hydrological features using the BEP of ANN model;

(7) To compare the classification results obtained from land use variables and hydrological features against the results based on water quality variables using the BEP of ANN model; and

(8) To determine the accuracy and sensitivity of the BEP of ANN model for classification of water quality based on the common land use variables and hydrological features.

6.2 STUDY AREA

6.2.1 Location and General Description

Eight catchment areas were chosen as units for evaluating the relationships between land use activity, hydrological features and water quality classification. These catchments were chosen due to the availability of the water quality data, land use data and the hydrological features. These eight catchments comprised of 29 sub-catchment areas, with 29 stations, as indicated in Table 6.1. The selected type of land use in Table 6.1 is based on their dominant features within a particular catchment. The locations are shown as in Appendix 6.1 (seven on Peninsular Malaysia and one in the state of Sabah). The details of land use distribution as of 1995 for each of these eight catchment areas is also shown in Appendix 6.1A to 6.1G, and Box 5.13 shows the five selected stations of Langat catchment area (selected stations from Pilot Study). The evaluation of land use activity is based on the estimate of the percent area of the sub-catchment, covered by urban (i.e town, residential, industrial and commercial), agriculture (i.e cropping, orchard, oil-palm and rubber) and forest (both primary and secondary). The descriptions of land use shown in Table 3.5 are useful for describing the land use within a particular catchment area as discussed in Section 3.6.

Catchment	Sub-catchment (name of river)	Type of Land Use*	Station No.	Station Designation
1. Ibai	1. Ibai	Res./Ind.	5231615	St1
2. Juru	2. Juru	Highly Ind.	5304604	St1
	3. Kilang Ubi	Agri/Nat. Forest	5304605	St2
	4. Pasir	Urban/Agri	5304606	St3
	5. Rambai	Urb/Agri/Nat.Forest	5304607	St4
	6. Ara	Urban/Agri.	5304608	St5
3. Kesang	7. Kesang	Urb/Agri/Nat.Forest	2125601	St1
	8. Chin Chin	Agriculture	2224603	St2
	9. Chin Chin	Agri/Nat.Forest	2324604	St3
4. Kuantan	10. Kuantan	Urb/Agr/Nat.Forest	3733601	St1
	11. Galing Kecil	Highly Urban	3833609	St2
	12. Galing Besar	Highly Urban	3833610	St3
5. Langat	13. Batang Labu	Urban/Agri	2817616	St3
	14. Semenyih	Agri/Nat.Forest	2817648	St5
	15. Middle Langat	Urban/Highly Ind.	3017612	St9
	16. Lui	Nat. Forest	3118645	St10
	17. Upper Langat	Nat. Forest	3118647	St11
6. Padas (State of Sabah)	18. Kemabong	Nat. Forest	4959604	St1
	19. Tenom	Agri/Nat.Forest	5158606	St2
	20. Beaufort	Urb/Agri/Nat.Forest	5359614	St3
7. Pinang	21. Dondang	Urban/Agri	5302606	St1
	22. Air Itam	Urb/Nat.Forest	5403601	St2
	23. Jelutong	Highly Urb/Ind.	5403602	St3
	24. Pinang	Urban/Nat.Forest	5403603	St4
8. Serting	25. Serting	Agri/Nat.Forest	2823610	St1
	26. Serting	Urb/Agri/Nat.Forest	2824608	St2
	27. Serting	Urb/Agri/Nat.Forest	2824609	St3
	28. Mokek	Agri./Nat.Forest	2824611	St4
	29. Serting	Agri./Nat. Forest	3024643	St5

Table 6.1. The selected eight catchment areas for classification
(Note: * Dominant type of land use.
Details of land use are described in Appendix 6.2)

6.2.2 Sources of Data

The 29 stations selected are those with complete records of water quality data, land use information and hydrological features for the period of 1990 to 1999. The data used in these analyses were obtained from various agencies, as indicated in Table 6.2. The summary of the land use variables, hydrological features, demographic data and the distribution of water quality data used for all eight catchments areas are shown in Appendix 6.2 and Appendix 6.3.

Type of Data	Year	Agency
1. Water Quality	1990 - 1999	DOE, Malaysia
2. Hydrological Features	1995, 1997	DOE, Malaysia
3. Rainfall	1990 - 1999	Malaysian Meteorological Service
4. Discharge	1990-1999	Drainage and Irigation Department, Malaysia
5. Land Use Maps	1995,1999	a) DOE, Malaysia, b) Department of Mapping & Survey, Malaysia. c) Agriculture Department, Malaysia. c) States Economic Development Corporation (N. Sembilan, Selangor, Penang, Melaka, Terengganu, Pahang and Johor). e) Forestry Department Malaysia f) Malaysian Industrial Development Authority.
6. Demographic	1991-1999	Statistics Depart. Malaysia

Table 6.2 Agencies that provided the data and other information.

6.3 METHODOLOGY

6.3.1 Classification Based on Water Quality Variables

The methodologies used in classifying the selected water quality stations in the 29 sub-catchment areas (eight catchment areas) using the DOE-WQI and the BEP of ANN models are indicated as in Section 5.4.2 and Section 5.3.1 respectively. However, the quantity of water quality data involved was much larger, given that these were data for 29 stations over 10 years period (Appendix 6.3). The highest frequency of sampling achieved was seven times per year.

(a) Training Phase

In case of the BEP of ANN model, a new training data set was created so as to produce a new network structure. This was done because the network structure may influenced by the normalisation of the training data set. In this case, the minimum and maximum values for the six variables obtained from the data set of the eight catchment areas were different as compared to the data set for the Langat catchment area as performed in the Pilot Study. Thus, the network created for this eight catchment areas was different as compared to the network produced for the Pilot Study. In the preparation for training data set in supervised learning, the random numbers based on the INWQS Table 2.2 were generated using Excel of Microsoft Office. The process in data normalising is indicated as in Box 5.8 and Box 5.9, so as to create a Pattern File which is then converted to Trained-set to finally produce a new network structure. In anticipation of the long training time, a robust selection of the number of patterns in the first trial was set in the range between 300 to 1200 training patterns as indicated in Table 6.3. Several combinations with different values of network parameters were performed and those with the lowest MSE were selected and tabulated for validation analysis.

No.	No. Training Patterns	Class 1	Class 2	Class 3	Class 4	Class 5
1	310	62	62	62	62	62
2	420	84	84	84	84	84
3	450	90	90	90	90	90
4	450	80	100	80	90	100
5	550	110	110	110	110	110
6	650	130	100	140	160	120
7	700	100	150	150	200	100
8	750	200	100	100	200	150
9	800	160	160	160	160	160
10	850	170	170	170	170	170
11	950	180	190	200	180	200
12	1000	200	200	200	200	200
13	1050	210	210	210	210	210
14	1150	230	230	230	230	230
15	1200	240	240	240	240	240

Table 6.3 The number of training patterns used in searching for the most reliable network.

(b) Validation Phase

The performance of the selected networks architecture needs to be validated using data that have not been used in the training phase. In this validation analysis, a total of 450 random numbers (of which each of the 90 samples were generated to validate Class I, Class II, Class III, Class IV and Class V) were generated using Excel of Microsoft Office (Table 6.4). The classification process is similar as performed for the Langat Catctment area. These random numbers were computed consecutively into each of the ten networks architectures as indicated in Table 6.5. All parameters such as the number of iterations, initialised weights and learning rates, were tested simultaneously for each of the network architectures. The results of validation were tabulated as in Table 6.6 and the network architecture (Box 6.1) with the lowest MSE value (shown graphically as in Box 6.2) was selected as shown in Table 6.7.

Class	No. of Patterns	No. of Variables
1	90	6
2	90	6
3	90	6
4	90	6
5	90	6
Total	450	6

Table 6.4 Number of patterns generated from random numbers from Excel of Microsoft Office

Selected Network Pattern	No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learning Rate	MSE
450	5	20,000	0.91, -0.91	0.2	0.69771
450	5	20,000	0.93, -0.93	0.2	0.68553
450	5	20,000	0.95, -0.95	0.2	0.68332
450	5	20,000	0.98, -0.98	0.2	0.67421
450	5	20,000	1.00, -1.00	0.2	0.65831
450	5	20,100	1.20, -1.20	0.1	0.69891
450	5	20,200	1.21, -1.21	0.1	0.70433
450	5	20,200	1.20, -1.20	0.2	0.72111
450	5	20,300	1.00, -1.00	0.1	0.73267
450	5	20,300	1.20, -1.20	0.2	0.78655

Table 6.5 The refined selected network parameters with the lowest MSE values

Selected Network Pattern	No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learning Rate	MSE	No. of sample falls within this class				
						Cl. I	Cl. II	Cl. III	Cl. IV	Cl. V
450	5	20,000	0.91, -0.91	0.2	0.69771	120	-	23	24	21
450	5	20,000	0.93, -0.93	0.2	0.68553	110	11	-	35	25
450	5	20,000	0.95, -0.95	0.2	0.68332	105	-	14	61	34
450	5	20,000	0.98, -0.98	0.2	0.67421	98	27	33	39	41
450	**5**	**20,000**	**1.00, -1.00**	**0.2**	**0.65831**	**100**	**33**	**39**	**36**	**100**
450	5	20,100	1.20, -1.20	0.1	0.69891	53	31	40	12	47
450	5	20,200	1.21, -1.21	0.1	0.70433	46	38	-	7	13
450	5	20,200	1.20, -1.20	0.2	0.72111	61	-	22	11	24
450	5	20,300	1.00, -1.00	0.1	0.73267	52	-	-	31	47
450	5	20,300	1.20, -1.20	0.2	0.78655	21	33	-	-	56

Table 6.6 The results of the network validation

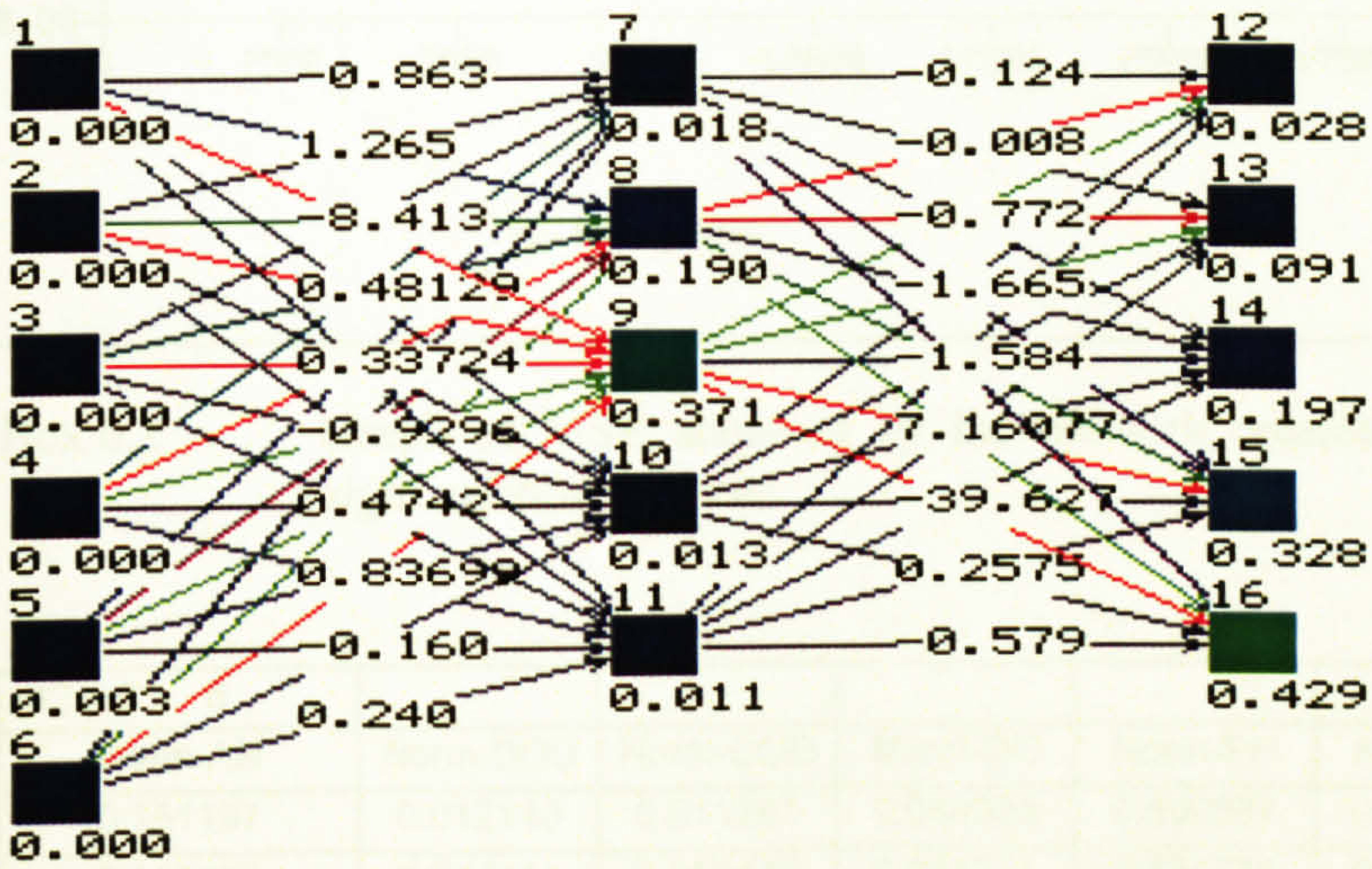
No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learnin g Rate	MSE	ANN Approach Selected
5	20,000 cycles	1.0, -1.0	0.2	0.6583 1	1. Standard Backpropagation 2. Randomised Weights

Table 6.7 Network parameters selected in a trained network structure

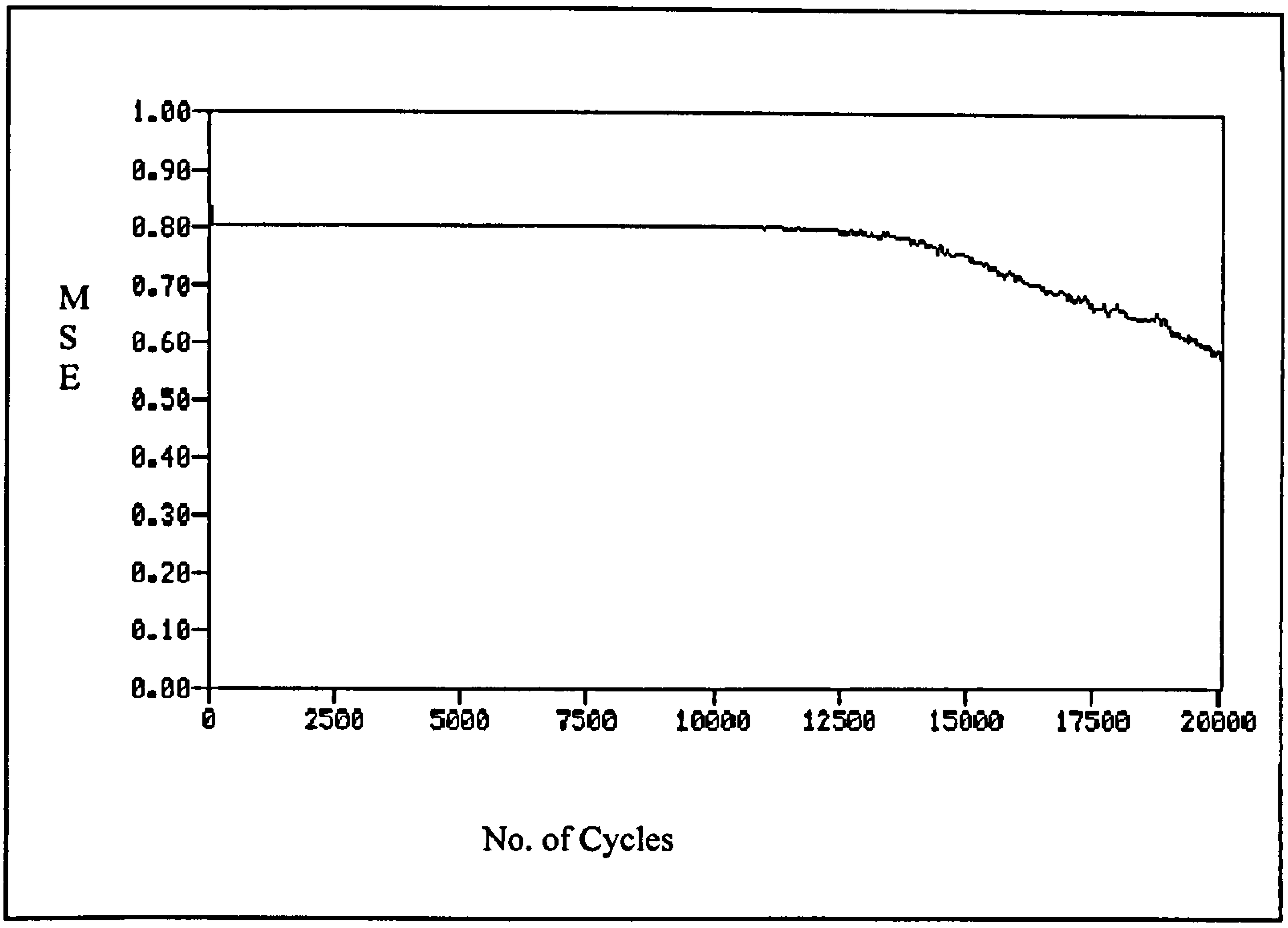
(c) Testing Phase

The testing phase was performed using independent water quality data (real data) taken from the eight catchment areas (29 sub-catchment areas) for the period of ten years between 1990 to 1999 (Appendix 6.3). These data were the observations taken from field measurements for a total of 29 stations. Data normalisation and formatting were carried out differently from that of trained set using Equation 5.14 as indicated in Box 5.13. These normalised values were saved into several ASCII

Text Files based on year of sampling for all 29 stations. As examples, Table 6.8 displays the normalised test data format in ASCII Text File for the first five samples for the 1993 and 1999 for all stations. Using the same interface program, the normalised test data were converted into Pattern File and ready to be activated consecutively (for data 1990-1999) into the selected trained set (Box 6.1) using the same SNNS software program. Example of the format of Test Pattern created is shown in Table 6.9, which displayed the first six input patterns without the five output pattern that needs to be computed.



Box 6.1 The network structure designated as $I_6H_5O_5$ created in the experiment (network created for the eight catchment areas).



Box 6.2 Graph of MSE acquired by the network created for the eight catchment areas.

142 0 6					
Norm-AN	Norm-BOD	Norm-COD	Norm-DO	Norm-PH	Norm-SS
0.151197	0.012110	0.011281	0.044338	0.599887	0.003998
0.111436	0.034411	0.018443	0.061211	0.624778	0.001477
0.122334	0.017662	0.006237	0.032986	0.499887	0.003011
0.015683	0.061073	0.034211	0.056122	0.644677	0.010123
0.133984	0.022133	0.006241	0.039571	0.499887	0.001135
141 0 6					
0.021153	0.001239	0.022313	0.249210	0.679988	0.005001
0.004669	0.005143	0.008217	0.199911	0.501113	0.011322
0.003112	0.001211	0.023666	0.188995	0.699876	0.003212
0.021774	0.002451	0.014531	0.185233	0.503478	0.312416
0.046551	0.000011	0.001037	0.311344	0.400113	0.004112

Table 6.8 Example of the normalised test data for the first five samples for 1993 (total sample is 142) and 1999 (total sample is 141).

SNNS	pattern	definition	file	V3.2		
generated	at	Mon	Jun	26	21:22:30	2001
No.	of	patterns	:	142		
No.	of	input	units	:	6	
#	Input	pattern	01:00			
0.000271	0.000021	0.000079	0.001321	0.002731	0.000021	
#	Input	Pattern	02:00			
0.000061	0.000071	0.000067	0.001411	0.002331	0.000049	
#	Input	Pattern	03:00			
0.000059	0.000031	0.000009	0.000713	0.001934	0.000089	
#	Input	Pattern	04:00			
0.000019	0.000138	0.000089	0.001075	0.002782	0.000041	
#	Input	Pattern	05:00			
0.000069	0.000027	0.000031	0.001332	0.001987	0.000039	

Table 6.9 Example of the format of Input Pattern for Test Data

The output classification values from SNNS are given in terms of probability density as shown in Table 6.10. These probability values were converted into probability distribution based on Equation 5.15 in Box 5.14, and the highest distribution was selected as the respective water quality class value. The probability densities from all 29 stations were transformed into probability distribution and finally, the water quality classes were obtained for all stations for the period of 1990-1999. The frequencies of classification of these stations were average for each year of the eight catchment areas and the results were tabulated as in Table 6.11.

SNNS	result	file	V1.4-3D			
generated	at	Tue	Jun	27	10:33:25	2001
No.	of	patterns	:	142		
No.	of	input	units	:	6	
No.	of	output	units	:	5	
startpattern	:	1				
endpattern	:	56				
#1.1						
0.17784	0.24755	0.20011	0.13236	0.04113		
#2.1						
0.16433	0.25414	0.20422	0.15381	0.08337		
#3.1						
0.05991	0.16988	0.21348	0.20311	0.17601		
#4.1						
0.15011	0.23532	0.20188	0.15579	0.08915		
#5.1						
0.12996	0.22435	0.20785	0.17223	0.09775		

Table 6.10 Example of the probability density obtained from the output results of the BEP of ANN model

6.3.1.1 Classification Analysis

The classification results for the eight catchment areas based on the BEP of ANN and the DOE-WQI models are summarised as in Appendix 6.4. In general, the results in Table 6.12 shows that the percentage of classification similarity as compared to the results obtained by the DOE-WQI model was 43%. However, in the Pilot Study for the Langat catchment area, the percentage of classification similarity between BEP of ANN to that of DOE-WQI was 45%. This different in percentage of similarity was not too wide. The overall average class indicated that six catchment areas posessed the same average class and two catchments were contradicted. The contradicted catchments were the Padas (Sabah) and Pinang (Peninsular).

Catchment Name	No. of Sub-Catchment	Station No.	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
(A) Ibai	1	5231605(St1)	-	4	2	2	3	4	2	3	3	4
(B) Juru	2	5304604(St1)	4	4	4	3	3	4	4	3	4	4
	3	5304605(St2)	4	5	4	5	4	4	5	5	4	5
	4	5304606(St3)	4	5	5	5	4	5	5	5	4	5
	5	5304607(St4)	4	5	5	5	4	4	5	5	4	5
	6	5304608(St5)	4	5	5	4	5	5	5	5	4	4
(C) Kesang	7	2125601(St1)	3	3	3	2	2	2	2	4	2	3
	8	2224603(St2)	1	2	2	2	2	3	1	3	3	2
	9	2324604(St3)	1	3	2	2	1	3	1	3	3	1
(D) Kuantan	10	3733601(St1)	2	2	2	2	2	2	2	4	2	2
	11	3833609(St2)	3	4	3	3	3	4	4	3	5	4
	12	3833610(St3)	4	3	4	4	4	5	5	3	5	4
(E) Langat	13	2817616(St3)	-	1	2	2	2	2	2	2	4	3
	14	2817648(St5)	-	2	2	2	2	2	2	2	2	1
	15	3017612(St9)	-	2	2	2	2	2	1	2	3	1
	16	3118645(St10)	-	1	1	2	1	1	1	2	2	1
	17	3118647(St11)	-	1	1	1	1	1	1	1	1	1
(F) Padas	18	4959604(St1)	1	1	1	1	2	1	2	2	1	1
	19	5158606(St2)	1	1	1	1	1	1	2	2	1	1
	20	5359614(St3)	1	1	1	1	1	1	1	1	2	1
(G) Pinang	21	5302606(St1)	-	-	-	5	5	5	4	3	3	3
	22	5403601(St2)	-	-	-	5	5	5	5	5	4	5
	23	5403602(St3)	-	-	-	5	5	5	5	5	5	5
	24	5403603(St4)	-	-	-	5	4	5	5	4	5	5
(H) Serting	25	2823610(St1)	5	4	4	4	3	2	4	4	3	3
	26	2824608(St2)	4	4	3	2	2	1	3	3	3	2
	27	2824609(St3)	4	4	3	2	3	1	3	2	2	2
	28	2824611(St4)	4	4	4	3	3	2	3	4	3	2
	29	3024643(St5)	3	3	3	3	3	3	2	3	4	3

Table 6.11 The average classification results based on the BEP of ANN model for each year of the eight catchment areas

No.	Name of Catchment Area	Percentage Similarity	Average Class (1990-1999)	
			DOE-WQI	BEP of ANN
1	Ibai	44	3	3
2	Juru	66	4	4
3	Kesang	53	2 & 3	2
4	Kuantan	30	3	3
5	Langat	38	2	2
6	Padas	20	2	1
7	Pinang	57	3	5
8	Serting	34	3	3
Average		43		

Table 6.12 Similarity of classification results as compared to the DOE-WQI model

6.3.1.2 Accuracy Analysis

The accuracy analysis of the network architecture (Box 6.1) was based on Confusion Matrix approach. Random Numbers were generated from Excel of Microsoft Office, of which a total of 450 Random Numbers were used. Out of this 450 samples, 90 samples that acquired Class 1 classification values, 90 samples acquired Class 2 classification values and the same number of samples for Class 3, 4 and 5. These 450 random numbers were computed into the selected network, $I_6H_5O_5$ as indicated in Box 6.1. Thus, a high performance network architecture will classify all 90 random numbers of Class 1 values to Class 1 correctly, 90 random numbers of Class 2 values to Class 2 correctly and so forth. However, a low performance network will acquire a poor classification capability or poor generalisation, which either mis-classifies some or all of the respective random numbers in used. The results of the accuracy analysis based on confusion matrix are shown in Table 6.13(a) and Table 6.13(b).

Class	No. of Random Sample Tested	No. of Random Sample falls into the Class
1	90	100
2	90	33
3	90	39
4	90	36
5	90	100
Total	450	308

Table 6.13(a) Number of random samples correctly classified using network as shown in Box 6.1.

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	100	3	1	0	0	104
Class 2	2	**33**	2	2	1	40
Class 3	2	3	**39**	3	2	49
Class 4	1	2	3	36	2	44
Class 5	0	1	0	1	**100**	102
Column Total	105	42	45	42	105	**339**

Table 6.13(b) Confusion Matrix for BEP of ANN model

No. of sample lost in the BEP of ANN system model = 450-308 = 142
Commission error = 10+10 (Class 1 and Class 5) = 20
Omission error = 5+9+6+6+5 = 31
Total no. of sample mis-classified = 20+31 = 51
Overall Accuracy for BEP of ANN model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (90+33+39+36+90)/339 = 288/339 = 84.9 %.

The evaluation of accuracy of the selected network produced for the eight-catchment area (Box 6.1) based on confusion matrix shows that the total number of sample lost in the system model was 142 out of 450, a relatively high difference when compared to those models as indicated in Table 5.43. However, the commission errors was the same (20) when compared to the commission errors produced by the network selected for Langat catchment area (Box 5.11), whereas the omission errors was higher by a difference of 1 (31). The total number of sample mis-classified was 51 which was higher by a difference of 1 (51) as compared to the total number of sample mis-classified by the Langat catchment area network. The overall accuracy of the eight-catchment area network was 84.9 %, less by 2 % as compared to the accuracy of network selected for the Langat catchment area. The performance of these two networks, the eight-catchment area and the Langat catchment area, were compared in terms of percentage similarity of the classification results in relation to the classification results of the DOE-WQI model and the results obtained were tabulated as in Table 6.14. It shows that the eight-catchment network had an average of 36% similarity as compared to 19% of the Langat catchment network. Thus, the network selected for the eight-catchment area is relatively more accurate or more generalised than that of the Langat catchment area.

Year	(a) Langat Catchment	(b) Eight Catchment
	Percentage	Percentage
1990	-	33
1991	13	23
1992	38	36
1993	14	39
1994	16	49
1995	21	34
1996	12	37
1997	20	35
1998	21	43
1999	-	33
Average	19	36

Table 6.14 Percentage similarity in classification results of the BEP of ANN to that of the DOE-WQI model;
(a) Langat catchment area, (b) Eight-catchment area

6.3.1.3 Sensitivity Analysis

Sensitivity analysis was performed to investigate the influence of each of the six variables on the new network architecture (Box 6.1). The steps taken were similar as described in Section 5.5.6, where random numbers were generated using Excel of Microsoft Office. Data preparation followed the normal procedures as illustrated in Box 5.8, and activated into the selected trained network (Box 6.1) using the same

SNNS programs. The results obtained for three selected years (1990, 1995 and 1999) were compared to that of the original results and the percentage of changes in classification results were tabulated as in Table 6.15. Based on this sensitivity analysis, the standard deviation of one-tenth and one-quarter were found to be very sensitive to DO as shown in Box 6.3. In particular, the standard deviation of one-quarter was the most sensitive to DO. These results are in accordance with the DOE-WQI mathematical formula (Equation 3.1), which assigned the highest weighting to DO (0.22). Thus, both models emphasis the importance of DO in classification of water quality. The next sensitive variables in descending order were pH, SS, AN, COD and BOD. These results contradicted to that of the DOE-WQI model (order of importance; DO>BOD>COD=SS>AN>pH).

Water Quality Variable	Standard Deviation (SD) Selected						Average %
	S.D 1/10			S.D 1/4			
	1990	1995	1999	1990	1995	1999	
AN	1	0.8	1	1	0.8	0.7	0.9
BOD	1	0.8	0.7	1	0	0.7	0.7
COD	1	0.8	0.7	1	0.8	0.7	0.8
DO	7	4	5	12	10	10	8.0
pH	2	0.8	1	4	2	2	2.0
SS	2	0.8	0.7	1	0.8	0.7	1.0
Average	2	1	2	3	2	2	

Table 6.15 Percentage sensitivity of the eight-catchment network

Comparisons made for both networks (Table 6.15 and Table 5.44) shows that the sensitivity results are similar for the first two variables as illustrated in Table 6.16. However, the order of sensitivity for the other four variables is different. The sensitivity of the Langat catchment network seems to be greater then that of the eight-catchment network, compared to the order represented by the DOE-WQI model. The higher sensitivity for the Langat catchment network is possibly due to the homogenous data distribution or the small volume of data set used whereas the data taken for producing the eight-catchment network were more heterogenous and in larger volume (taken across national scale).

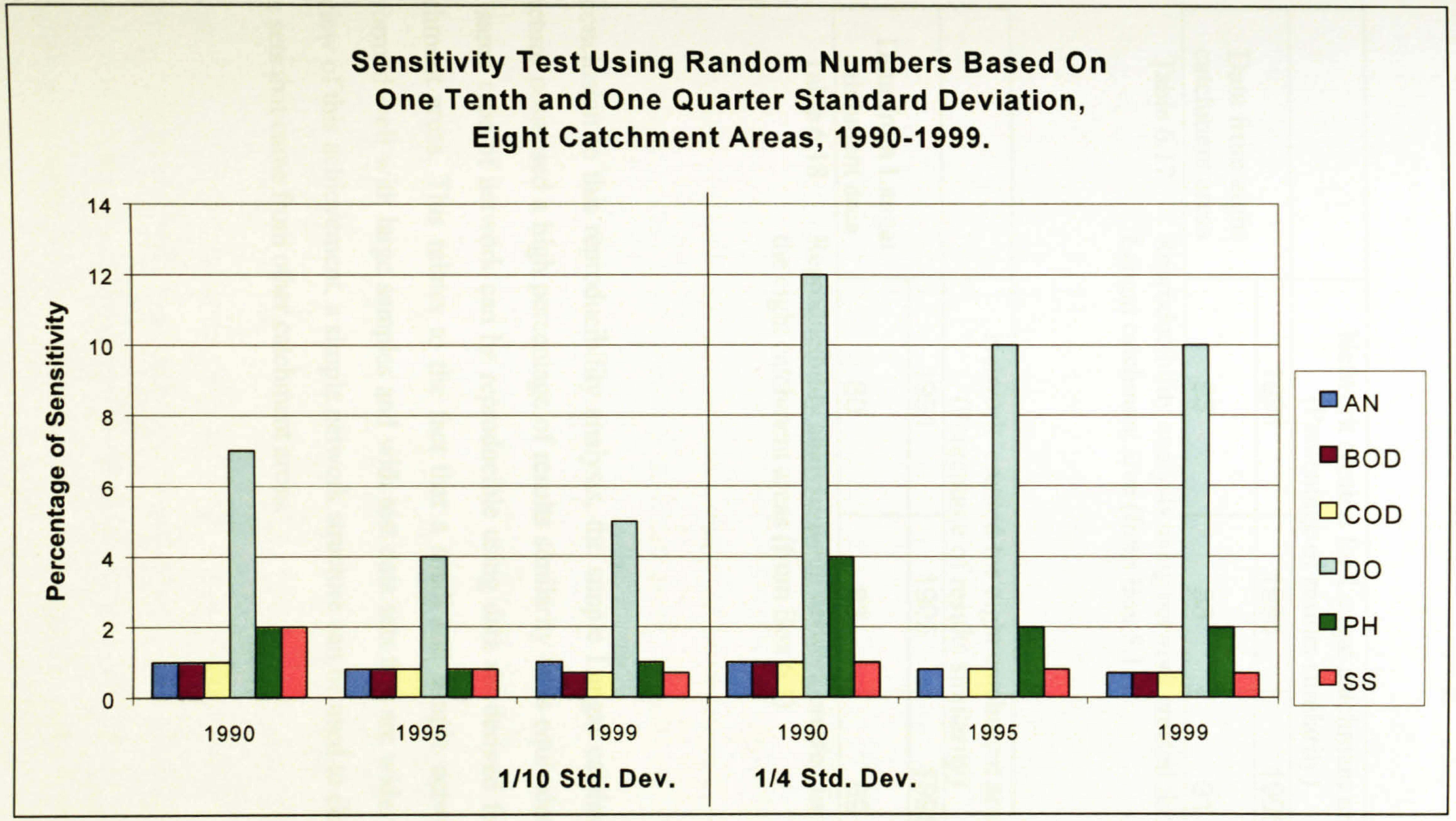
6.3.1.4 Reproducibility of the Network

The distribution of water quality data may have an influence on the training of the pattern data set and consequently on the performance of the network structure created. This influence is confined to the minimum and maximum values of the six variables involved in the normalisation process. The network structure created for the eight catchment had a different magnitude of errors compared to the network for the Langat catchment. In this situation, the performance of these two network structures can be tested by cross-validation using the same data set (but in an opposite manner of computation). The results for the classification obtained can be compared with that of their original results. If their performance is the same, then the effects of normalisation is negligible and the single network structure can be used to classify the data taken from the eight catchment areas. If otherwise, it can be concluded that normalisation has a strong effect on the performance of the network. Generally, based on rigorous experiments, if the single network structure can be applied in the classification of any catchment area, then this situation confirms the reproducibility of the network. In view of this, reproducibility analysis was performed for both the network created for Langat catchment and the network created for the eight catchment areas.

Approach	Order of Sensitiveness/Importance
1. DOE-WQI	DO>BOD>COD=SS>AN>pH
2. BEP of ANN: Eight-catchment area network (from Table 6.6)	DO>pH>SS>AN>COD>BOD
3. BEP of ANN: Langat catchment area network (from Table 5.39)	DO>pH=SS>BOD=COD>AN

Table 6.16 Comparisons of sensitiveness of each individual variable

The analysis of reproducibility for the two networks was carried out for three selected years; 1991, 1995 and 1998. Data from the eight catchment areas were computed using the network (Box 5.11) created for Langat catchment area and the results were compared from the original results using the network created for eight catchment areas (Box 6.1). The results were evaluated in terms of percentage similarity as shown in Table 6.17. The same steps were performed for data obtained from Langat catchment area using the network created for the eight catchment areas (Box 6.1) and the results were compared from the original results using the network (Box 5.11) created for Langat catchment area. These results are presented in Table 6.18. Based on reproducibility analysis, the performance of the network created for Langat catchment (Box 5.11) using the data from the eight catchment areas was much better then the performance of the network created for the eight catchment areas (Box 6.1) using the data from the Langat catchment area. These results were supported by the results of the MSE, in that the Langat catchment network had a lower MSE value (0.65020), compared to that of eight-catchment network (0.65831).



Box 6.3 Histograms of sensitivity using one-tenth and one-quarter standard deviation.

	Network created for Langat catchment area. (Percentage of results similarity)		
	1991	1995	1998
Data from eight catchment areas	93	83	91

Table 6.17 Reproducibility analysis using network created for Langat catchment area (from Box 5.11).

	Network created for eight catchment areas. (Percentage of results similarity)		
	1991	1995	1998
Data from Langat catchment area	80	83	69

Table 6.18 Reproducibility analysis using network created for the eight catchment areas (from Box 6.1).

In conclusion to this reproducibility analysis, the simple Langat catchment network structure possessed a high percentage of results similarity or is equivalent to say that the same type of network can be reproducible using data set derived from the eight catchment areas. This relates to the fact that a small and simple network structure performed well with large samples and with test data sets that are widely distributed. In view of this achievement, a simple network structure can be used to classify the test data sets that came from other catchment areas.

6.3.2 Classification of Water Quality Based on Land Use Variables and Hydrological Features (LUVHF)

The application of BEP of ANN in classification of water quality was based on physico-chemical variables. The methodologies for these classifications were discussed in Section 5.4.5 for Langat catchment area and Section 6.2.3 for the eight catchment areas. It has also been shown in Section 5.5.3 that classification based on hydrology-geomorphic and land use classification (HGLUC) was a robust estimation of water quality, where the class grade assigned for the selected parameters was based on qualitative criteria. The results from HGLUC revealed that this assessment is relevant for qualitative assessment only. However, using the same BEP of ANN model approach, the land use variables and hydrological features can be used to classify water quality quantitatively. In the subsequent analysis, **a common land use variables and hydrology features (LUVHF) will be determined and using the same methodogies, new network architecture will be created from LUVHF to classify 29 water quality stations as indicated in Table 6.1.** The sources of data for LUVHF are indicated as in Table 6.2 and the details are shown in Appendix 6.2.

6.3.2.1 Methodology for Network Creation Based on LUVHF

The methodologies of evaluations were described in Section 6.2.3 and the classification results were tabulated as in Table 6.11. These results were tabulated with their corresponding LUVHF obtained for each of the 29 stations as shown in Appendix 6.5. Based on this Table (Appendix 6.5), the classification grade was arranged in ascending order as in Table 6.19. Those stations that possess the same water quality class grade were regrouped together with their corresponding LUVHF (Table 6.19). Using these groupings based on class value, a range of the LUVHF was tabulated as in Table 6.20 and this LUVHF will be used to create a new trained data set for acquiring a new network structure. Based on these ten variables as indicated in Table 6.20, Class 1 water quality was represented by the ten variables as represented by second row of this Table and Class 2 represented by the third row of the same Table and so forth.

(a) Training Phase

In training phase, the process of creating the Trained Set is similar to that of the network created for the eight-catchment areas (Section 6.2.3). Using Table 6.20, the minimum and maximum values of LUVHF were selected and tabulated as in Table 6.21. These minimum and maximum LUVHF values were used in normalisation process as indicated in Box 5.8 and Box 5.9. In this preparation for training data set in supervised learning, random numbers were generated using Excel of Microsoft Office based on the ten variable values as indicated by each of the five classes in Table 6.20. The Pattern File was created and converted to Trained data set.

Training was performed to obtain the most generalised network structure of LUVHF. In anticipation of the laborious analysis and long computation time, the experiments started with the robust selection of 100 to 1200 patterns (as performed for eight-catchment network in Section 6.3.2) and from 4 to 11 hidden nodes as indicated in Table 6.22. Several combinations with different values of network parameters were performed and those with the lowest MSE were selected. It was found that the networks with 450 number of patterns, 10 input nodes and 6 hidden nodes with different range of network parameters as indicated in Table 6.23 acquired the lowest MSE values, which needs to be validated in the next phase.

Station No.	Area of Sub-Catchment (Sq.km)	Strahler Stream Order	Stream Density	Mean Annual Rainfall (mm)	Mean Annual Discharge (Cumec)	Pop. Density (1995)	Population (1995)	% Area Agric. (1995)	% Urban Area (Res., Ind., Comm.) (1995)	% Forest Area (1995)	Water Quality Class	
											DOE-WQI (1995)	BEP of ANN (1995)
3118645(St10)	101.50	5	2.380	2565	1.736	23.6	2657	12	3	85	2	1
3118647(St11)	215.30	5	3.230	2675	2.513	7.4	1767	8	2	90	2	1
4959604(St1)	3139.10	5	0.636	2250	327.700	2.0	7135	8	4	88	2	1
5158606(St2)	7945.40	6	0.531	2250	327.700	5.6	50565	12	8	80	2	1
5359614(St3)	8482.00	6	0.544	2250	327.700	5.7	54944	12	9	79	2	1
2824608(St2)	261.30	5	2.000	1875	7.209	235.0	66338	50	15	35	2	1
2824609(St3)	572.50	6	2.180	1875	30.401	210.0	129880	62	12	26	2	1
2125601(St1)	636.40	6	1.590	2000	21.300	172.0	118833	60	15	25	2	2
3733601(St1)	1138.00	7	4.970	3000	15.000	226.8	289174	28	21	51	3	2
2817616(St3)	241.80	4	3.190	2455	3.414	70.5	18909	82	5	13	2	2
2817648(St5)	577.30	6	2.930	2565	3.616	144.5	92529	41	15	44	3	2
3017612(St9)	273.30	6	3.320	2675	6.364	292.5	88670	45	20	35	3	2
2823610(St1)	129.30	5	3.640	1875	1.674	146.0	20394	15	12	73	3	2
2824611(St4)	45.40	4	1.410	1875	0.629	260.0	12752	52	8	40	2	2
2224603(St2)	168.0	5	2.310	2000	1.607	51.2	9339	87	5	8	2	3
2324604(St3)	112.00	5	2.500	2000	1.677	135.7	16499	85	5	10	3	3
3024643(St5)	838.40	6	1.130	1875	35.113	211.0	191109	64	9	27	2	3
5231605(St1)	91.00	4	1.120	3125	1.760	1444.0	146608	71	15	14	3	4
5304604(St1)	63.10	5	0.490	1844	12.560	1794.0	120740	61	25	14	4	4
5304605(St2)	12.49	4	1.680	1844	0.250	119.0	1585	79	8	12	4	4
5304607(St4)	12.49	4	1.440	1844	0.260	151.3	2016	82	6	12	4	4
3833609(St2)	24.90	5	2.240	3000	0.280	226.8	6338	3	86	11	3	4
5304606(St3)	5.25	3	1.330	1844	0.055	120.0	672	85	12	3	4	5
5304608(St5)	3.98	4	1.780	1844	0.031	134.0	569	91	5	4	4	5
3833610(St3)	37.50	5	2.390	3000	0.440	1636.0	9529	8	88	4	3	5
5302606(St1)	4.69	3	1.910	2200	0.020	3799.1	19005	63	29	8	5	5
5403601(St2)	14.51	5	2.310	2200	0.280	2078.8	32172	14	33	53	4	5
5403602(St3)	5.86	5	0.530	2200	0.076	7421.9	46389	1	99	0	5	5
5403603(St4)	50.97	6	0.810	2200	3.495	7421.9	403439	11	48	41	4	5

Table 6.19 The water quality classification results based on the DOE-WQI and the BEP of ANN model for the eight catchment areas arranged in descending order

Water Quality Class (BEP of ANN model)	Sub-catchment area (sq.km) (SCA)	Strahler Stream Order (SSO)	Stream Density (SD)	Mean Ann. Rainfall (mm) (MAR)	Mean Annual Disch. (Cumec.) (MAD)	Pop. Density (1995) (PD)	Population (1995) (POP)	% Agric. Area (1995) (AGRIC)	% Town, Ind., Res., Area (1995) (URBAN)	% Natural Forest (1995) (FOR)
1	101.5 – 8482.0	5 – 6	0.53 – 3.23	1875 – 2675	1.74 – 327.70	2.0 – 235.0	1767 – 129880	8.0 – 62.0	2.0 – 15.0	26.0 – 90.0
2	45.4 – 1138.0	4 – 7	1.41 – 5.00	1875 – 3000	0.63 – 21.30	70.5 – 292.0	12752 – 289174	15.0 – 82.0	5.0 – 21.0	13.0 – 73.0
3	112 – 838.4	5 – 6	1.13 – 2.50	1875 – 2000	1.61 – 35.11	51.2 – 211.0	9339 – 191109	64.0 – 87.0	5.0 – 9.0	8.0 – 27.0
4	12.5 – 91.0	4 – 5	0.50 – 2.24	1844 – 3000	0.25 – 12.56	119.0 – 1794.0	1585 – 146608	3.0 – 82.0	6.0 – 86.0	11.0 – 14.0
5	4.0 – 51.0	3 – 6	0.53 – 2.39	1844 – 3000	0.02 – 3.50	120.0 – 7421.0	569 – 403439	1.0 – 91.0	5.0 – 99.0	0.0 – 53.0

Table 6.20 The range of five classes of LUVHF created from water quality classification results (from Table 6.19).

	SCA	SSO	SD	MAR	MAD	PD	POP	AGRIC	URBAN	FOR
Min	4.0	3.0	0.5	1844.0	0.02	2.0	569.0	1.0	2.0	0.0
Max	8482.0	7.0	5.0	3000.0	327.70	7421.0	403439.0	91.0	99.0	90.0
Range	8478.0	4.0	4.5	1156.0	327.68	7419.0	402870.0	90.0	97.0	90.0

Table 6.21 The minimum and maximum values from LUVHF used in normalisation for creating trained data set.

No.	No. of Input Nodes Selected	No. of Hidden Nodes Tested	No. Training Patterns	Class 1	Class 2	Class 3	Class 4	Class 5
1	10	4,5,7,9,10,11	100	20	20	20	20	20
2	10	4,5,7,9,10,11	200	40	40	40	40	40
3	10	4,5,7,9,10,11	300	60	60	60	60	60
4	10	4,5,7,9,10,11	400	80	80	80	80	80
5	10	4,5,6,7,8,10,11	450	90	90	90	90	90
6	10	4,5,6,7,8,10,11	500	100	100	100	100	100
7	10	4,5,7,9,10,11	550	110	110	110	110	110
8	10	5,6,7,8,9,10,11	600	120	120	120	120	120
9	10	4,5,7,9,10,11	650	130	130	130	130	130
10	10	4,5,7,9,10,11	700	140	140	140	140	140
11	10	5,6,7,8,9,10	750	150	150	150	150	150
12	10	4,5,7,9,10,11	800	160	160	160	160	160
13	10	4,5,6,7,8,9,10	850	170	170	170	170	170
14	10	4,5,7,9,10,11	900	180	180	180	180	180
15	10	4,5,6,7,8,9,10	950	190	190	190	190	190
16	10	5,6,7,8,9,10	1000	200	200	200	200	200
17	10	5,6,7,8,9	1050	210	210	210	210	210
18	10	5,6,7,8,9	1100	220	220	220	220	220
19	10	5,6,7,8,9	1150	230	230	230	230	230
20	10	5,6,7,8	1200	240	240	240	240	240

Table 6. 22 The number of training patterns used in searching for the most reliable network.

Selected Network Pattern	No. of Input Nodes	No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learning Rate	MSE
450	**10**	**6**	**25,000**	**1.00, -1.00**	**0.2**	**0.21185**
450	10	6	25,000	0.98, -0.98	0.2	0.22011
450	10	6	24,000	0.95, -0.95	0.1	0.23883
450	10	6	25,000	0.95, -0.95	0.1	0.23992
450	10	6	26,000	0.98, -0.98	0.2	0.24887
450	10	6	24,000	1.00, -1.00	0.2	0.24931
450	10	6	25,000	1.21, -1.21	0.1	0.25433
450	10	6	25,000	1.20, -1.20	0.2	0.25671
450	10	6	24,000	1.00, -1.00	0.1	0.25967
450	10	6	26,000	1.00, -1.00	0.2	0.26008
450	10	6	26,000	1.20,-1.20	0.1	0.27113
450	10	6	26,000	1.21,-1.21	0.2	0.27456

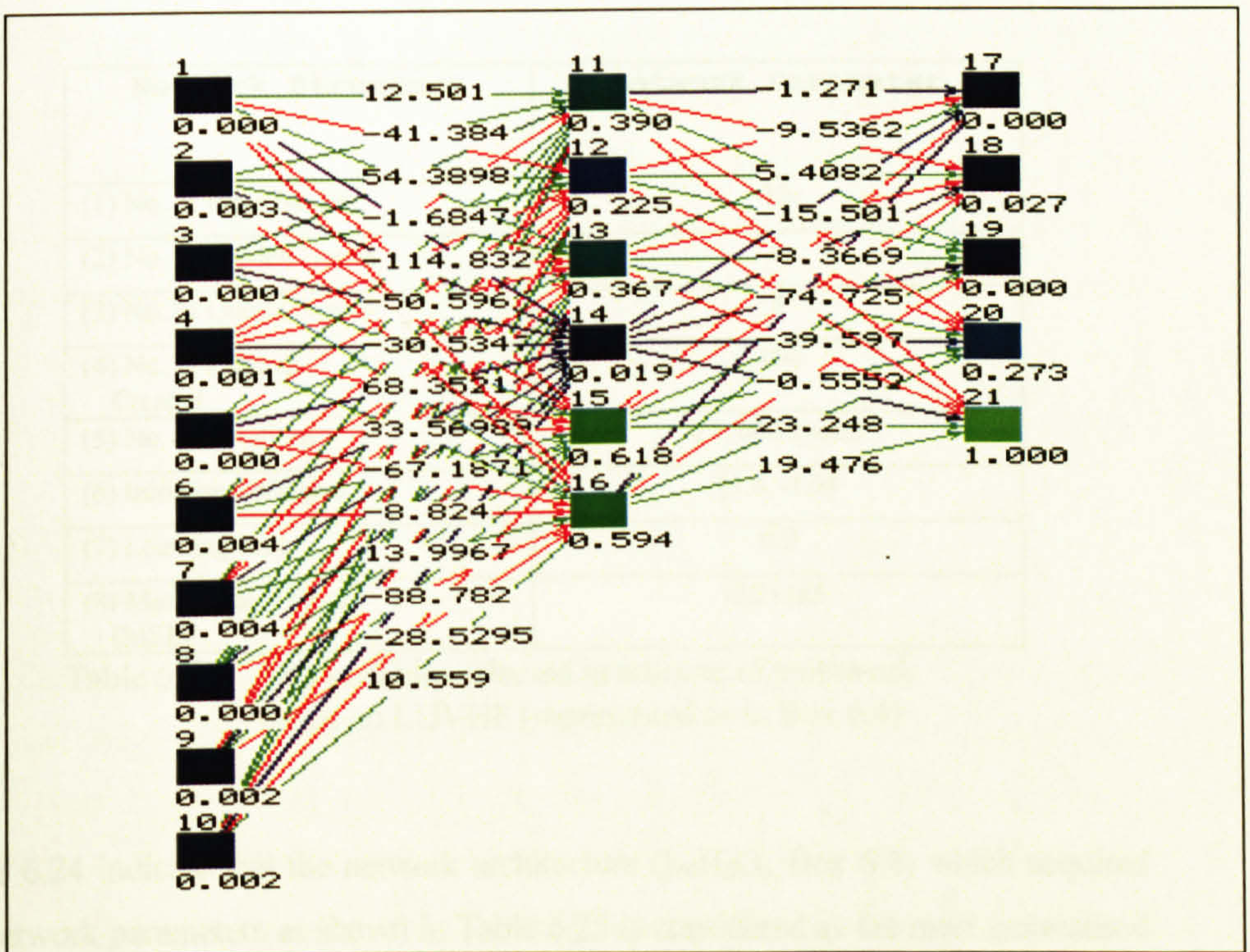
Table 6.23 The refined selected network parameters with the lowest MSE values.

(b) Validation Phase

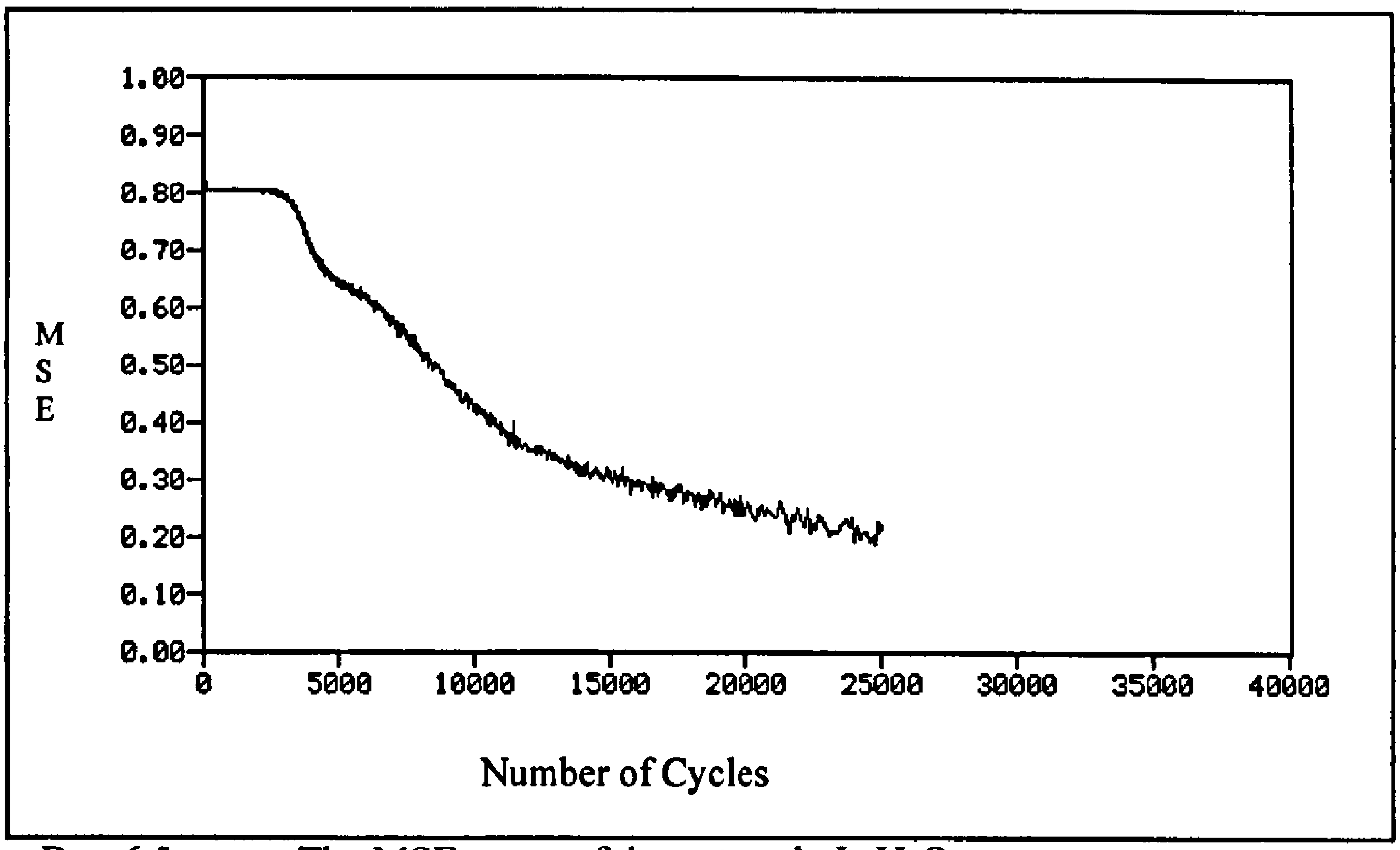
The performance of the selected networks architecture (Table 6.23) needs to be validated using data that have not been used in the training phase. In this validation analysis, a total of 450 random numbers (of which each of the 90 samples was generated to validate Class 1, Class 2, Class 3, Class 4 and Class 5) were generated using Excel of Microsoft Office. The classification process is similar as performed for the Langat catchment area and the eight catchment area. These random numbers were computed consecutively into each of the 12 networks architectures as indicated in Table 6.23. All parameters such as the number of iterations, initialised weights and learning rates, were tested simultaneously for each of the network architectures. The results of validation were tabulated as in Table 6.24 and the network architecture (Box 6.4) with the lowest MSE value (shown graphically as in Box 6.5) was selected as shown in Table 6.25.

Selected Network Pattern	No. of Input Nodes	No. of Hidden Nodes	No. of Iterations (Epoch)	Initialised Weights	Learning Rate	MSE	Percentage of sample falls within this class				
							Cl. I	Cl. II	Cl. III	Cl. IV	Cl. V
450	**10**	**6**	**25,000**	**1.00, -1.00**	**0.2**	**0.21185**	**100**	**33**	**39**	**36**	**100**
450	10	6	25,000	0.98, -0.98	0.2	0.22011	100	27	15	30	100
450	10	6	24,000	0.95, -0.95	0.1	0.23883	95	31	-	40	80
450	10	6	25,000	0.95, -0.95	0.1	0.23992	86	20	-	-	25
450	10	6	26,000	0.98, -0.98	0.2	0.24887	78	-	-	30	18
450	10	6	24,000	1.00, -1.00	0.2	0.24931	79	5	-	-	30
450	10	6	25,000	1.21, -1.21	0.1	0.25433	80	12	-	-	34
450	10	6	25,000	1.20, -1.20	0.2	0.25671	71	20	-	-	30
450	10	6	24,000	1.00, -1.00	0.1	0.25967	97	28	15	-	-
450	10	6	26,000	1.00, -1.00	0.2	0.26008	63	42	-	-	18
450	10	6	26,000	1.20,-1.20	0.1	0.27113	58	26	11	-	-
450	10	6	26,000	1.21,-1.21	0.2	0.27456	48	34	9	-	-

Table 6.24 The results of the network validation



Box 6.4 Neural network structure for LUVHF, $I_{10}H_6O_5$



Box 6.5 The MSE curve of the netwrok, $I_{10}H_6O_5$

Network Structure	Network Parameter
(1) No. of Input Nodes	10
(2) No. of Hidden Nodes	6
(3) No. of Output Nodes	5
(4) No. of Patterns Created	450
(5) No. of Iterations	25, 000 cycles
(6) Initialised Weights	[1.0, -1.0]
(7) Learning Rate	0.2
(8) Mean Square Errors (MSE)	0.21185

Table 6.25 The variables selected in training of a network based on LUVHF (represented as in Box 6.4)

Table 6.24 indicate that the network architecture ($I_{10}H_6O_5$, Box 6.4) which acquired the network parameters as shown in Table 6.25 is considered as the most generalised network among the 12 networks tested using random numbers. The acquired MSE curve (Box 6.5) of the network selected ($I_{10}H_6O_5$) achieved almost complete global minima. This network (Box 6.4) will be used to classify the test data set that will be created from random numbers.

(c) Testing Phase

The testing phase was performed using new random numbers created using Excel of Microsoft Office from data in Table 6.20. A set of 450 new random numbers were generated for each of the five classes and for 10 LUVHF variables, thus a total of 4500 random numbers were created. The minimum and maximum values of each of the 10 variables were selected from these random numbers generated. These values were used for the normalization of the test data set and the process was similar as indicated in Section 6.2.3 (Testing Phase). The 4500 normalized values were saved as ASCII Text Files. Using the same interface program, the normalised test data were converted into Pattern File and ready to be activated consecutively into the selected trained set ($I_{10}H_6O_5$, Box 6.4) using the same SNNS software program. In this testing phase, the process was different from other testing methodologies, since no real field data was involved, only data generated from random numbers. The output classification values from SNNS were given in terms of probability density and were then converted into probability distribution. The frequencies of classification values for all of the 29 sub-catchments were determined, averaged and tabulated as in Table 6.26.

6.3.2.2 Classification of Water Quality Based on LUVHF Network

The classification results of the eight catchment areas (Table 6.26) based on LUVHF (network Box 6.4) are compared to the results of the eight catchment areas based on water quality variables (network Box 6.1) and the results from DOE-WQI models, and are tabulated as in Table 6.27. The outcomes of these results suggests that 55 % of the classification results based on LUVHF are similar to that of classification results obtained from water quality variables using the eight-catchment network (Box 6.1). When comparison was made on the classification results obtained from the DOE-WQI model, the percentage similarity achieved by the LUVHF network ($I_{10}H_6O_5$, Box 6.4) is 24%, whereas the similarity based on water quality variables using eight-catchment network ($I_6H_5O_5$, Box 6.1) is 31%. These results show that the performance of the network based on $I_{10}H_6O_5$, (Box 6.4) is poor. This poor network performance was also shown by a contradicted result as indicated by Station 2 (Station No. 5403601), Air Itam River (Pinang catchment). This station is located in a highly populated area and mis-classified as Class 2 (also refer to trend analysis as in Appendix 6.6). The DOE-WQI model and the network (Box 6.1) based on water quality variables classified this station as Class 4 and Class 5 respectively.

No.	Name of catchment area	Name of sub-catchment area	Station No.	BEP of ANN using LUVHF (Box 6.4)
1	Langat	Lui	3118645(St10)	1
2	Langat	Upper Langat	3118647(St11)	1
3	Padas	Kemabong	4959604(St1)	1
4	Padas	Tenom	5158606(St2)	1
5	Padas	Beaufort	5359614(St3)	1
6	Serting	Serting	2824608(St2)	3
7	Serting	Serting	2824609(St3)	3
8	Kesang	Kesang	2125601(St1)	3
9	Kesang	Chin Chin	2224603(St2)	2
10	Kesang	Chin Chin	2324604(St3)	3
11	Kuantan	Kuantan	3733601(St1)	2
12	Langat	Batang Labu	2817616(St3)	2
13	Langat	Semenyih	2817648(St5)	2
14	Langat	Middle Langat	3017612(St9)	4
15	Serting	Serting	2823610(St1)	3
16	Serting	Mokek	2824611(St4)	3
17	Serting	Serting	3024643(St5)	3
18	Ibai	Ibai	5231605(St1)	4
19	Juru	Juru	5304604(St1)	4
20	Juru	Kilang Ubi	5304605(St2)	3
21	Juru	Rambai	5304607(St4)	3
22	Kuantan	Galing Kecil	3833609(St2)	5
23	Juru	Pasir	5304606(St3)	3
24	Juru	Ara	5304608(St5)	3
25	Kuantan	Galing Besar	3833610(St3)	5
26	Pinang	Dondang	5302606(St1)	5
27	Pinang	Air Itam	5403601(St2)	2 *
28	Pinang	Jelutong	5403602(St3)	5
29	Pinang	Pinang	5403603(St4)	5

Table 6.26 Average classification for all 29 stations based on LUVHF

No.	Name of catchment area	Name of sub-catchment area	Station No.	Water Quality Classification		
				DOE-WQI using Water Quality Variables	BEP of ANN using water quality variables (network Box 6.1)	BEP of ANN using LUVIIF (network Box 6.4)
1	Langat	Lui	3118645(St10)	2	1	1
2	Langat	Upper Langat	3118647(St11)	2	1	1
3	Padas	Kemabong	4959604(St1)	2	1	1
4	Padas	Tenom	5158606(St2)	2	1	1
5	Padas	Beaufort	5359614(St3)	2	1	1
6	Serting	Serting	2824608(St2)	2	1	3
7	Serting	Serting	2824609(St3)	2	1	3
8	Kesang	Kesang	2125601(St1)	2	2	3
9	Kesang	Chin Chin	2224603(St2)	2	2	2
10	Kesang	Chin Chin	2324604(St3)	3	2	3
11	Kuantan	Kuantan	3733601(St1)	3	2	2
12	Langat	Batang Labu	2817616(St3)	2	2	2
13	Langat	Semenyih	2817648(St5)	3	2	2
14	Langat	Middle Langat	3017612(St9)	3	2	4
15	Serting	Serting	2823610(St1)	3	2	3
16	Serting	Mokek	2824611(St4)	2	2	3
17	Serting	Serting	3024643(St5)	2	3	3
18	Ibai	Ibai	5231605(St1)	3	4	4
19	Juru	Juru	5304604(St1)	4	4	4
20	Juru	Kilang Ubi	5304605(St2)	4	4	3
21	Juru	Rambai	5304607(St4)	4	4	3
22	Kuantan	Galing Kecil	3833609(St2)	3	4	5
23	Juru	Pasir	5304606(St3)	4	5	3
24	Juru	Ara	5304608(St5)	4	5	3
25	Kuantan	Galing Besar	3833610(St3)	3	5	5
26	Pinang	Dondang	5302606(St1)	5	5	5
27	Pinang	Air Itam	5403601(St2)	4	5	2 *
28	Pinang	Jelutong	5403602(St3)	5	5	5
29	Pinang	Pinang	5403603(St4)	4	5	5

Table 6.27 Comparisons of the classification results based on the three approaches.

Note: * contradict to values in column 5 and 6.

6.3.2.3 Accuracy Analysis

The accuracy analysis of the network architecture ($I_{10}H_6O_5$, Box 6.4) was based on Confusion Matrix and the approach has been discussed in Section 6.3.2. Random numbers were generated from Excel of Microsoft Office, of which a total of 450 random numbers were used. Out of this 450 samples, 90 samples that acquired Class 1 classification values, 90 samples acquired Class 2 classification values and the same number of samples for Class 3, 4 and 5. These 450 random numbers were computed into the selected network, $I_{10}H_6O_5$ (Box 6.4). The results of the accuracy analysis based on confusion matrix are shown in Table 6.28(a) and Table 6.28(b).

Class	No. of Random Sample Tested	No. of Random Sample falls into this class
1	90	75
2	90	37
3	90	26
4	90	31
5	90	82
Total	450	251

Table 6.28(a) Number of random samples correctly classified using network as shown in Box 6.4 ($I_{10}H_6O_5$).

	Class 1	Class 2	Class 3	Class 4	Class 5	Row Total
Class 1	75	5	3	2	2	87
Class 2	4	37	5	4	3	53
Class 3	5	4	26	3	5	43
Class 4	2	2	5	31	4	44
Class 5	5	4	6	5	82	102
Column Total	91	52	45	45	96	329

Table 6.28(b) Confusion Matrix for BEP of ANN model based on Box 6.4

No. of sample lost in the BEP of ANN system model = 450-251 = 199
Commission error = 0
Omission error = 16+15+19+14+14 = 78
Total no. of sample mis-classified = 78+0 = 78
Overall Accuracy for BEP of ANN model = No. of sample correctly classified divide by the total no. of sample evaluated by the system model = (75+37+26+31+82)/329 = 251/329 = 76.3%.

The evaluation of accuracy of the selected network (Box 6.4) produced for the LUVHF shows that the total number of sample lost in the system model was 199 out of 450, a relatively high differences when compared to the eight catchment network (Box 6.1) with a total lost of 142. However, there was no commission error produced for network $I_{10}H_6O_5$, Box 6.4, whereas the omission errors was 78, higher than the eight catchment network (Box 6.1) by a difference of 27 (78-51). The overall accuracy of the LUVHF network was 76.3%, less than 8.6% and less than 10.6% as compared to the accuracy of the eight catchment area network (Box 6.1) and the Langat catchment area network (Box 5.11) respectively. Thus, the network selected for the eight-catchment area is relatively more accurate or more generalised than that of the LUVHF network.

6.3.2.4 Sensitivity Analysis for LUVHF Network

The sensitivity of the LUVHF network (Box 6.4) was tested in the same manner as for the eight-catchment area network (Box 6.1). However, only five commonly significant land use variables were selected; sub-catchment area, population, agriculture, urban (residential, commercial and industrial) and forestry. Since these variables were based on data set taken in 1995, the results obtained reflect this particular year only. Other variables were considered to remain as constant. The results shown in Table 6.29 shows that the selected standard deviation of one-quarter and one-half of the random numbers were found to be sensitive to changes in the percentage of agriculture area. Therefore, based on the common land use data, agriculture activity is considered as one of the greatest contribution to changes in water quality.

Land Use Variables	Standard Deviation			
	1/10	1/4	1/2	3/4
1. Sub-catchment Area	0	0	0	0
2. Population	0	0	0	0
3. Agriculture (%)	0	7	3	0
4. Urban (%)	0	0	0	0
5. Forest (%)	0	0	0	0

Table 6.29 Percentage sensitivity of the LUVHF network (from Box 6.4)

6.4 SUMMARY OF RESULTS AND EVALUATION

The main aims of Chapter Six are to investigate the reliability and the performance of the two selected neural networks using physico-chemical data from the eight catchment areas and the selected network based on the results of their relationships between the land use variables, hydrological features and the classification analysis. These eight catchment areas were generally categorised according to three main land use categories; highly developed areas, moderately developed areas and forested areas. Classification analyses were carried out using only two models; the DOE-WQI and the BEP of ANN. These analyses involved large number of data (225 samples) from 29 water quality stations over a period of 10 years (from 1990 to 1999).

Using data from the eight catchment areas, a new network structure was created with six inputs, five hidden and five output nodes ($I_6H_5O_5$). Since this network and the Langat catchment network were fixed with the same number of input (six variables) and output nodes (five classes), the experiment began with the selection of similar network parameters (20,000 training cycles and the learning rate value of 0.2). The only differences were the initialised weights and the acquired MSE value. The MSE values were 0.65831 for the eight catchment network and 0.65020 for Langat catchment network respectively. Based on the difference of the MSE values, the eight-catchment network was higher by 0.00811 then that of the MSE result acquired by the Langat catchment network. This supported the classification results for the eight-catchment network which was less accurate then the results obtained for the Langat catchment network. This conclusion was further supported by the higher accuracy and sensitivity results acquired by the Langat catchment network. In general, both networks are sensitive to DO, a condition that is similar to the DOE-WQI model.

As discussed in Chapter Four, the MSE measures the errors acquired by the network during the training process. The magnitude of the MSE value for the network structure has the same impact on the classification accuracy of the test data. However, based on the results of the experiments, the network with lowest MSE value may not always guarantee that this network is capable of providing highly accurate classification results. Such example is the MSE value acquired by the Langat catchment network, which is lower then the eight-catchment network. However, when the performance of these two networks were compared in terms of percentage similarity of the classification results in relation to the classification results of the DOE-WQI model, the eight-catchment network had an average of 36% similarity as compared to 19% of the Langat catchment network (Table 6.14). Thus, for the eight-catchment network, the probability of acquiring one of the five classes for each sample was relatively equal and the potential of being dominated by Class 1 or 5 was minimal when compared to the Langat catchment network. This implies that the results of classification of eight-catchment network were more accurate then the results from Langat catchment network.

Reproducibility of a model is an important factor in the general assessment of water quality. A model that is highly reproducible can be applied in any situation, irrespective of the type or nature of the data distribution that has to be evaluated. Based on the results of reproducibility analysis, the simple Langat catchment network possessed a high reproducibility value, using data set derived from the eight catchment areas. This relates to the fact that, a small and simple network performed well with large samples and with test data set that are widely distributed. Based on this analysis, a simple network structure can be used to classify the test data set that came from other catchment areas. The difference between these two networks reflects the network's creation. In the process of creating the pattern data set before training is performed, the minimum and maximum value of each variable used for normalisation needs to be determined. The determination of these values is relatively a simple process. These values are selected from the test data that came from the respective catchment area. The minimum and maximum values of the six variables used for Langat catchment area and that of the eight catchment areas were not very different. However, this small difference had a considerable impact on the final classification results. Therefore, it is concluded that based on this evaluation, for all designated catchment areas across a particularly large geographical area, a simple and highly reproducible network that is capable of classifying water quality effectively can be created provided all requirements needed are available.

In the application of neural network for water quality classification, it was noticed that the performance of the network was reflected from the results of accuracy analysis using confusion matrix approach. In this approach, data used was generated from random numbers in relation to the values of the five classes of INWQS (Table 2.2). The results of confusion matrix performed for Langat catchment network, Class 4 was not classified by any random samples (Table 5.39(a)), yet the network is capable of classifying water quality for Class 4 samples, when test data were activated into this network. However, the chances of water quality being rated as Class 4 were the least, compared to other classes. Since the classified random samples acquired by Class 1 and 5 were relatively higher then Class 2 and 3, and both classes, Class 1 and Class 5 scored 100 % in accuracy analysis (Table 5.39(b)), this network tends to be dominated by Class 1 for high water quality sample and Class 5 dominated by the low water quality sample. Based on the results of the confusion matrix, the BEP of ANN acquired the highest number of sample lost and commission errors generated in the system model (Table 5.43). This reduced the performance of the Langat catchment network with the overall accuracy of 86.9%, the lowest among the six models evaluated.

In addition, the accuracy of classification results was influenced by the distribution of the test data activated into the eight-catchment network. The data sets used were relatively large as it represented eight catchment areas. Therefore, these data sets had a great influence on the performance of the network because they increased its generalisation capability and consequently increased the accuracy of the classification results. Based on these justifications, the eight-catchment network was considered more generalised then that of Langat catchment network. In conclusion, a network with higher generalisation capability can be constructed if the values of probability density across the five classes are evenly distributed, with its total value not less then 0.9 and not exceeded the value of one. Finally, based on this research, the network performance can be summarised as in Table 6.30. If choices are to be made, the eight-catchment network can be selected as it gave better classification results.

Using the eight catchment areas classification results, the LUVHF for all 29 stations were arranged in descending order according to their respective water quality classes. Consequently, the range of these LUVHF values selected was tabulated for evaluation and can be used as referenced values for the future analysis of water quality assessment. The selected LUVHF network, $I_{10}H_6O_5$, was highly reliable with a relatively low MSE value as compared to the Langat catchment and the eight-catchment networks. This shows that the LUVHF network achieved a relatively high generalisation capability. However, the similarity of classification results as compared to the used of water quality variables was only 55 %. This indicated that the classification performance was relatively poor.

The results from sensitivity analysis shows that the selected LUVHF network was capable of categorising which or what type of land use activity that has great influenced on the changes in water quality. Based on the four out of the ten most common LUVHF, the slight changes in percentage of agriculture area (activity) has produced the most significant change on the level of water quality. The critical catchment area that acquired this changes was the Juru catchment area that has affected Station 1 (St. No.: 5304604), Station 3 (St. No.: 5304606) and Station 5 (St. No.: 5304608), as shown in Appendix 6.7. These results tallied with the real condition of these rivers, as reported by the Annual DOE Report (DOE, Malaysia, 1999). Therefore, this network was capable of categorising the type of land use activity that significantly affected the water quality within a particular catchment area. These results provide important inputs for the management of water pollution and the planning of future water resources.

Type of Analysis	Langat Catchment Network (Box 5.8)	Eight-Catchment Network (Box 6.1)	LUVHF Network (Box 6.4)
1. Mean Square Errors	0.65020	0.65831	0.21185
2. Overall Accuracy:	86.9%	84.9%	76.3%
(a) Commission Error,	20	20	0
(b) Omission Error,	30	31	78
(c) No. of random sample mis-classified	50	51	78
(d) Random sample lost the network system model.	69	142	199
3. Sensitivity	High	Low	Low
4. Order of variable sensitivity / importance as compared to DOE-WQI	Better	Fairly Good	-
5. Reproducibility	High	Low	-
6. Classification performance as compared to DOE-WQI classification results	19 %	36 %	-

Table 6.30 Comparisons on the performance of the two networks.

In comparison to the classification results obtained from DOE-WQI model, the percentage similarity achieved by LUVHF and eight-catchment networks was only 24 % and 31 % respectively. Based on these results, the LUVHF network is not considered adequate to support the classification of water quality based on the common land use variables and hydrological features. However, its performance can be improved if more samples were available and a wider range of land use variables and hydrological features were included. In particular, the percentage of agriculture, urban, industrial, residential and forest areas can be explored in details and tabulated into several sub-categories such as percentage of oil-palm or rubber, heavy or medium industry, residential, commercial or mining areas for creating a highly performance network.

In general, this chapter shows that the BEP of ANN model can be applied to the classification of water quality, based on either water quality or land use variables, and hydrological features. In situations where water quality variables are difficult to monitor, land use variables and hydrological features can replace the use of water quality variables for water quality classification, provided that the data set are readily available. Normally, remotely sensed data from satellite can be used for the assessment of water quality, but the cost of acquiring this data is enormous. Thus, in areas with no monitoring stations such as remote areas where accessibility is impossible, and in particular, for the long term water resources planning, land use variables and hydrological features may helps to assess and estimate the possible future water quality based on the BEP of ANN model. In view of these achievements, the objectives to investigate the land and topographic features, the type and magnitude of land use activities that contribute significantly to the changes in water quality, and the classification of water quality based on these variables through the application of the BEP of ANN model have been achieved.

In the next chapter, the achievements based on each of the aim of this research will be highlighted. Where ever necessary, the justification of the related findings based on different approaches will be discussed according to the scope of the study and finally, the overall findings will be summarised and concluded. There are several suggestions on the related areas that needs for further research in continuation of this study.

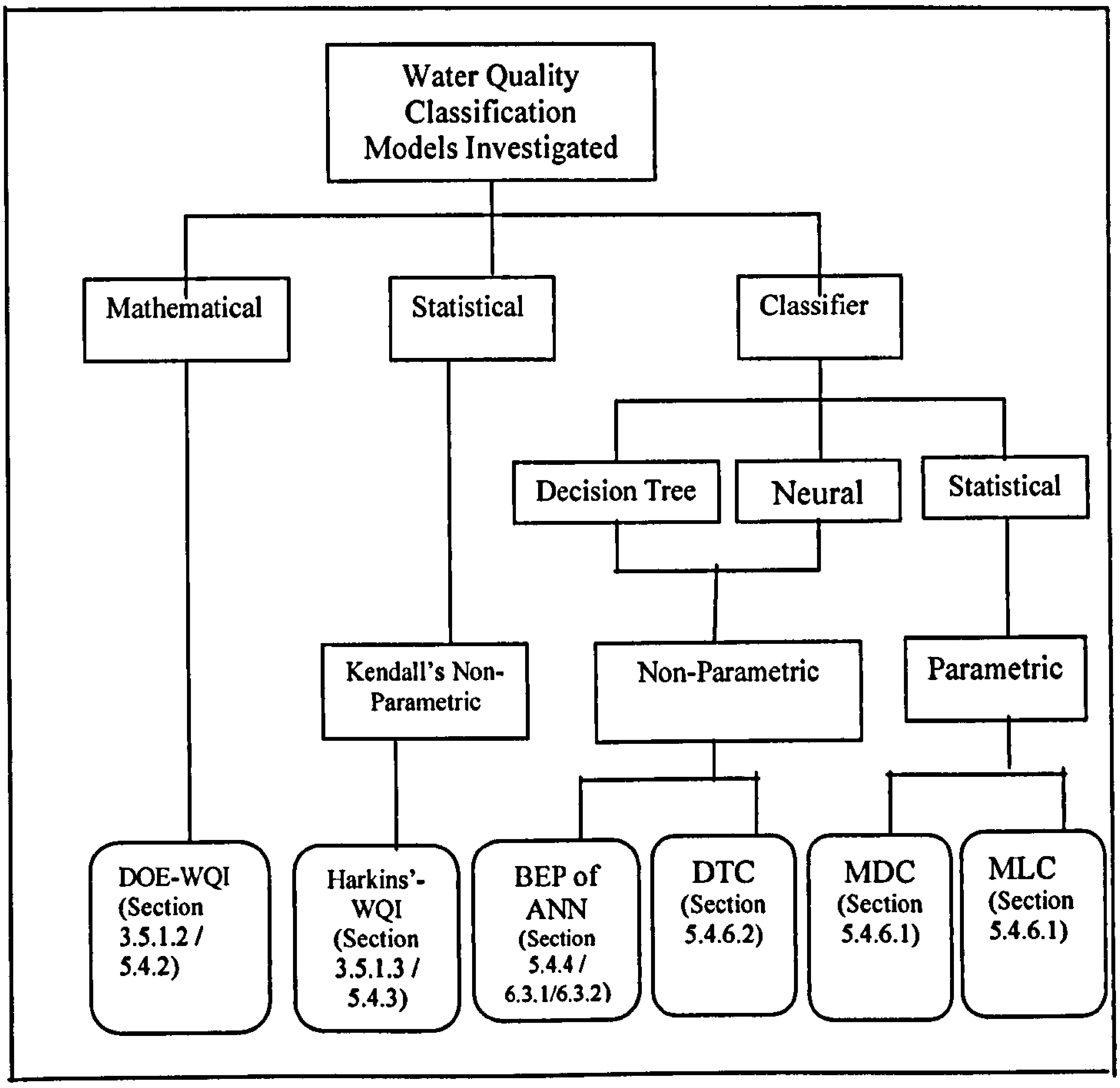
CHAPTER SEVEN

CONCLUSIONS AND RECOMMENDATIONS

7.1 BACKGROUND

The concept in water quality index development originated from Horton's (1965) findings is discussed in detail in Chapter Two. From this basic concept, two other alternative concepts for classification of water quality were also investigated, namely the statistical and the classifier of the PR approaches as indicated in Box 7.1. Based on these three concepts, the advantages and limitations of the existing water quality assessment systems with several selected models were literaturally reviewed. The reviews on the mathematical and statistical approaches are discussed in Chapter One and Chapter Two. The outcomes of these review defines one of the main aims of the research. For each of these approaches, a model was selected, which include; the DOE-WQI, a mathematical model and the Harkins'-WQI, a non-parametric statistical model. These models are being applied by the DOE in Malaysia and are discussed in Chapter Three. The concepts of these models were compared with the classification concept based on PR.

The theory and concept of PR was represented by the classifier approach and in view of this, a neural classifier was selected based on its unique characteristics. The details are discussed in Chapter Four and comparisons are made with the other related classifiers. The selected algorithm that performed well with neural classifier is the BEP of ANN. Based on this BEP of ANN model, 11 water quality monitoring stations in Langat catchment were classified and the methodology was described in details in Chapter Five. The outcomes of this basic evaluation, another main aim of this research were achieved. Subsequent evaluation and results comparison were made based on the general findings, trend and sensitivity analysis, and accuracy testing for the selected three models; the BEP of ANN; the DOE-WQI and the Harkins'-WQI. The advantages and limitations of these models were discovered. In view of all classification results, a general comparison were made in relations to the results obtained from PR related models and these achievements have also met another aim of the research.



Box 7.1 The types of models used in water quality classification

The performance of the BEP of ANN model was further expanded and tested using data from eight catchment areas as described in Chapter Six. The data tested were the physico-chemical water quality variables, land use and topographic features, the type and the magnitude of land use, and hydrologic features. The selected variables were screened and modified so as to classify the water quality based on the common land use variables and hydrological features (LUVHF). Classification results obtained from the LUVHF were compared to those results based on water quality variables. Although the results obtained were not convincing, however, the methodology based on the BEP of ANN model can be refined further and more LUVHF data were needed to achieve better results. Thus, the overall capability and the suitability of the BEP of ANN model are highlighted in Chapter Six. The achievement reveals that this model is reliable for the assessment of water quality, although there are some limitations that need to be resolved through further research. As such, the overall aim of the research, which is specifically focussed on the reliability of the application of BEP of ANN model in classifying water quality in compliance to the INWQS has been achieved. The summary of the overall research methodology is described in Appendix 7.1. The experiences gains from this study are presented and the recommendations for future research are highlighted at the end of this chapter.

7.2 CONCLUSION BASED ON THE CLASSIFICATION PERFORMANCE OF THE SIX MODELS

The evaluations based on the performance and accuracy of the classification results reveals that the DOE-WQI mathematical model surpasses the other five models. The Harkins' non-parametric statistical and the classifier models tends to be less accurate compared to the mathematical model. Consequently, the classification results obtained from DOE-WQI model were used as referenced in comparing the results from other models. The classification results of Harkins'-WQI, MLDC, MDC, DTC and the BEP of ANN models were closest to that of DOE-WQI respectively.

The percentage similarity of classification results to that obtained from DOE-WQI model shows that the models with non-parametric characteristics such as the Harkins'-WQI, BEP of ANN and DTC model were relatively lower then that of parametric model. Thus, in water quality classification, the parametric model performed considerably better compared to the non-parametric model.

7.3 CONCLUSION ON WATER QUALITY CLASSIFICATION SYSTEM

In the detailed analyses, investigations were based on three fundamental approaches, which include; the water quality index system, the classification scheme and the classification based on neural classifier. However, the results from the index system can be linked or transformed into classification scheme, whereas in neural classifier, the classification results emerge simultaneously as an index value assigned as probability density (readily converted into probability distribution) and also as class grade value. In transforming the index value into classification grade value, the approach taken by DOE's, Malaysia is lengthy, whereas, the BEP of ANN provides fast and direct transformation. The advantages and disadvantages of applying the index system and classification scheme is discussed in Section 2.4 and summarised as in Table 2.10. Based on these findings, Table 7.1 provides the brief summary of the comparison between the BEP of ANN model and the two assessment systems that are being used by the DOE, Malaysia.

7.3.1 Comparison of Results Between the DOE-WQI and the BEP of ANN Model

The results from this research confirmed that the DOE-WQI model remains as the most reliable among the three models. However, there exist some other advantages of the BEP of ANN over DOE-WQI beside the ease of generation of output. The relationship between these two models for use in water quality classification is illustrated in Box 7.2. The following are the key issues:

7.3.1.1 Variable Selection

The limitation of index systems (Horton, 1965) is that the number of selected variables should not be too large. If too many variables are incorporated in the mathematical formula, the index system is unwieldy. Therefore, only those variables of greatest significance across the country are used. In some cases, variable selection frequently becomes a controversial issue among the water quality experts. This gives rise to the development of different forms of water quality index, either in the form of general water quality index, specific water quality index or statistical water quality index model, as indicated in Table 2.8. The applications of too many models in a particular geographical area will create more complications for those directly involved in water resources planning and management. It should be more useful to apply only one or two models across the whole country.

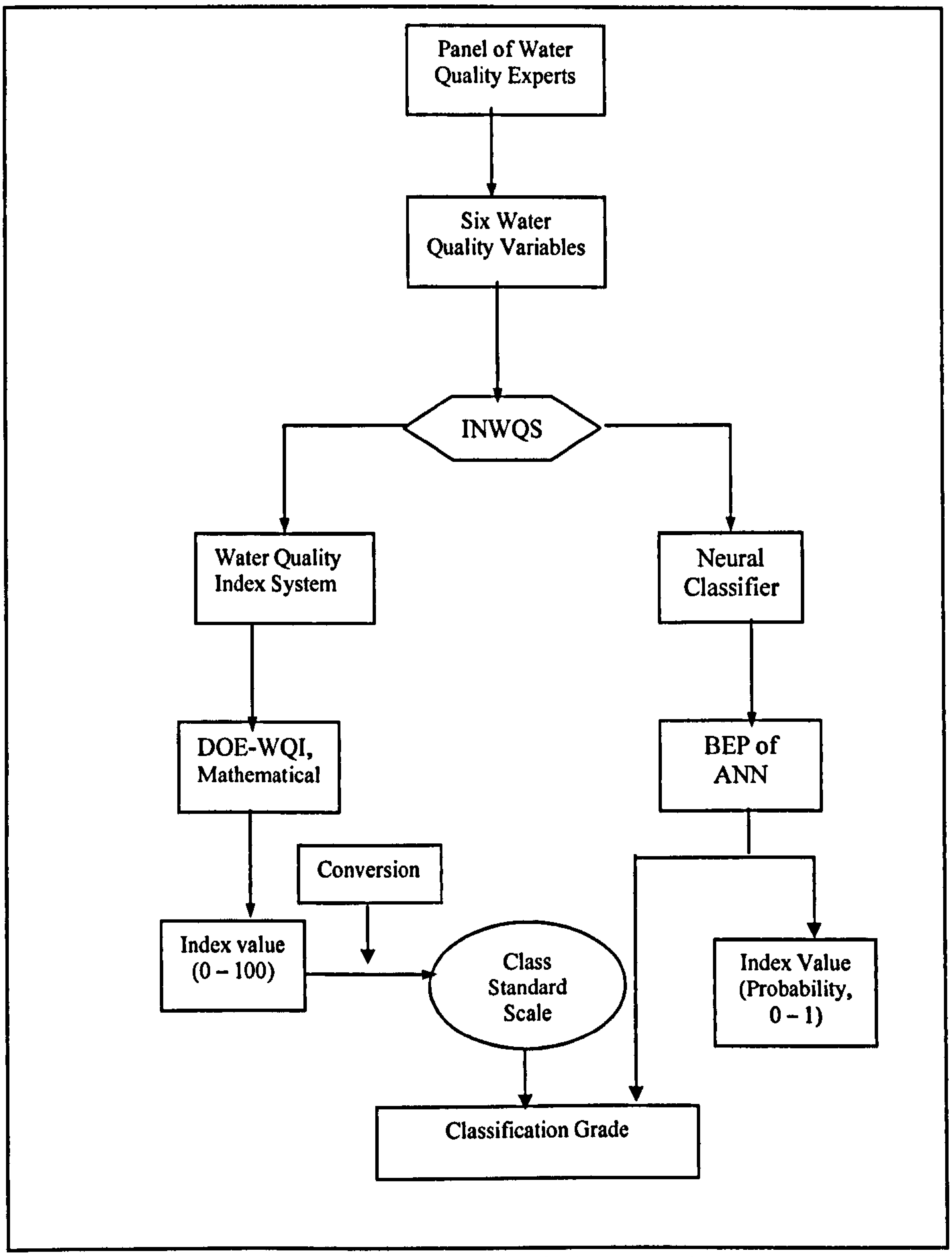
Characteristic	DOE-WQI	Harkins'-WQI	BEP of ANN
(a) Result Presentation	Single Numeric	Single Numeric	Dual result presentations. Probability value and class grade value. For each sample, all five classes acquired probability values. The highest value is the class grade of that sample.
(b) Classification Grade	Needs simple transformation from index value to class grade value.	Needs simple transformation from index value to class grade value.	No transformation needed. Provide direct class grade value.
(c) Index Scale	0 – 100 (Descending Order)	0 -100 (Ascending Order)	0 – 1, probability value (Readily transform to %)
(d) Descriptor	Yes	Yes	Yes
(e) Reproducibility	Yes	Yes	Yes
(f) Model Structure	Too rigid. Does not cater new variables	Flexible. Cater for new variables	Flexible. Cater for new variables
(g) Limitations	Distortion in the designed of the model. Thus, unavoidable loss of information.	The result from one data set (one catchment area) cannot be compared with other data set, unless all data set (all catchments) are ranked together.	Training process to obtain a single network with high generalisation capability may take longer time.

Table 7.1 A summary of the advantages and disadvantages of the three models

The application of BEP of ANN model allows an unlimited number of variables to be included into the input layer. This is in contrast to the Horton's recommendation. The problem of "unwieldiness" is eliminated. However, the six variables used did not produce optimal network performance, except the network created for LUVHF. Hence, the results obtained were not convincing, as indicated in Section 6.3. In order to produce an optimal network, the number of variables used should be increased. As in the case of index system approach, different networks can be designed specifically for different categories of water uses. Since most authors agree that it should be economically practical to develop only one or two models, rather then too many models, in the assessment of water quality, the BEP of ANN model like the index system has great potential to be used effectively for all forms of water uses. In case of DOE-WQI, its application in classifying the water quality throughout Malaysia has never been reviewed since it was first introduced in 1986. Based on the present extensive land use activity, it is timely for DOE, Malaysia to review the application of the existing six variables. Any addition of new or deletion of insignificant variable in the assessment of water quality may acquire the application of BEP of ANN model.

7.3.1.2 Model Structure

The application of DOE-WQI model for classification of water quality is complex and time consuming. The aggregation of subindices into the main index structure inevitably results in the loss of information that affects the accuracy of the classification. The neural classifier of the BEP of ANN model, which acts as 'black-box', is much simpler. It provides direct and rapid classification, without the needs of any numeric conversion of values into classification grades. The accuracy of the BEP of ANN model can be increased by performing more experiments with different combinations of input nodes and network parameters, so as to reduce the errors (MSE) acquired during the training process. Thus, there is great potential for acquiring a network with highest generalisation capability in the BEP of ANN model. In addition, the performance of this network increases with the use of widely distributed test data that are readily available from all monitoring stations across the country.

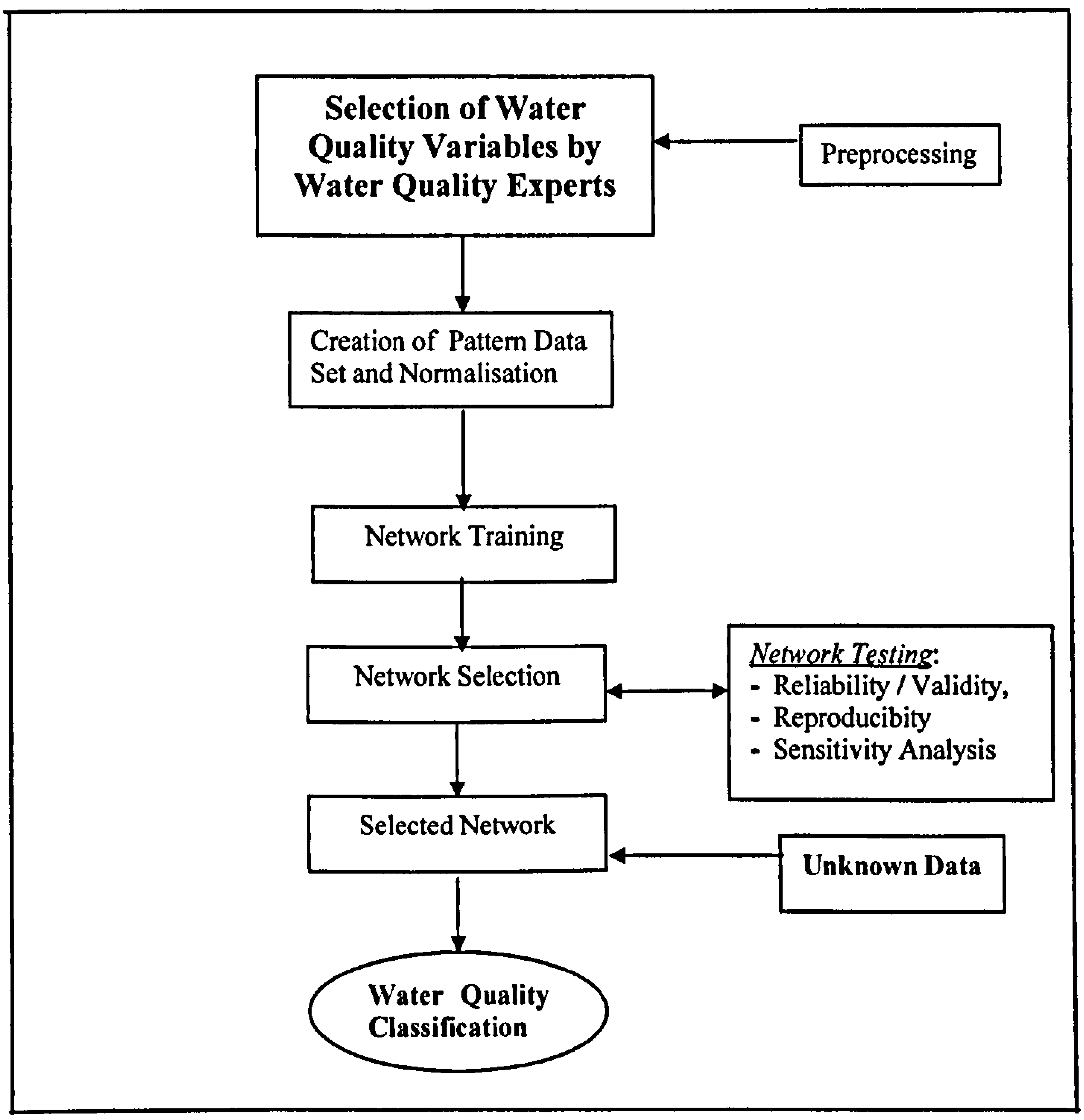


Box 7.2 Flowchart showing the relationship between the DOE-WQI model and the BEP of ANN model in classification of water quality

The structure of DOE-WQI mathematical model is too rigid for the inclusion of new variables or deletion of obsolete one. This poses critical issues in water resource management, especially in areas of rapid urbanisation and industrialisation, where new types of pollutants that have not been monitored before are becoming common. At some point, the existing index and classification values calculated may not represent its true values, leading to an erroneous interpretation. Any variables that need to be added or deleted necessitate reconstruction of the mathematical formulae so as to cater for the new weightings given for each variable. This results in a very long, tedious and complicated process of designing a new mathematical model, as compared to the time taken in creating a new neural network. It involves large number of water quality experts with different backgrounds that needs to perform several stages of evaluations through questionnaires provided by the water quality controlling agency as indicated in Box 2.5.

The BEP of ANN model is by contrast relatively flexible. New variables can be added or deleted by the water quality experts whenever it is deemed necessary. However, a new network has to be created, since the performance of the network is influenced by the minimum and maximum value of each of the selected variables. In general, a complete process starting from network creation that ended with classification results of the unknown data is shown as in Box 7.3. As compared to Box 2.5, these processes are less complicated and involve minimum input from water quality experts. Therefore the process is faster and simpler. The two mains issues that need to be anticipated are the selection of the new or deletion of old variables and the time of network training.

Some authors have noted that the baseline concentration levels of the selected variables vary at the national scale or between different geographical areas (Lohani and Todino, 1984; House, 1986; Smith, 1989; Dojlido et al., 1994). Thus, their occurrence and significance may vary between rivers. Based on this justification, when water quality index and classification schemes are linked to water quality criteria and standards, the need to produce one specific mode of assessment for each geographical area is inevitable. This is one of the reasons that different water quality standards should be adopted in different geographical areas or sometimes in different areas within the same state. Consequently, to produce a new mathematical model that resembles the DOE-WQI takes a longer time. The acquisition of such models for each geographical area is therefore impractical. In addition, for a specific period of time the need to assess the effectiveness to some of the management programmes such as river rehabilitation or clean river campaigns using the existing assessment system are equally important. In such a situation, a flexible and simpler model, as portrayed by the BEP of ANN, is more practical when compared to that of DOE-WQI mathematical model.



Box 7.3 The general network creation process and classification of unknown data using the BEP of ANN model.

7.3.1.3 Variable Weightings

In a group of selected variables, each individual variable as well as the combination or association of two or more variables, may exert different effects either on people or aquatic species. These variables are assigned different weightings, based on their degree of importance as in DOE-WQI model. Some authors objected to the application of these weightings, on the grounds that the occurrence and significance of these variables may vary at the national scale, or between different geographical areas (Lohani and Todino, 1984; House, 1986; Smith, 1989; Dojlido et al., 1994). If weightings are assigned differently for different rivers even though the selected variables are common at the national scale, comparisons are difficult to make. In addition, if the number of the variables selected for index system is large, the number of weightings would tend to make values converge, and their importance would be diminished (SDD, 1976; House, 1986; Dojlido et al., 1994). Weightings may also have little effect if the water quality index ratings of selected variables (such as COD and SS in DOE-WQI model) are similar for samples taken from high water quality and a large difference if the samples come from relatively low water quality water body (SDD, 1976; House, 1986; Dojlido et al., 1994).

In addition, if precision is the main concern, particularly for technical requirements, then in the application of water quality criteria and standards, weighting as indicated in DOE-WQI is inappropriate when applied to different geographical areas (Lohani and Todino, 1984; House, 1986; Smith, 1989; Dojlido et al., 1994). In particular, the enforcement carried out by the DOE, Malaysia using this model for different geographical areas will be questionable. It probably should not be applied universally across the country. This may pose a critical challenge to the enforcement agency if there exists scientific findings by other agencies that show the selected variables acquired different baseline concentration levels across some of the designated water quality regions, and therefore should possess different standard values.

Although the BEP of ANN model does not incorporate weighting, based on the results of sensitivity analysis, the importance and significance of the selected variables were justified as discussed in Section 6.3.4. The results obtained from the two selected networks confirmed that Dissolved Oxygen was the most important and sensitive variables. Therefore, no requirement for the weighting of variable as far as the BEP of ANN model is concerned. This justifies with the findings from some authors involved in the development of water quality index system (Smith, 1989; Dojlido, 1993) which concluded that Dissolved Oxygen is the most significant variable in the assessment of water quality.

7.3.1.4 Presentation of Results

One of the main ideas behind designing a specific model is to provide the simplest method of describing the status of water quality that can be easily interpreted by the layman and utilised effectively by the technical person. In the application of the DOE-WQI model, the subindices for the six variables need to be calculated first before it is transformed into the main formula. The result presented as a single numeric index, is converted into classification grade using an interface program based on the dBase IV programming language. The assignment of a scale range between 0 – 100 (Appendix 2.2), which corresponds to specific range of threshold values that describe the status of water quality, has oftenly been disputed. Some authors disagreed with the lower portion (towards zero values) of this scale, while others argued that it does not cater for relatively smaller or even larger subindex value. Thus vital information may be lost (Dunnette, 1979; House, 1986; Smith, 1989). This gives rise to different forms of index system, strictly based on the objectives for its development as indicated in Table 2.8. One may conclude that an index system with an appropriate scale range that can hold most information in all situations is difficult to design.

In case of the BEP of ANN model, the classification result for a single sample is displayed rapidly as a probability density values for each class of the five classes, and also as a classification grade. Probability density value shows the user at a glance which class the sample belongs. This probability density value is readily transformed into probability distribution. The ability to display the refined changes in probability density value of each of the five classes indicates explicitly the magnitude of information loss within a single water quality sample. This situation never exists in the application of the DOE-WQI model or other type of water quality models. The amount of information loss may possibly relate to the MSE value for the neural network. Consequently, this reflects the fact that training may stop at local minima, and so error remains in the network structure. To acquire global minima for optimum network performance is difficult. However, there is a possibility of acquiring global minima, with minimum value of MSE or minimum level of information loss, by testing with one or two more significant variables.

The BEP of ANN model does not cater for the assessment of any individual variable as in the DOE-WQI model, where the scale range between 0 – 100 is assigned for each of the six variables. Thus avoids the problem of disagreement between water experts.

7.3.2 Comparison of Results Between the Harkins'-WQI and the BEP of ANN Model

A characteristic of the non-parametric model is that the underlying data distribution is non-Gaussian. Thus, it is expected that the classification results are not as precise as those of the parametric method. However, the advantage is that it can be used with any data set. In case of the Harkins'-WQI model, the panel of water quality experts has selected the same water quality variables as applied in the DOE-WQI model, based on their importance in pollution contribution. Therefore, variable selection was not performed in a parsimonious manner, as claimed by most of the statistical WQI developers. Thus, it still remains a subjective approach. The application of this model by the DOE in Malaysia is to provide a 'check-and-balance', specifically to compare individual results obtained from that of the DOE-WQI model.

The main limitations of the Harkins'-WQI model is that the classification results obtained should not be used to compare the results from other data sets or results from other catchment areas. This is due to the ranking procedure used. If one needs to make comparisons, then data sets from all catchment areas need to be ranked together into a single set of calculations. This is impractical, although it can be performed with the most powerful computers. The range of index values obtained for Class 1 to Class 5 is unrestricted, the gaps between classes can be quite small, or it can be far apart. Thus, the range of criteria and standards values that fit into a single class can be wide, and this gap can be occupied by various criteria that represent various potential or beneficial uses of water. If it is too narrow, the potential uses of water that fit this gap become more specific. Therefore, to rely only on the Harkins'-WQI for result comparison with that of the DOE-WQI is inadequate. This justifies the needs to apply one more model to complement the DOE, Malaysia water quality assessment systems.

In case of the BEP of ANN model, a single network can be used to classify data from different data sets, provided that the minimum and maximum values for the selected variables represent all the respective data sets. These values have considerable influence over the network performance. Then only classification results can be compared for all of the respective water quality regions. Since it is non-parametric, precision can be improved further. This is due to the fact that the BEP of ANN model is highly flexible, in the sense that by altering the input variables and the network parameters can reduce the error induced into the network system.

7.3.3 Comparison of Results between the Classification Scheme and the BEP of ANN Model

Generally, the physico-chemical and biological variables are used together in the classification of water quality. Classification schemes provide subjective interpretation, in the sense that the decisions made from classification results may not necessarily reproducible by another user. It may show the general trends of water quality based on changes in class value, but it could not provide the refined changes based on score point system. Thus, it is insensitive and becomes more difficult to indicate an exact difference between stations having the same class value. Classification schemes that relate to four or five banded classes may pose some difficulty that limits the potential uses of water. Similar to the case of the Harkins'-WQI, the range of criteria and standard values that fit into a single class can be wide. This gap can be occupied by various criteria that represent various potential or beneficial uses of water. A single class may represent several potential uses of water.

The dual result presentation facilitated by the BEP of ANN model explicitly displays its objectivity and sensitivity. In each of the water quality samples investigated, every one of the five classes was assigned probability values. This provides important inputs in water resources management, pollution control and for the river conservation management or for designation of the site of special scientific interest areas where the classification results obtained can be applied directly.

7.4 CONCLUSION BASED ON THE BEP OF ANN MODEL

The reliability (validity) of the BEP of ANN model as another technique in classification of water quality has been thoroughly investigated. Based on the results obtained from the Pilot Study (Langat catchment) as indicated in Section 5.3, the achievement in reliability testing and accuracy estimation was 73.6% and 86.0% respectively. When two neural networks were obtained from different data set and tested accordingly, the reliability for Langat catchment network was higher than the eight-catchment network. Consequently, the result of sensitivity analysis shows that both of these networks are sensitive to Dissolved Oxygen, a condition that is similar to the DOE-WQI model. It is noted that DO is the vital component of most of the water quality models. However, the Langat catchment network was relatively more sensitive then that of the eight-catchment network. In comparison to that of the DOE-WQI, the orders of sensitivity for the other five variables are considerably different. These orders of sensitivity are relatively similar for the two types of neural networks. This indicates that the sensitivities of these variables have gradually changed over time as a result of changes in land use activities. In addition to reproducibility analysis, the performance of the network created for Langat catchment area (Box 5.8) using the data from the eight catchment areas was much better than the performance of the network created for the eight catchment areas (Box 6.1) using the data from the Langat catchment. Finally, it can be concluded that a small and simple network performed well with large samples and with test data that are widely distributed.

The BEP of ANN model was also investigated to classify rivers based only on the commonly selected LUVHF. When compared to the classification results obtained from the DOE-WQI model, the performance of LUVHF and eight-catchment networks was only 24% and 31% respectively. This was rather too weak to support its application in classification of water quality based on the common LUVHF. However, its performance can be improved, if more samples, wider range of land use variables and hydrological features, and wider range of neural network parameters were selected.

In the application of the BEP of ANN model, the critical issue is the training process needed for the creation of the most reliable neural network. The selected network should be considered the one with higher performance or which acquires higher generalisation capability. In other words, the complexity of the network, which is determined by the size of all layers, is one of the important components of the network structure. Normally, the size of an input layer is equal to the number of input variables for which the classification is based. Whereas, the size of output layer corresponds to the number of output classes, thus only the hidden layer is available for adjustment. However, several suggestions for the exact number or sizes of the hidden layer on the network performance have been put forward, but none are universally accepted.

Based on the experiments described in this thesis, the critical factor that has exerted great influence on the creation of a highly generalised neural network for classification of water quality was the fixed number of input and output variables. The input layer was designed with six variables or nodes, whereas the output layer was fixed with five nodes to represent five classes. The only possible network layer that needs to be investigated was the hidden layer. This has left only few options either by increasing and decreasing the number of hidden nodes, and the selection of different combinations of the neural network parameters. These are the main factors that limit the accuracy or reliability of the BEP of ANN model. Thus, the highest achievable performance in classifying water quality was indicated by the network as in Box 5.8 created for Langat catchment area, and Box 6.1 created for the eight-catchment area network respectively. One of the factors that measure this performance was the MSE value. Both networks achieved MSE value of 0.6, which is high. Since the number of input and output nodes were fixed, the input and output layers could not exert any influence, so as to further reduce the value of MSE in the training process. However, having high MSE values does not mean that the classification results were not useful. The performance of the network was also triggered by the type and the magnitude of the test data set used. In this case, the volume of data set used was large, and found to provide relatively more accurate classification results in relation to the results obtained from the DOE-WQI model. Therefore, it is also concluded that the network can achieve high generalisation capability when it is activated with the influenced of highly distributed test data set. A driving force behind this research has been to reduce the operational complexity as portrayed in the DOE-WQI model and the significant processing time required to train the network.

The main issue facing the creation of water quality assessment system is that the uses for water are manifold and the quality of water demanded for each purpose varies with their objectives. Based on the original intention of selecting the six variables, the results obtained are meant for general-use that includes; public water supply, aquatic wildlife and fisheries, irrigation, recreation and industrial. Finally, the BEP of ANN model provides great potential for the effective classification and utilisation of a water body, based on these intended uses of water especially when referring to the distribution of probability density acquired by each of the five classes. These values seem to be much easier for interpretation by the laymen and the technical person.

7.5 SUGGESTION FOR FUTURE RESEARCH

In continuation to this research, two categories of recommendations are suggested for the future work, which include; the application of the BEP of ANN model in classification of water quality and the application of BEP of ANN model in classification of water quality in Malaysia.

7.5.1 The Application of the BEP of ANN Model in the Classification of Water Quality

The existing approaches being used in the assessment of water quality which involve large number of variables are generally based on mathematical and statistical formulae. However, this research has portrayed several achievements using the concept of PR where several models were investigated in the assessment of water quality. The focussed was given to the BEP of ANN model in view of its unique characteristics. Thus, based on the concept of PR, a new research frontier is initiated and the following suggestions are proposed for the future research:

- Comparisons of the reliability, accuracy, sensitivity, reproducibility and classification results based on the BEP of ANN model using different number of input variables and output classes;

- Comparisons of the reliability, accuracy, sensitivity, reproducibility and classification results based on the BEP of ANN model using non-standard Back-Error-Propagation approach and non-randomise weights;

- Comparisons of the reliability, accuracy, sensitivity, reproducibility and classification results based on the BEP of ANN model using one input layer with different number of input nodes, two layers of hidden nodes and one layer of output nodes with different number of classes;

- The creation of network based on the monitoring data and the results of reliability, accuracy, sensitivity, reproducibility and classification grade are compared to results of network created from the INWQS Table;

- The classification of water quality using the BEP of ANN model based on the combinations of physico-chemical water quality variables, land use variables, hydrological features and biological or ecological variables; and

- The classification of water quality using the BEP of ANN based on toxic or hazardous variables.

7.5.2 The Application of the BEP of ANN Model in Classification of Water Quality in Malaysia.

The existing DOE-WQI mathematical model, which is being used by the DOE in Malaysia, is too rigid to include new variables or exclude obsolete variables. The advantages and limitations of this model are discussed in details. Since this model was introduced in 1985, no review has been done before. Another model being used is the Harkins'-WQI, which is to 'cross-check' the classification result obtained from DOE-WQI model for an individual station only. Harkins'-WQI model should not be used to compare results from other water quality stations across national scale and the advantages and limitations are discussed in the literature review. Based on the concept of PR and the achievements of the BEP of ANN model, the following suggestions are proposed to enhance and strengthen the water quality assessment system in Malaysia taking into consideration on the suggestions for the future research as stated in Section 7.5.1 above.

- Since the DOE of Malaysia has been using only one model that is DOE-WQI to assess the state of water quality based on the six physico-chemical variables and in view of the country's rapid land use changes, therefore it is timely for the DOE to review the used of these six variables and to continue this research based on the application of BEP of ANN model;

- The Malaysian DOE should investigate the effectiveness of the application of a single assessment system, the DOE-WQI mathematical model in relation to the BEP of ANN model across the national scale, in particular the assessment of water quality for the state of Sabah and Sarawak in the Island of Borneo;

- In areas where accessibility are difficult, the land use variables, hydrological features or Strahler Stream Order, and the topographic features can be incorporated together through the application of the BEP of ANN model, provided further research should be carried out to this model with the intention to use it as another water quality assessment system;

- If the DOE-WQI mathematical model and the Harkins'-WQI non-parametric statistical model are to be continued for the assessment of water quality, than the application of the BEP of ANN model, which is based on PR approach, will complement the existing assessment systems, provided further research should be carried out to this model; and

- Due to the rapid land use changes, in particular the vigorous industrial activities, the Malaysian DOE may needs to assess the water quality using the BEP of ANN based on toxic or hazardous variables, thus further research should be carried out for this model.

This thesis has discussed the deficiencies in our current approaches to the classification of water quality using DOE-WQI mathematical and Harkins'-WQI non-parametric statistical approaches. It has shown that this leads to problems in the context of a developing country such as Malaysia. The contribution to knowledge that this thesis has made is that it has shown that ANN can be used effectively in the classification of water quality. This approach offers new and flexible ways in the assessment of water quality and the findings have contribute to science in several ways, namely:

- The most remarkable contribution is that it provides a practical approach in classification of river water quality. Within a single ANN computation, the results obtained were categorised into two portions, the probability value and the class grade value. Thus, it shortens the process of calculations as acquired by the traditional classification methods. The result obtained for each sample displayed the magnitude of probability distribution that acquired by each class.

- It provides dual result presentations from computation of every sample based on the BEP of ANN, either as a single probabilistic value or as classification grading value. Thus, it helps to shorten the process of calculation required by the traditional classification methods. The trend and the refined changes in water quality are determined explicitly in either way that can be easily interpreted by both the technical and non-technical person.

- The next aspect of contribution is that the approach developed is operationally simple and relatively flexible in the sense that it can readily modified to cater for the diverse geographical regions on regions with rapid land use activity. Thus, the technique of assessment as portrayed by the BEP of ANN is relatively flexible where new variables can readily be added or deleted from inclusion for a particular region. This reflects the real state of water quality based on the standards set forth for each geographical region.

- The BEP of ANN model provides a new approach in classifying water quality based on the common land use variables and hydrological features. This application is critically suitable for remote areas, where accessibility is relatively impossible. In addition, it may also provide vital inputs for the estimation of water quality for water resources management and development planning purposes. The changes in water quality can be performed and determined effectively in terms of the percentage changes in township area (either industrial, residential, agriculture or forest), population or other significant changes in land use variables and hydrological features. Therefore, areas to be designated as conservation, a forest reserve or a special site of scientific interest can be assessed effectively at the earlier planning stage.

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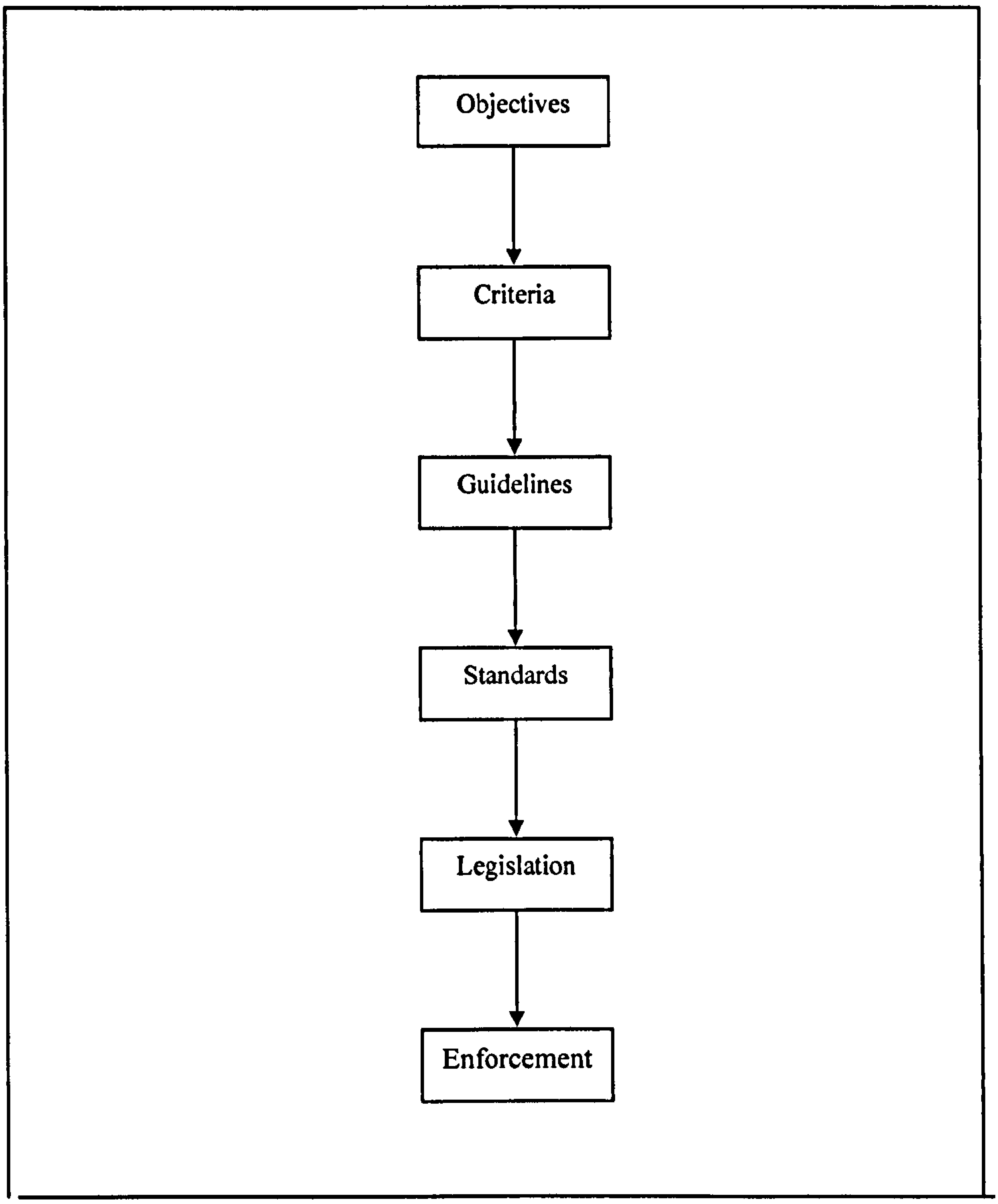
Appendix 2.1

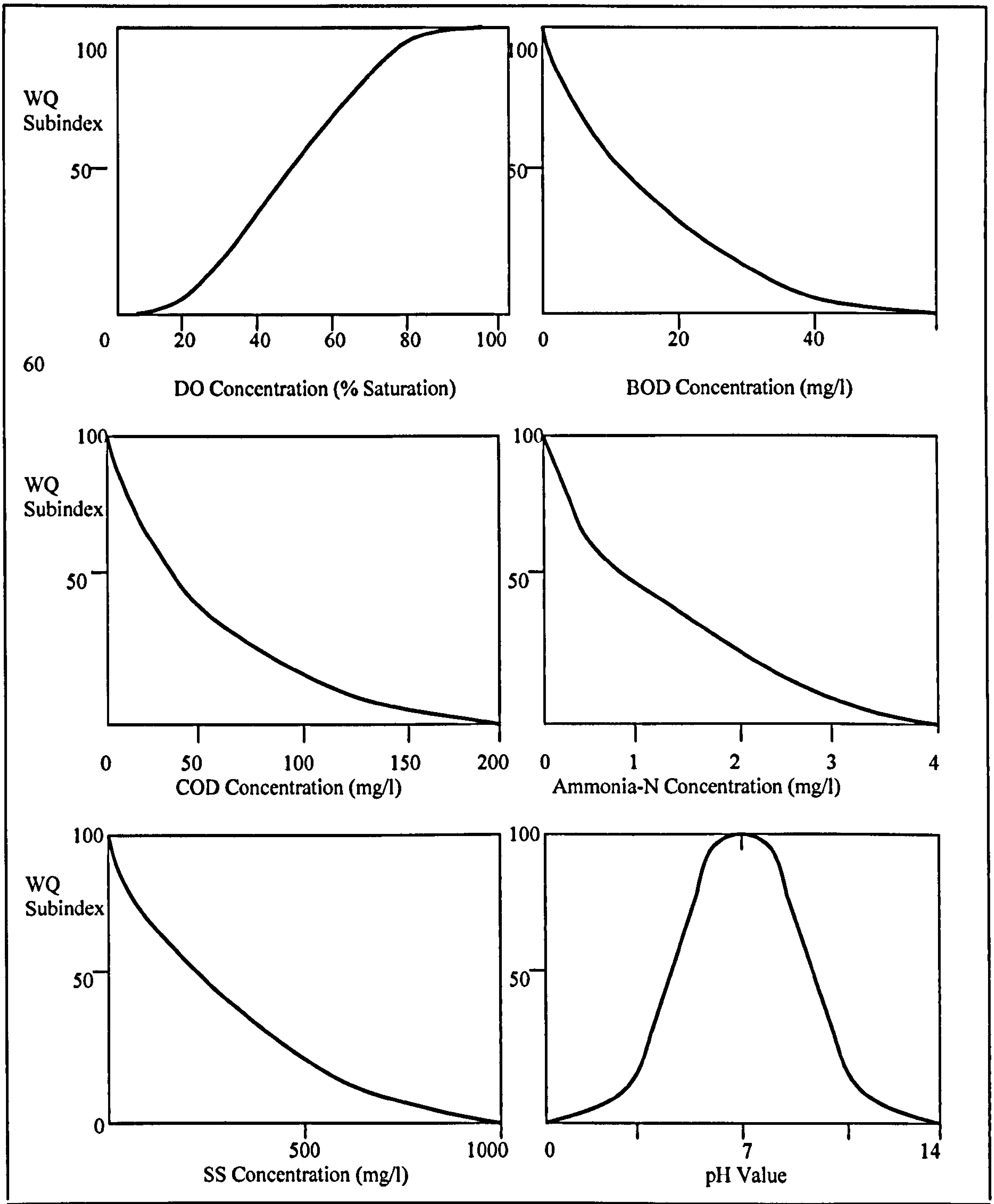
Water quality management strategy



(Source: Modified from Thanh and Tam, 1990;Viesman and Hammer, 1998)

Appendix 2.2

Water quality subindex rating curves for the six variables from DOE, Malaysia



(Source: DOE, Malayisa, 1986).

Increasing linear subindex function

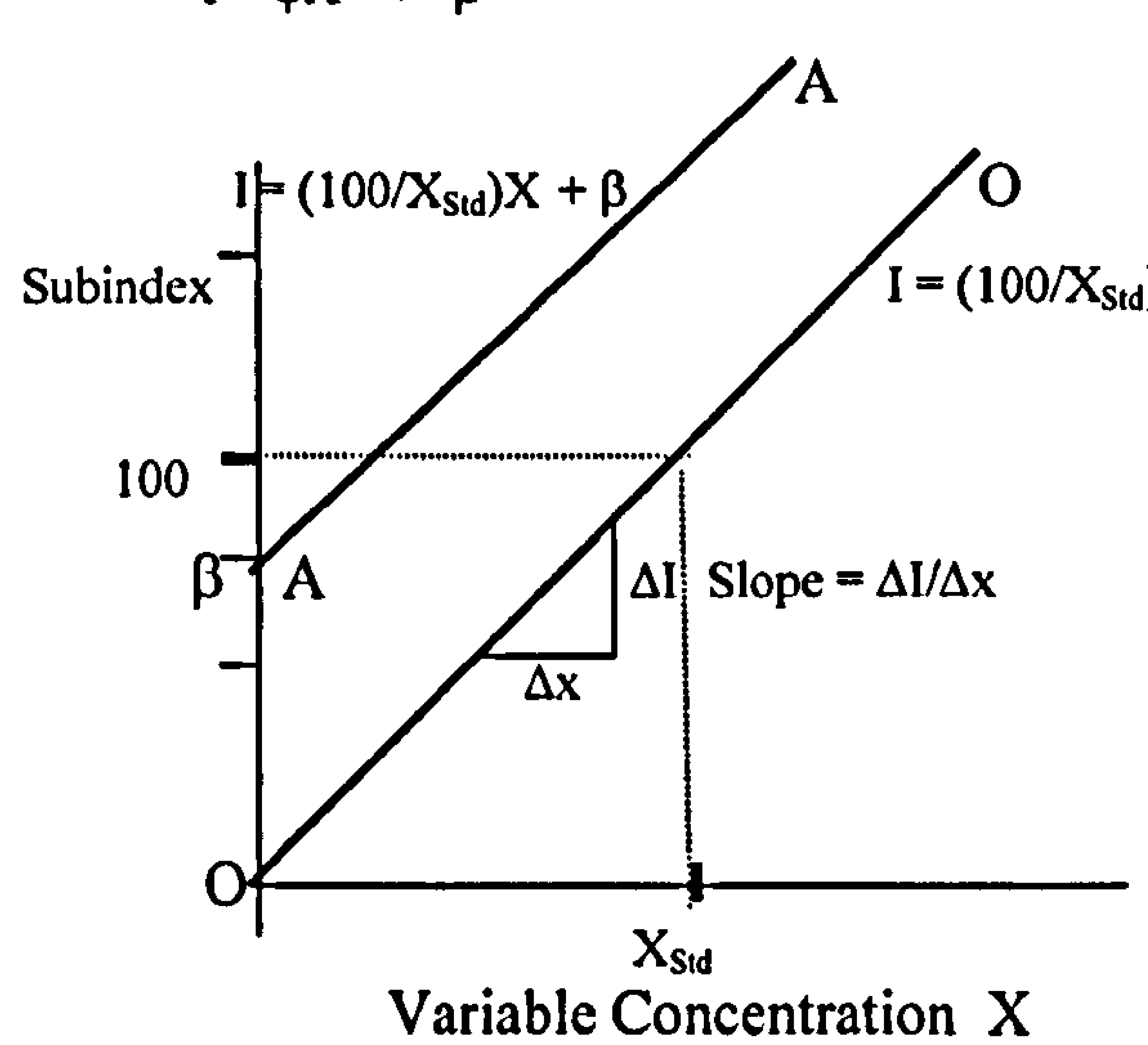
Equation 2.2 indicates that the subindex value is directly proportional to the variable concentration. The slope of the line graph OO indicates that for every change in ΔX, the subindex I changes by $\varphi\Delta X$ units (or $\Delta I = \varphi\Delta X$) where φ is the subindex function, which is the slope of the graph. If φ is positive value ($\varphi > 0$), the subindex, I is an increasing scale. Therefore, line graph OO is an increasing linear subindex function. When the slope φ is negative ($\varphi < 0$), either $\varphi = - \Delta I/\Delta x$, line OO sloping downward and the subindex I, is a decreasing scale. Subindex I, which is assigned with an increasing scale, means higher subindex value corresponds to higher water quality and vice versa for decreasing scale.

Based on Equation 2.2, if subindex I represent a water quality standard of a particular variable, for a selected scale of 100, then $I = 100$ if $X = X_{Std}$ for increasing scale. Then the linear function, $\varphi = 100/ X_{Std}$, is also the percentage of the standard variable concentration and the line OO is represented as $I = (100/X_{Std})X$ as in Equation 2.3. Normally, $X_{Std} = 0$ is a standard value for heavy metals or any toxic chemicals in which their existence in surface water body is intolerable (Horton, 1965). However, the line OO that pass through the origin may also be represented as line AA which starts at $I = \beta$, and β is a constant as represented in Equation 2.4. This equation indicates that, when the value of $X = 0$, subindex value is equivalent to the value of β.

$I = \varphi X$ -------- Equation 2.2

$I = (100/X_{Std})X$ -------- Equation 2.3

$I = \varphi X + \beta$ -------- Equation 2.4

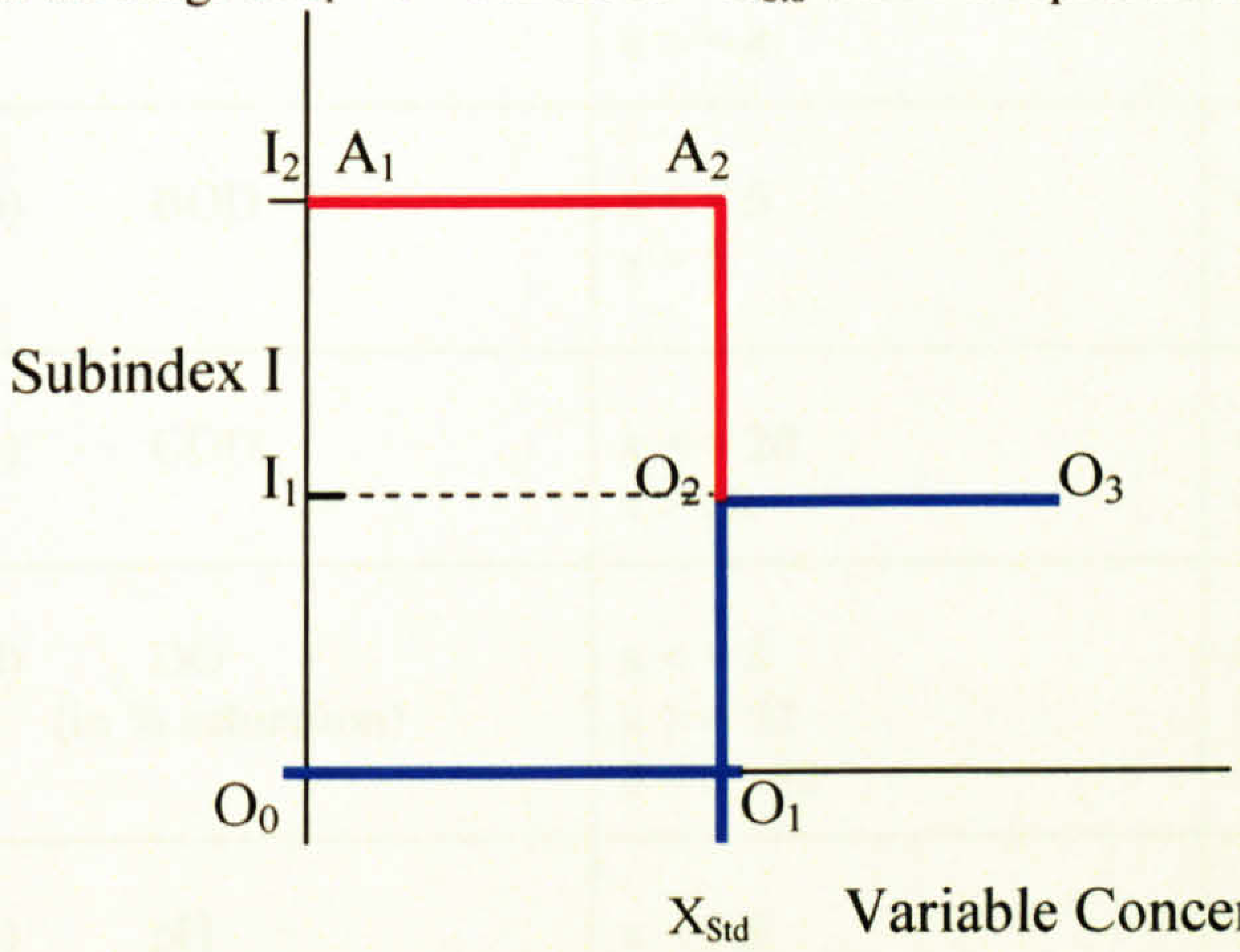


(Source: Ott, 1978; Jacques, 1995)

Appendix 2.4

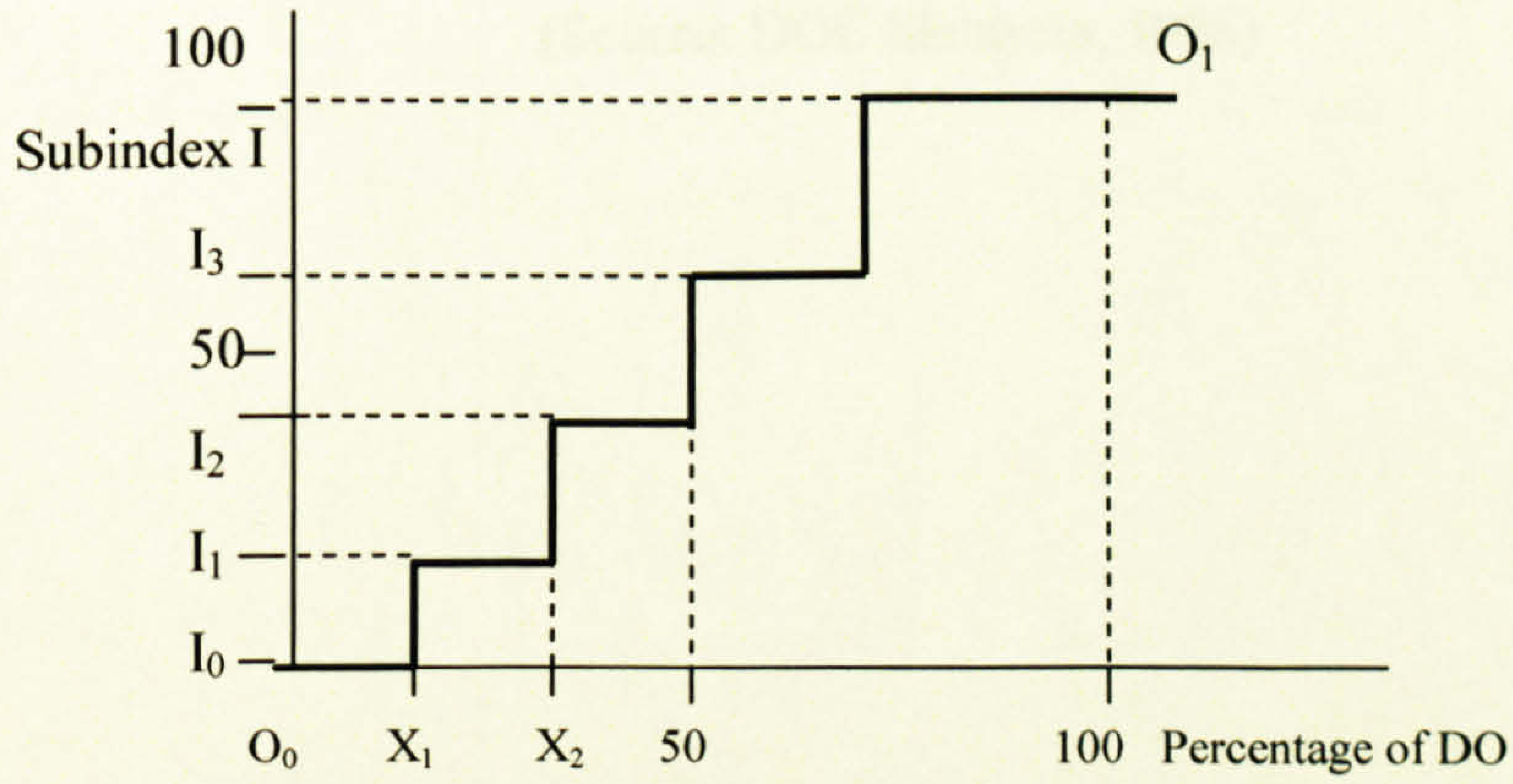
Segmented linear function

When $X \leq X_{Std}$, no adverse effects occur at below standard concentration limit. When $X_1 > X_{Std}$, an extremely and serious effects occurred and this is illustrated by line $O_0O_1O_2$ (light blue line) in Box 2.4a. This give rise to a condition known as 'hockey stick' function or segmented linear function which described a situation of an extreme case where the subindex I = 0 for $X \leq X_{Std}$. (for decreasing scale). In certain case, subindex I may takes two value either I = 0 for $X \leq X_{Std}$ and I = 1 for $X > X_{Std}$. This condition is known as 'dichotomous' or two state where the slope of the line $O_0O_1O_2O_3$ vary between zero and infinity. However, for increasing scale, subindex I_2 = 100 for $X \leq X_{Std}$ and subindex I may falls in the range of $I_1 < I < 100$ for $X > X_{Std}$ which is represented by $A_1A_2O_2O_3$.



Box 2.4a Segmented linear function for increasing and decreasing subindex scale (Source: Ott, 1978)

In The first segment indicates that subindex $I_i = 0$ for $X_i \leq X_1$, and as soon as $X_i = X_1$, subindex I_i falls in the range of $I_0 < I_i \leq I_1$. The second segment indicates that subindex I_i falls in the range of $I_1 < I_i \leq I_2$ for $X_1 < X_i \leq X_2$. This implies that two conditions of an extreme improvement in water quality occur when the percentage of DO, $X_i = X_1$ and $X_i = X_2$ with sudden increase in subindex I_1 and I_2.



Box 2.4b Staircase step function for DO (Source: Horton, 1965)

Appendix 2.5

Best-fit equations for the estimation of the various subindex values of the DOE-WQI

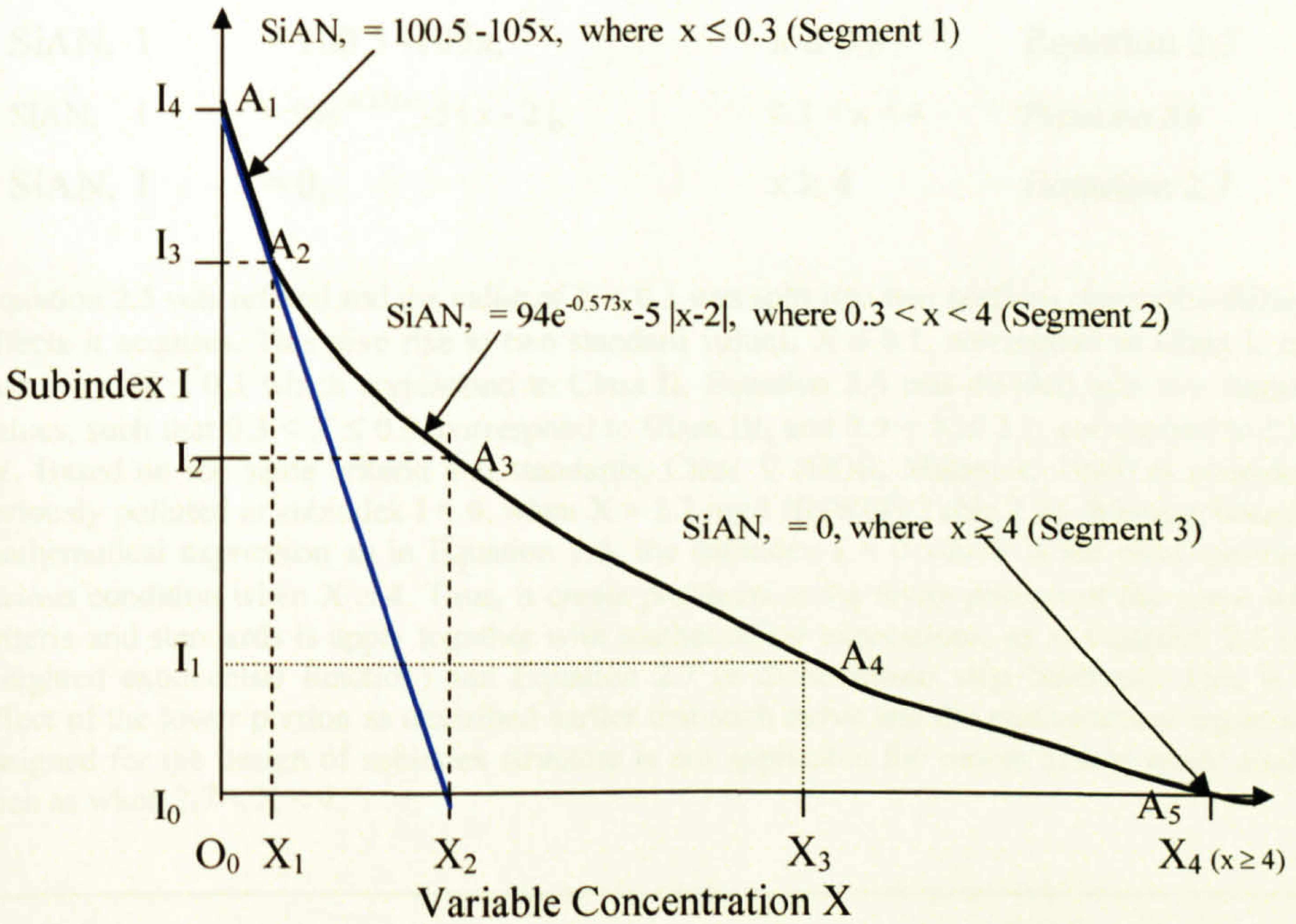
Sub-Index	Concentration (mg/l)	Formula
(a) AN	$x <= 0.3$ $0.3 < x < 4$ $x >= 4$	$= 100.5 - 105x$, $= 94e^{-0.573x} - 5 \mid x - 2 \mid$, $= 0$,
(b) BOD	$x <= 5$ $x > 5$	$= 100.4 - 4.23x$, $= 108e^{-0.055x} - 0.1x$,
(c) COD	$x <= 20$ $x > 20$	$= -1.33x + 99.1$, $= 103e^{-0.0157x} - 0.04x$,
(d) DO (in % saturation)	$x <= 8$ $x >= 92$ $8 < x < 92$	$= 0$, $= 100$, $= -0.395 + 0.03x^2 - 0.0002x^3$,
(e) pH	$x < 5.5$ $5.5 <= x < 7$ $7 <= x < 8.75$ $x >= 8.75$	$= 17.2 - 17.2x + 5.02x^2$, $= -242 + 95.5x - 6.67x^2$, $= -181 + 82.4x - 6.05x^2$, $= 536 - 77.0x + 2.76x$,
(f) SS	$x <= 100$ $100 < x < 1000$ $x >= 1000$	$= 97.5e^{-0.00676x} + 0.05x$, $= 71e^{-0.0016x} - 0.015x$, $= 0$,

(Source: DOE Malaysia, 1986)

Appendix 2.6

Mixed segmented linear and nonlinear functions

The curve A_1 to A_5 comprises of three segments; Segment 1 is a linear function represented by A_1A_2. Segment 2 is non-linear function represented by line $A_2A_3A_4$ and Segment 3 is an exponential function represented by line A_4A_5. This curve may conform to certain administrative requirements in compliance to water quality criteria and standards. Based on this curve, subindex values will falls in the range of between I_3 to I_4 when $X \leq X_1$ (the highest achievable concentration of X), between I_2 and I_3 when $X_1 < X \leq X_2$, between I_1 and I_2 when $X_2 < X \leq X_3$, between I_0 and I_1 when $X_3 < X \leq X_4$ (polluted) and $I = 0$ when $X > X_4$. The straight line A_1X_2 (light blue line) constitute a linear function and after point A2, the characteristic of the curve becomes non-linear.



(Source: Modified from DOE, Malaysia, 1990)

Transformation from the curve to the mathematical equation

Base on these rating curves, the best-fit mathematical equations can be developed. Examples are the subindices of AN designed by the DOE, Malaysia which comprises of three mathematical equations as illustrated by Equations 2.5, 2.6 and 2.7 from Appendix 2.6. Equation 2.5 designed to acquire a limit of threshold not exceeded 0.3 mg/l ($X \leq 0.3$) and Equation 2.6 with the range of threshold level represented as $0.3 < x < 4$ and Equation 2.7 which is the most extremely serious condition $x \geq 4$ mg/l respectively. These three equations resemble the curve in Appendix 2.6, Segment 1 represented by Equation 2.5, Segment 2 is Equation 2.6 and Segment 3 is Equation 2.7 respectively.

SiAN, I	$= 100.5 - 105x,$	$x \leq 0.3$	Equation 2.5
SiAN, I	$= 94e^{-0.573x} - 5 \mid x - 2 \mid,$	$0.3 < x < 4$	Equation 2.6
SiAN, I	$= 0,$	$x \geq 4$	Equation 2.7

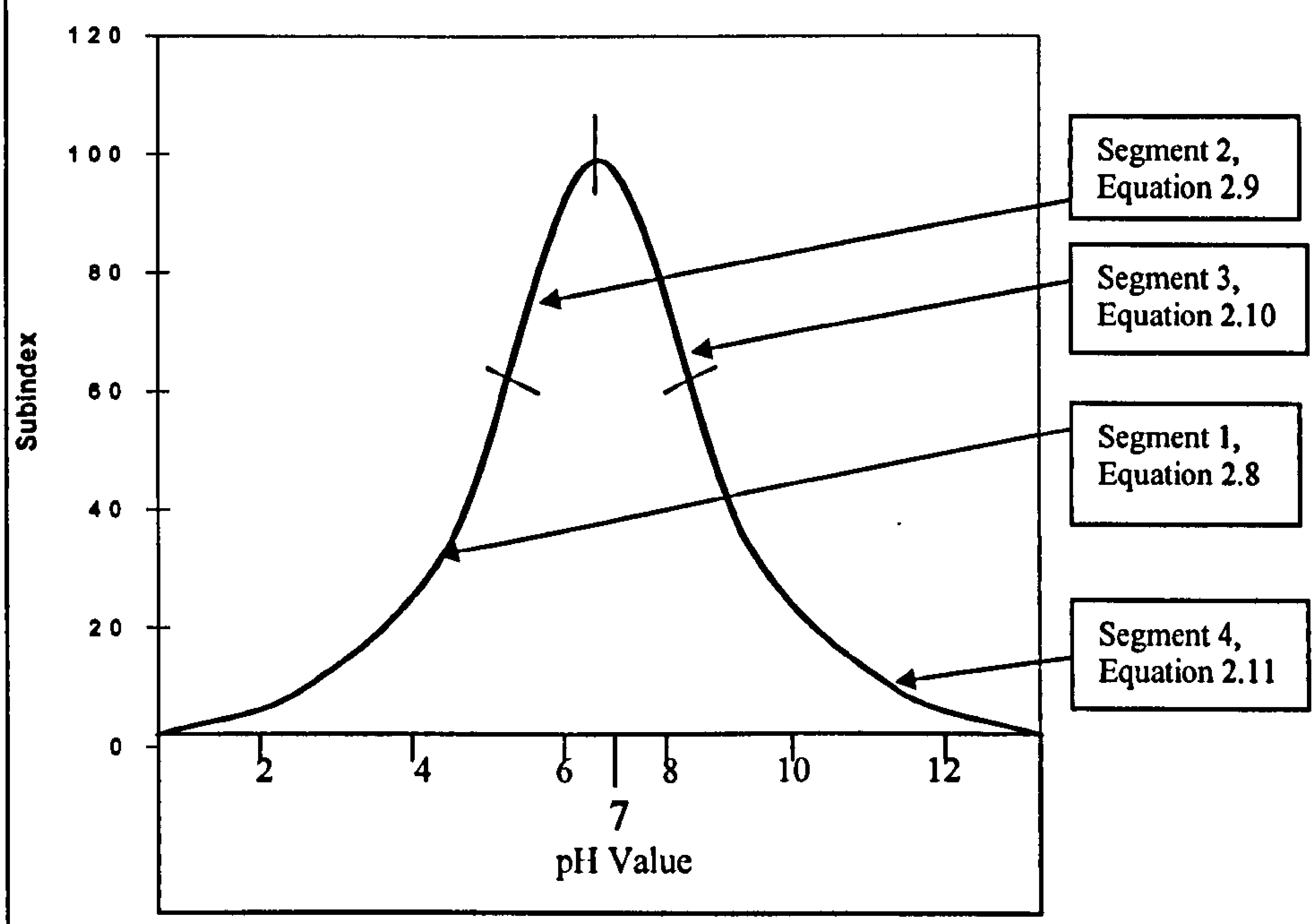
Equation 2.5 was refined and the value of $X \leq 0.3$ was split into two portions due to the different effects it acquires. This give rise to two standard values, $X \leq 0.1$, correspond to Class I, such that $0.1 < X \leq 0.3$ which correspond to Class II. Equation 2.6 was divided into two standard values, such that $0.3 < X \leq 0.9$, correspond to Class III, and $0.9 < X \leq 2.7$, correspond to Class IV. Based on the same criteria and standards, Class V (DOE, Malaysia, 1990) is considered seriously polluted or subindex $I = 0$, when $X > 2.7$ mg/l (INWQS Table 2.2). Whereas based on mathematical expression as in Equation 2.6, the subindex $I = 0$ which is the most extremely serious condition when $X \geq 4$. Thus, it create problems at the lower portion of the curve when criteria and standards is apply together with mathematical expressions, as in Equation 2.6 (is a weighted exponential function) and Equation 2.7 (a dichotomous step function). This is the effect of the lower portion as described earlier that such curve and the mathematical expression assigned for the design of subindex structure is not applicable for waters of low water quality, such as when $2.7 < X < 4$.

(Source: DOE, Malaysia, 1990)

Segmented nonlinear subindex function for pH

The pH value is measured in Standard Units (SU), where 7 SU is equivalent to subindex I = 100. However, acidic condition is considered to be five times more detrimental than an alkaline condition (Harkin's, 1974). Thus, in the assessment of water quality, acidic condition exerts more weight than alkaline condition. As shown in Table 2.2, for pH, the INWQS emphasis only on acidic condition and below pH 5.0 as acidity increases, the detrimental effects to human and all aquatic species are similar. Based on this INWQS table, it is obvious that Segment 2 (Equation 2.9) and Segment 3 (Equation 2.10) of curve should exist in the range of Class 1. Since the acidic condition exerts greater impacts than the alkaline condition, the quality limits as stated in INWQS is such that $6.0 < X(pH) \leq 7.6$ falls within Class 1, whereas for the mathematical Equation 2.9, the range of $5.5 \leq X(pH) < 7$ falls in the same Class 1.

$SipH_a$	$= 17.2 - 17.2x + 5.02x^2$	$x < 5.5$	.....Equation 2.8
$SipH_b$	$= -242 + 95.5x - 6.67x^2$,	$5.5 \leq x < 7$	.....Equation 2.9
$SipH_c$	$= -181 + 82.4x - 6.05x^2$,	$7 \leq x < 8.75$	.....Equation 2.10
$SipH_d$	$= 536 - 77.0x + 2.76x^2$	$x \geq 8.75$	.....Equation 2.11



(Source: DOE, Malaysia, 1990)

Nonlinear function for SiBOD

In non-linear function, generally the variable is raised to a power greater than 1 (subindex $I = X^a$, $a \neq 1$) where the curve of slope decreases or increases rapidly. Basically, exponential function can be represented as in Equation 2.12 where φ, β are constants and e is assigned natural logarithm (Jacques, 1995). Example of the rating curve of subindex BOD (SiBOD) is the curve below, represented as Equation 2.13 (from Appendix 2.5). Line A_1A_2 is linear function such that the range of subindex values falls between I_1 and I_2 when $X_1 \leq 5$. Line A_2A_3 is an exponential function such that the range of subindex falls between I_0 and I_1 for $X_1 > 5$. As X_1 approaches X_3, the effect becomes more extreme. The problems of the lower portion for the BOD curve is similar to that of AN curve that makes mathematical formula less responsive for low water quality area.

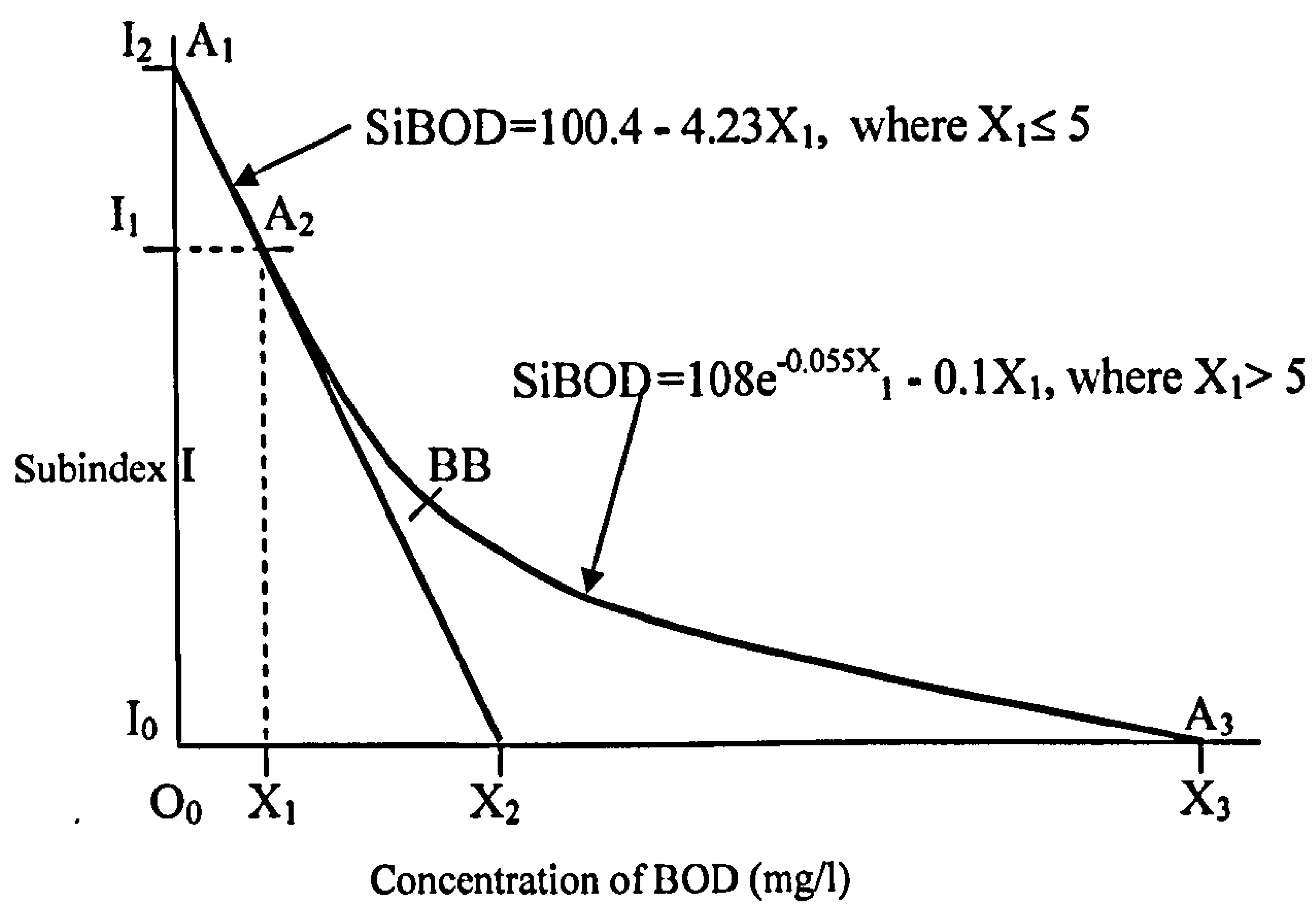
$$I = \varphi e^{\beta X} \quad \text{......Equation 2.12}$$

where φ, β = constants

e = natural logarithm

$$\text{SiBOD} = 100.4 - 4.23X_1, \quad X_1 \leq 5 \quad \text{....Equation 2.13}$$

$$\text{SiBOD} = 108e^{-0.055X_1} - 0.1X_1, \quad X_1 > 5 \quad \text{.....Equation 2.14}$$



(Source: Modified from DOE, Malaysia, 1990)

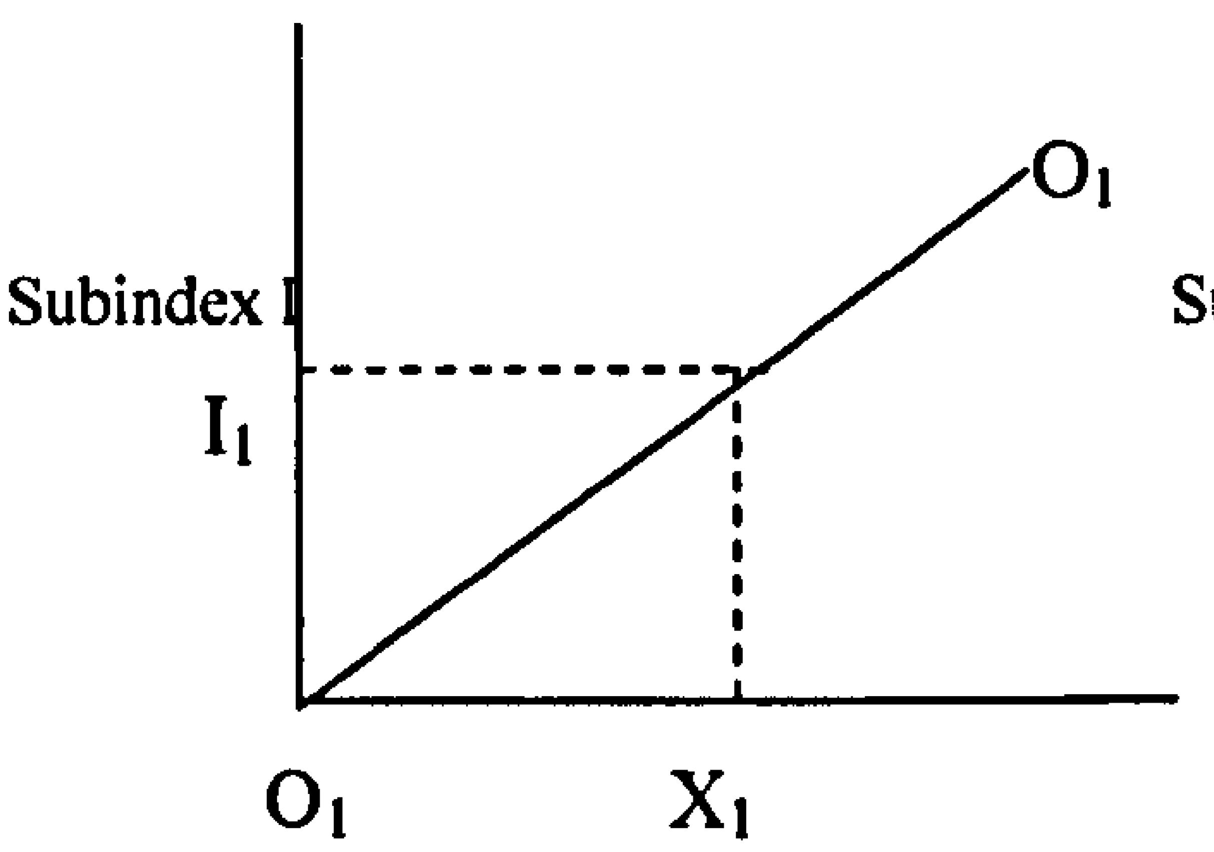
Two increasing linear subindices I_1 and I_2

$$I = \sum_{i=1}^{n} I_i \qquad \text{.....Equation 2.16}$$

where I_i = subindex for variable i

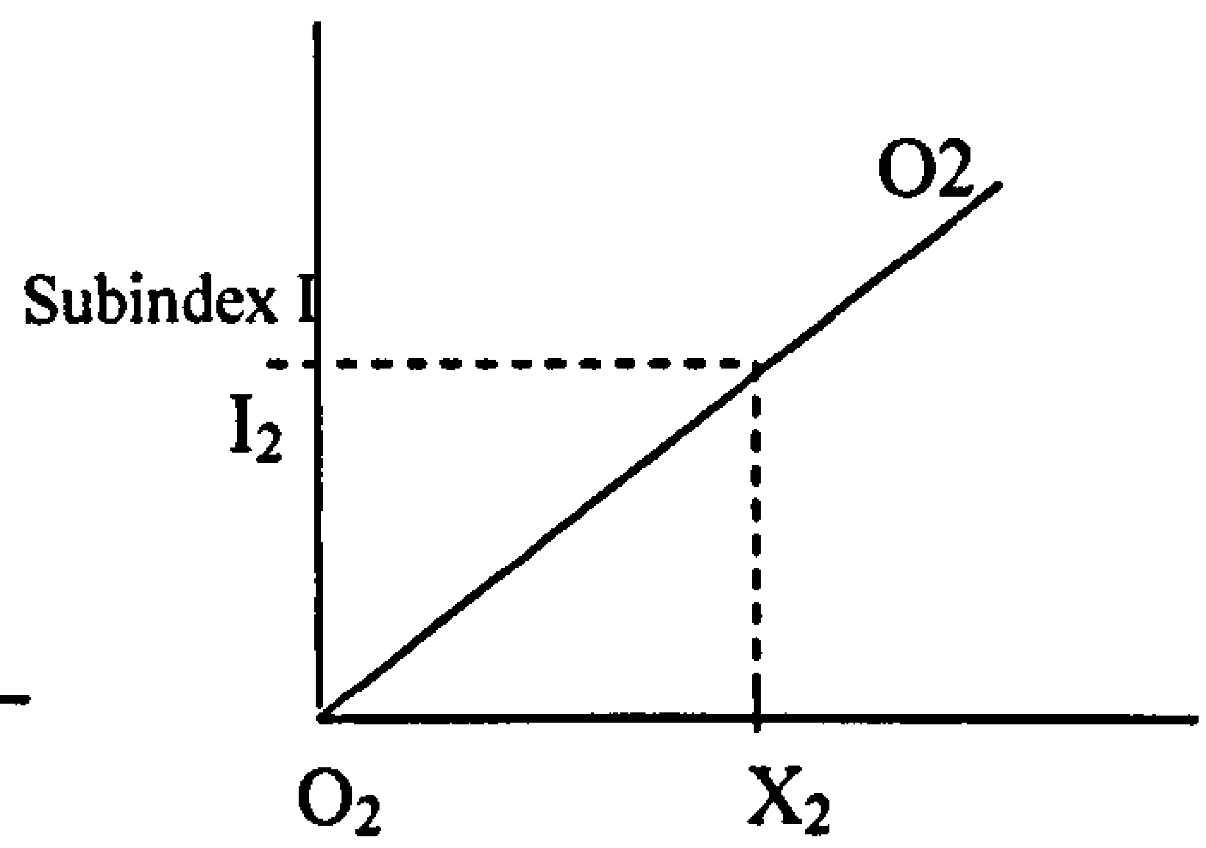
n = number of variables

$$I = I_1 + I_2 \qquad \text{.....Equation 2.17}$$



Concentration of variable X_1

Graph A



Concentration of variable X_2

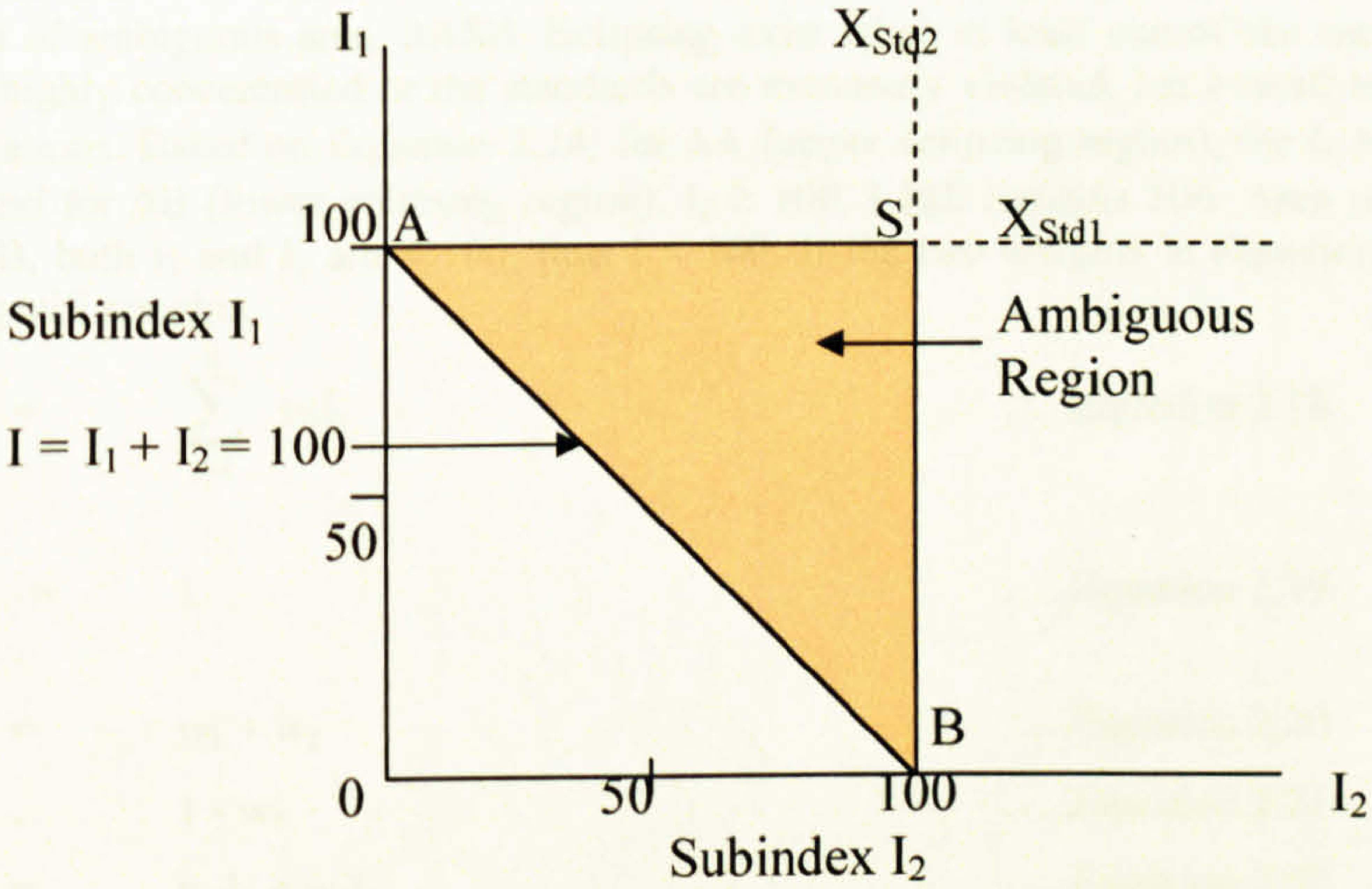
Graph B

Based on the two graphs, when subindex $I_1 = 0$ and $I_2 = 0$, index $I = 0$ which described a condition of zero pollution or high water quality for the corresponding variables X_1 and X_2. In an increasing scale index, higher value indicates poor water quality. Suppose that the subindex limit of 100 is taken as poor water quality. Based on Graph A, when concentration is at X_1, subindex $I_1 = 100$ and another concentration is at X_2, subindex $I_2 = 100$ (Graph B), when summed up, index $I = 200$, thus index I exaggerated. If $X_1 = X_{Std1}$ and $X_2 = X_{Std2}$, both taken at highest standard limits, when $I_{1(Std1)} + I_{2(Std2)}$, then index $I \geq 100$, violation of the standard limits has occurred. At some point where $X_1 < X_{Std1}$, either $I_1 < 100$ and $X_2 < X_{Std2}$, $I_2 < 100$, where no standard violation occurred for both variables. However, when these subindices are summed-up, index $I > 100$ where violation is said to occur. Other ambiguous condition exist when $I_1 = 50$ and $I_2 = 60$, where actually no violation of standards occurred for variables X_1 and X_2, but the final index I indicates an explicit violations. This similar situation occurs for other range of combinations when subindex I_1 is added to subindex I_2.

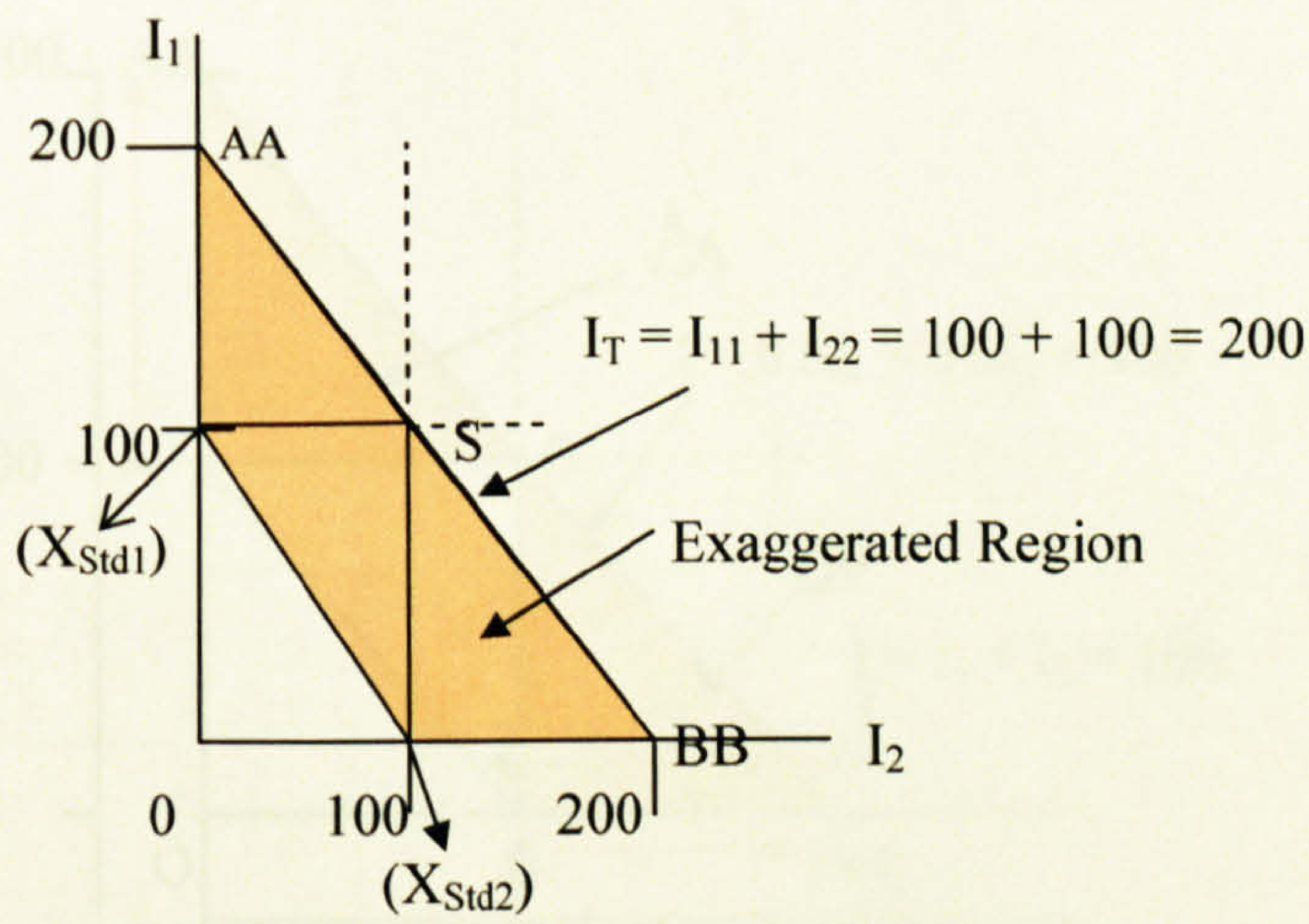
(Source: Modified from Ott, 1978)

Ambiguous and exaggerated region

In the case of dichotomous subindices (involvement of two variables), the ambiguous value can be represented as in Graph A below. Triangle ASB is the magnitude of an ambiguous area and S is a point where the line of standard limit for X_1 and X_2 coincide. Obviously, when one variable has violated, whereas other is not, the final index may also indicate violation of standard limit. Exaggeration increases when both I_1 and I_2 increases simultaneously such that I can reach 200 as represented by the line AA and BB as in Graph B. Thus, the linear sum function may exaggerate and creates an ambiguous water quality index value.



Graph A Ambiguous region in unweighted linear sum



Graph B Exaggerated region in linear sum

(Source: Ott, 1978)

Appendix 2.12

Removal of ambiguous region and formation of eclipsing region

Based on Equation 2.17 (Appendix 2.10), when I_1 and I_2 = 100, index I = 200 (highly polluted). However, the weight can be used to remove the ambiguous region (ΔASB) as in Graph A, Appendix 2.11. When weights w_1 and w_2 are assigned a value of 0.5 as in Equation 2.23 and represented graphically as in Graph C below, the ambiguous region ΔASB is removed, where I = 100 as in Equation 2.25. The line AB is shifted to AABB and the slope remains the same. Although the weighted linear sum managed to remove the ambiguous region, the new line AABB produces two serious regions known as *eclipsing region* denoted by ΔA and ΔB. Eclipsing regions are the underestimated areas. Based on areas of triangle, the lost of information due to eclipsing areas (ΔA + ΔB) is twice larger than that of ambiguous area, ΔASB. Eclipsing exist when at least one of the two variables or subindices are highly concentrated or the standards are extremely violated, but overall index does not reveal this violations. Based on Equation 2.24, for ΔA (upper eclipsing region), for $I_1 \geq 100$, index I remains 100, and for ΔB (lower eclipsing region), $I_2 \geq 100$, I still remains 100. Area represented by rectangle OASB, both I_1 and I_2 are < 100, thus I < 100. If the two weights in Equation 2.22 are not equal, eclipsing still remains.

$$I = \sum_{i=1}^{n} w_i I_i \quad \text{.....Equation 2.18}$$

$$\sum_{i=1}^{n} w_i = 1 \quad \text{.....Equation 2.19}$$

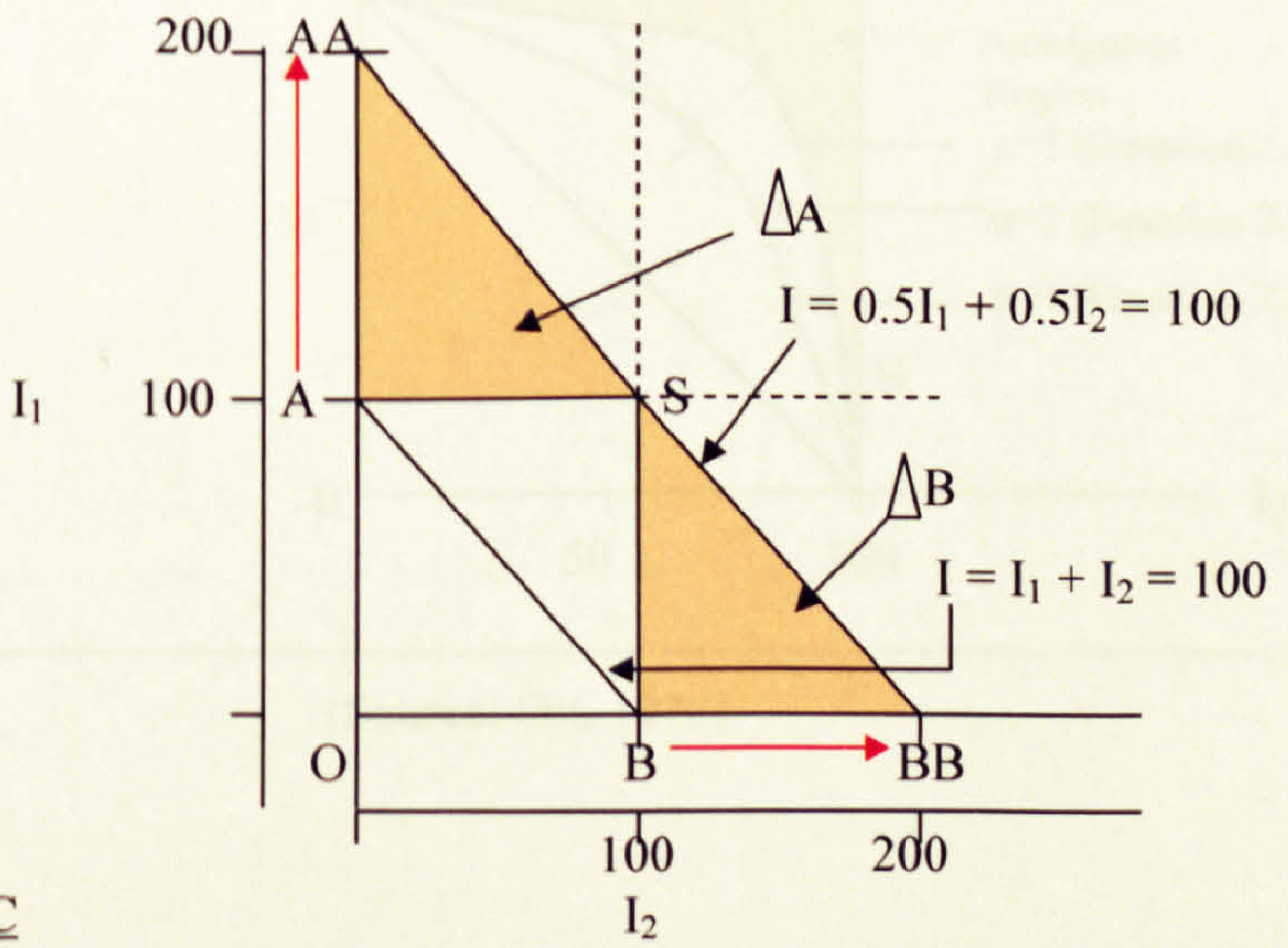
$$1 = w_1 + w_2 \quad \text{.....Equation 2.20}$$

$$w_2 = 1 - w_1 \quad \text{.....Equation 2.21}$$

$$I = w_1 I_1 + w_2 I_2 \quad \text{.....Equation 2.22}$$

$$I = 0.5 I_1 + 0.5 I_2 \quad \text{.....Equation 2.23}$$

$$I = I_1 + I_2 = 100 \times 0.5 = 100 \quad \text{.....Equation 2.24}$$



Graph C

(Source: Ott, 1978)

Elimination of ambiguous and eclipsing regions in nonlinear Root-Sum-Square function

Equation 2.25 shows that the subindex is raised to a power, p (a positive real number) and the whole expression is taken as p*th* root. If p = 1, the curve represented by line AB below and ambiguous region is covered by ΔASB. When p = 2 and 3, ambiguous region becomes smaller where indices I are expressed as in Equation 2.27 (known as root-sum-square as curve ACB) and Equation 2.28 (root-sum-cube as curve ADB) respectively. When p increases, the curvature becomes sharper. Thus as p approaches infinity, the ambiguous and eclipsing region almost eliminated. Therefore, root-sum-power function is an effective mean for aggregating subindices. However, due to its limiting function, it is unwieldy to be applied (Ott, 1978).

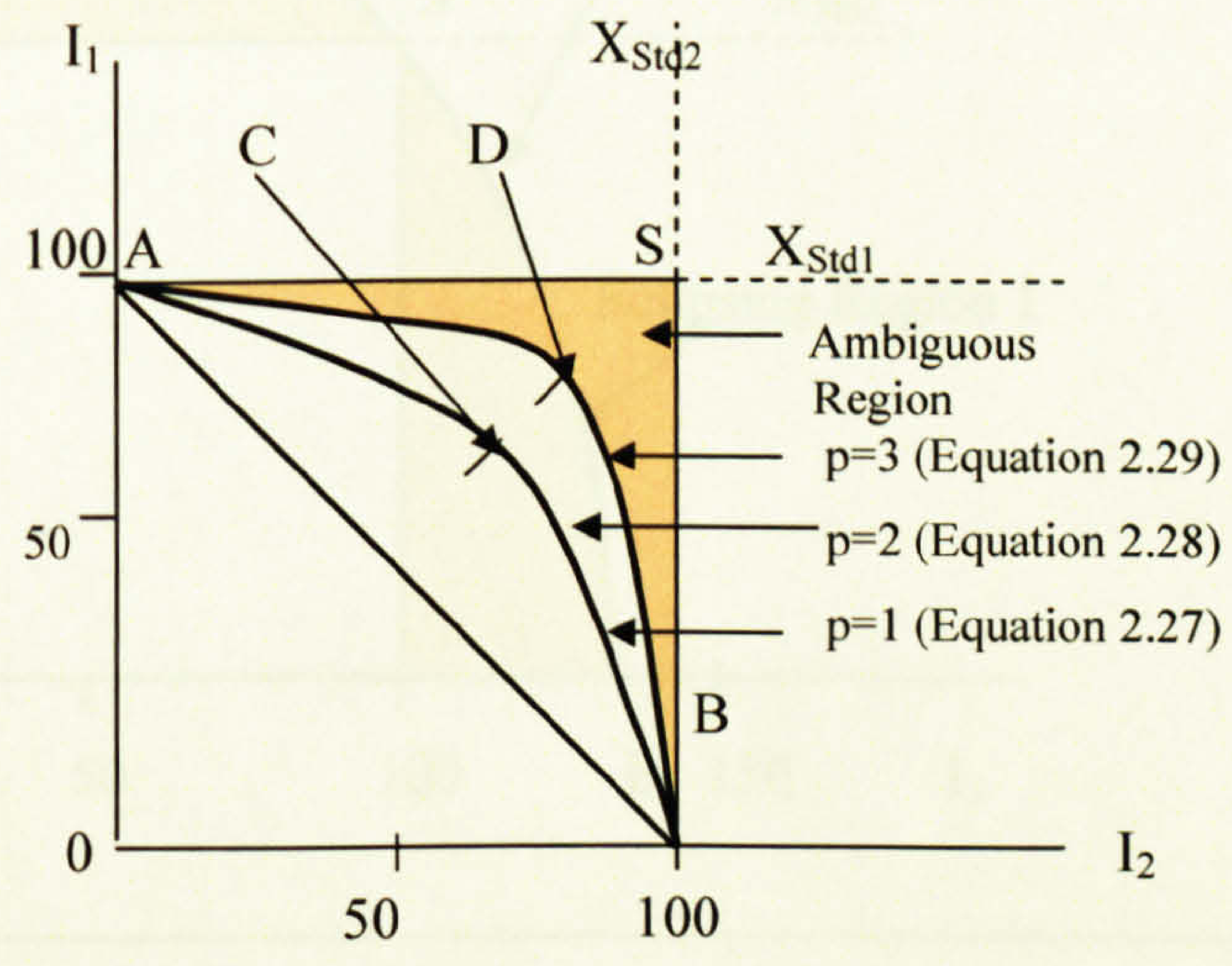
$$I = [\sum_{i=1}^{n} I_i^{\,p}]^{1/p} \qquad .....\text{Equation 2.25}$$

$$I = [(I_1)^p + (I_a)^p]^{1/p} \qquad .....\text{Equation 2.26}$$

$$= I_1 + I_2, \quad p = 1 \qquad .....\text{Equation 2.27}$$

$$I = \sqrt{(I_1)^2 + (I_a)^2}, \quad p = 2 \qquad .....\text{Equation 2.28}$$

$$I = \sqrt{(I_1)^3 + (I_a)^3}, \quad p = 3 \qquad .....\text{Equation 2.29}$$



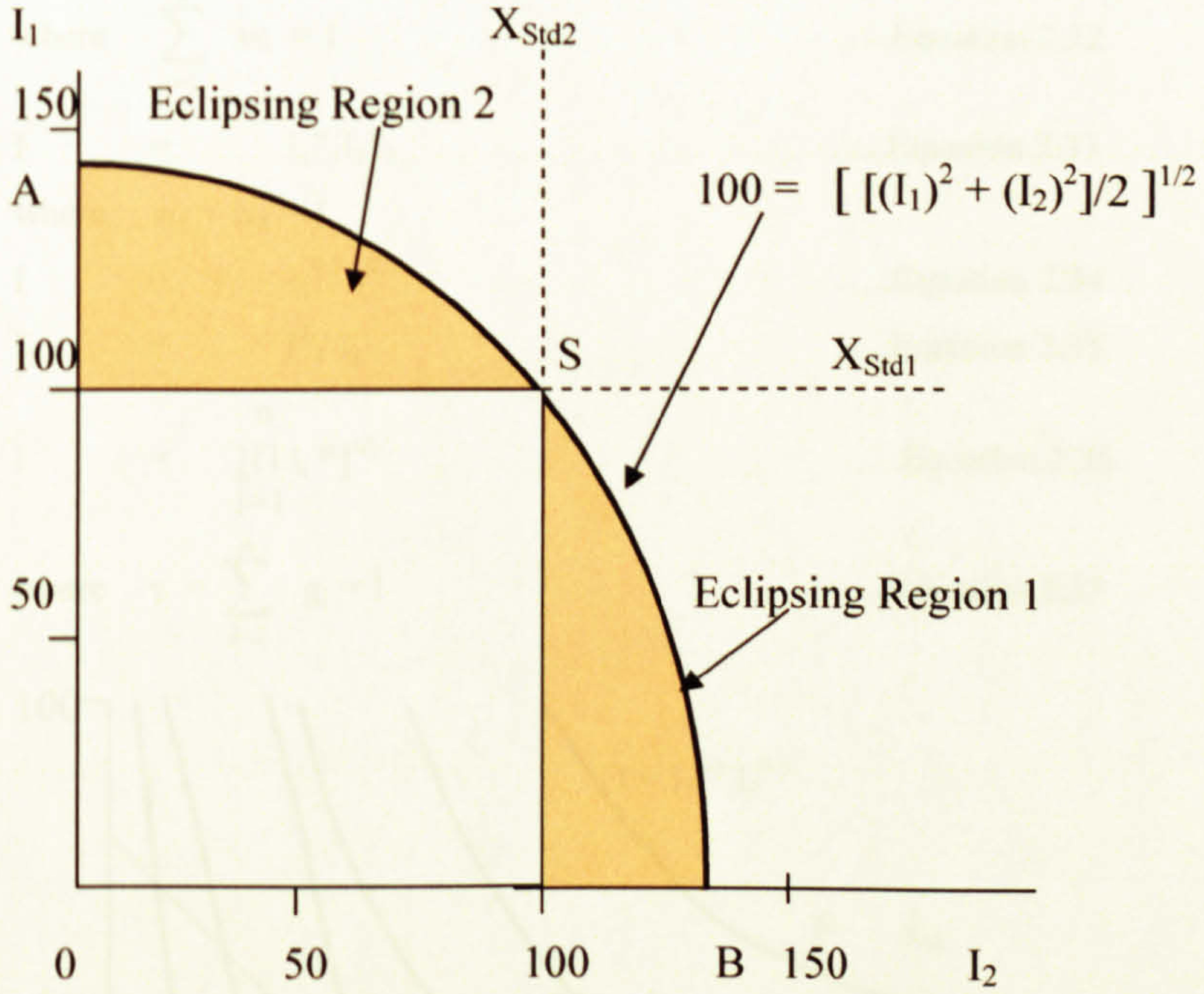
(Source: Ott, 1978)

Appendix 2.14

The Root-Mean-Square with two eclipsing regions

The root-sum-square as in Equation 2.28 can be converted into root-mean-square. In this case, the mean of the square of subindices, I_1 and I_2 is calculated first before the square root is taken. Thus, the index I of the root-sum-square as in Equation 2.28 can be transformed as root-mean-square as represented in Equation 2.30. Based on similar subindex value, I_1 and I_2, the ambiguous area under the curve ΔASB-ΔADB of the curve in Appendix 2.13 can be eliminated by extending the curve ASB outward as illustrated in graph below. However, this curve exhibits two Eclipsing Regions 1 and 2. Thus, for non-linear aggregation function, an ambiguous area can be eliminated, but creating two eclipsing areas, which contribute to lost of information.

$$I = [\,[(I_1)^2 + (I_2)^2]/2\,]^{1/2}, \quad p = 2 \qquad \text{.....Equation 2.30}$$



(Source: Ott, 1978)

Multiplicative aggregation function for equal weights

Based on Equation 2.32, if each subindex $I_i = 100$, then index $I = 100$, which implies that for all $0 < I_i < 100$, then $0 < I < 100$. However, when two subindices are aggregated as in Equation 2.22 for weighted linear sum, aggregation in multiplicative function can be represented as in Equation 2.33. As in the previous example, both w_1 and w_2 is given a value of 0.5, which is represented as Equation 2.34. In order to investigate whether eclipsing still exist, I_1 in Equation 2.34 is written as Equation 2.35. Based on Equation 2.34 and 2.35, I_1 and I_2 is plotted as a curve below, which displays a series of hyperbolic curves convex towards the origin with negative slopes ([dy/dx]= -1) at points 45° bisecting the I_1 and I_2 axes. At points A,B,C,D,E and F, $I_1 = I_2 = I$ for which the weight w_1 and $w_2 = 0.5$. If $w_1 \neq w_2$, then the shape of curves will change and $I_1 \neq I_2 \neq I$, which still remains convex towards the origin. When index I becomes smaller, the curvature increases, and in the limit as I approaches zero, the curve approaches a right angle nearly touching the two axes. Since $I_1 \neq 0$ and $I_2 \neq 0$, index I is always greater than zero, the curve will never touches both axes, thus eclipsing will never occur.

$$I = \prod_{i=1}^{n} I_i^{w_i} \qquad \text{.....Equation 2.31}$$

$$\text{where} \quad \sum_{i=1}^{n} w_i = 1 \qquad \text{.....Equation 2.32}$$

$$I = I_1^{w_1} I_2^{w_2} \qquad \text{.....Equation 2.33}$$

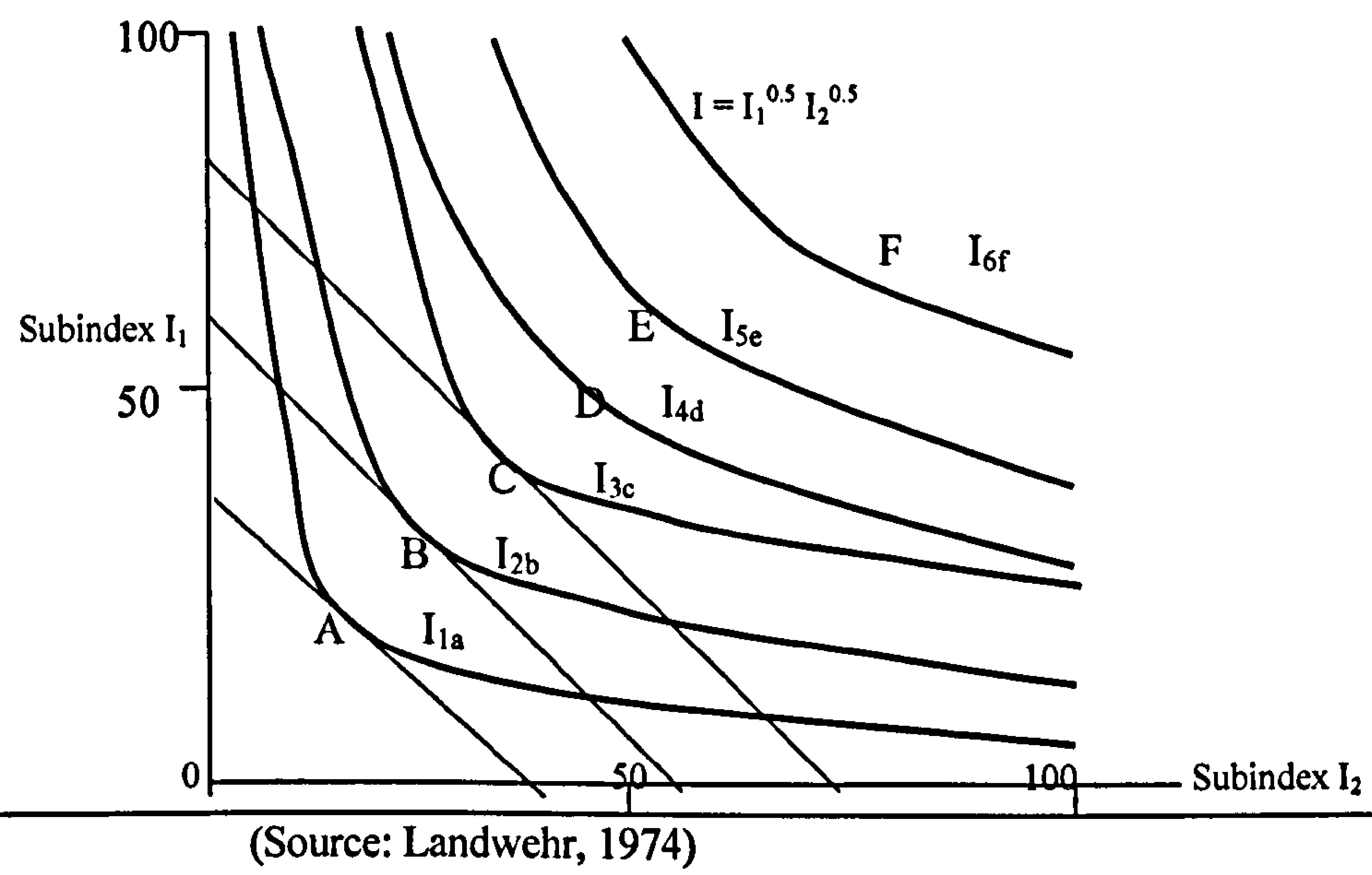
$$\text{where,} \quad w_1 + w_2 = 1$$

$$I = I_1^{0.5} I_2^{0.5} \qquad \text{.....Equation 2.34}$$

$$I_1 = I^2 / I_2 \qquad \text{.....Equation 2.35}$$

$$I = \left[\prod_{i=1}^{n} I_i^{g_i}\right]^{1/\gamma} \qquad \text{.....Equation 2.36}$$

$$\text{where} \quad \gamma = \sum_{i=1}^{n} g_i = 1 \qquad \text{.....Equation 2.37}$$



(Source: Landwehr, 1974)

Maximum and minimum operator

The index I in maximum operator is determined by the maximum value of any subindices such that I = 0 when $I_i = 0$ for all i. If two subindices, I_1 and I_2 are aggregated as in the previous examples, maximum operator function can be represented as in Equation 2.39 and graphically illustrated as in Figure 2.16a below. The horizontal line AA_1 satisfies a condition where index I = 100, such that subindex $I_1 = 100$, and only if $0 \leq I_2 < 100$. In other case, a vertical line BA_1 satisfies a condition where index I = 100, such that $I_2 = 100$, and only if $0 \leq I_1 < 100$. These two lines joined at right angles. As I_1 and I_2 is increased, index I is increased with the same proportion of I_1 and I_2. This produces several plots as in Figure 2.16a, which also indicates that no eclipsing region occurs. Thus, if one subindex exhibits low water quality, the overall index I, exhibits low water quality. Besides that, no ambiguous region occurs for the overall index I since both subindices I_1 and I_2 exist in opposite manner. These properties mainly suit dichotomous subindices. However, the drawback of maximum operator function is that it could not provide the fine degradation of the overall index I and becomes more complex when more then two subindices are aggregated. Therefore, it is difficult to apply for investigating the changes in water quality overtime specifically for trend analysis.

$$I = \max\{I_1, I_2, \ldots I_i \ldots\ldots I_n\} \qquad \text{.....Equation 2.38}$$

$$I = \max\{I_1, I_2\} \qquad \text{.....Equation 2.39}$$

$$I = \min\{I_1, I_2, \ldots I_i \ldots\ldots I_n\} \qquad \text{.....Equation 2.40}$$

$$I = \min\{I_1, I_2\} \qquad \text{....Equation 2.41}$$

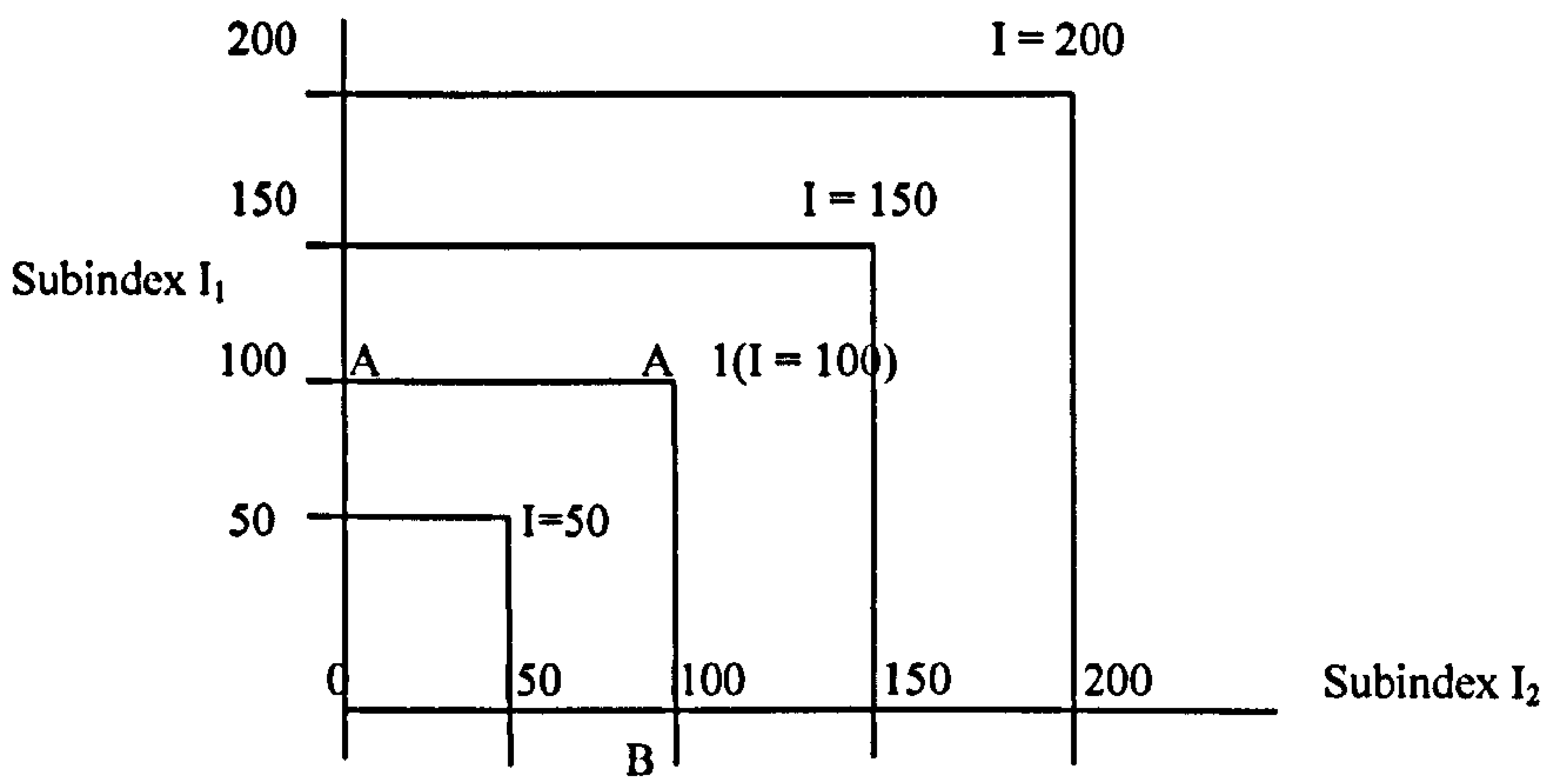


Figure 2.16a Maximum operator function for $I = \max\{I_1, I_2\}$

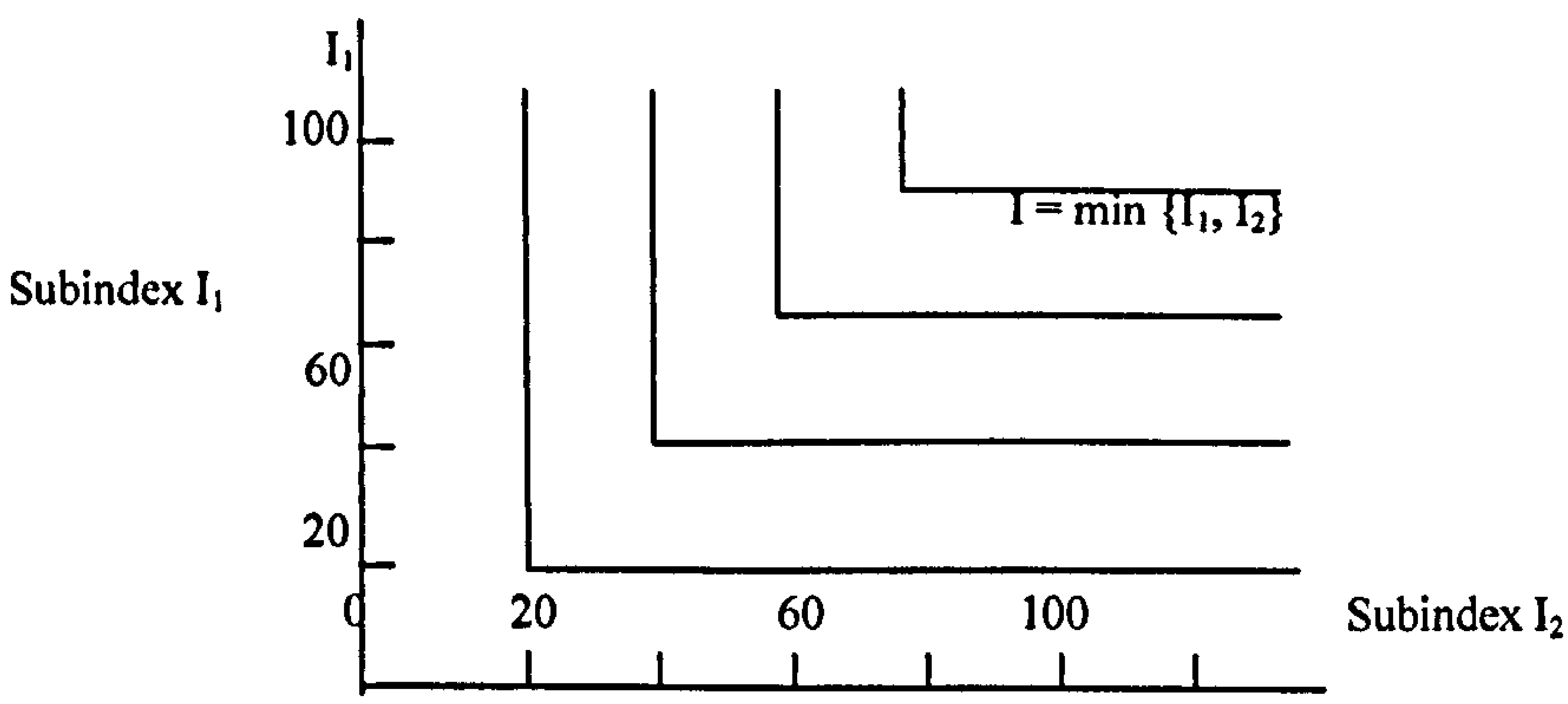


Figure 2.16b Minimum operator function for $I = \min\{I_1, I_2\}$

(Source: Ott, 1978; Smith, 1989)

Number of banded classes in some European Union countries.

Country	Method	Number of Banded Class	Class Grade Designation
Belgium	Water oxygen balance	5	1 2 3 4 5
France	Multipurpose Scale	5	1A 1B 2 3 No classification
Germany	Standard Procedure	7	I I-II II II-III III III-IV IV
Ireland	National classification scheme	3	A B C
Luxembourg	Water oxygen balance	5	1 2 3 4 5
Netherlands	Water oxygen balance	5	1 2 3 4 5
UK: England & Wales	NWC river classification	5	1A 1B 2 3 4
Scotland	Chemical classification scheme	4	1 2 3 4
Northern Ireland	NWC river classification.	5	1A 1B 2 3 4

(Sources: Newman, 1988)

Appendix 2.18

Characteristics of aggregation function

Aggregation Function	Increasing Scale Indices	Decreasing Scale Indices
1. Additive Forms:		
a) Linear Sum	Ambiguity; no eclipsing.	No eclipsing; ambiguity.
b) Weighted Sum	Eclipsing; no ambiguity.	Eclipsing; no ambiguity.
c) Root-Sum-Power	Minimises eclipsing and ambiguity as power approaches ∞.	Eclipsing; no ambiguity. Posses limiting factor.
2. Multiplicative Forms:		
a) Weighted Product	Not applicable.	Some eclipsing; no ambiguity.
b) Geometric	Not applicable.	Nonlinear if weights are small.
2. Maximum Operator	No eclipsing; no ambiguity	Not applicable.
3. Minimum Operator	Not applicable	No eclipsing; no ambiguity.

(Source: Ott, 1978).

Appendix 2.19

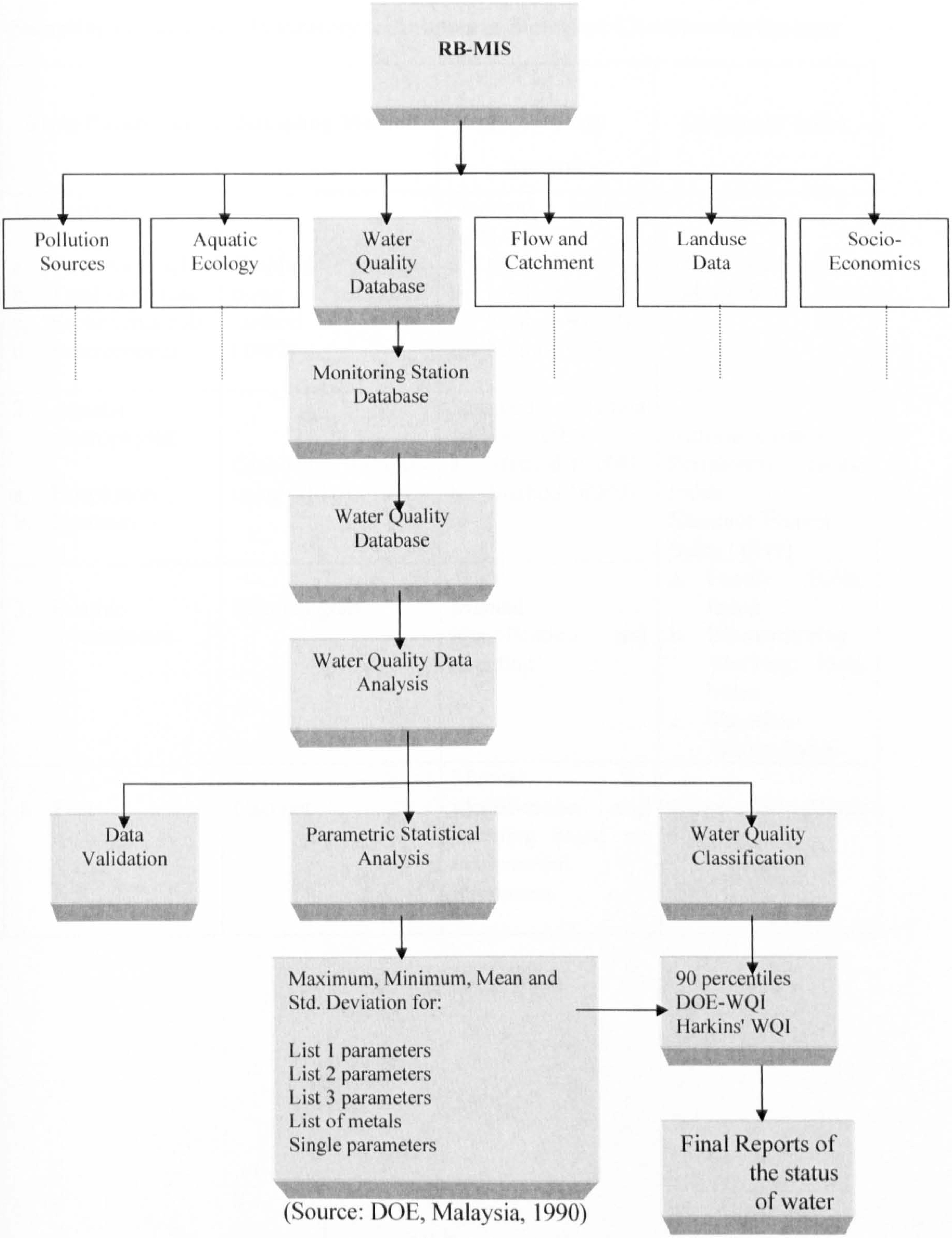
Comparison of the water quality assessment techniques

Realm	Physico-chemical	Biological
(1)Precision (i.e. pollutant concentration assessment)	Good	Poor
(2) Discrimination (what kind of pollution)	Good	Poor
(3) Reliability (how representative is a single or a limited number of samples)	Poor	Good
(4) Measure of ecological effects	No	Yes
(5) Cost	Relatively High	Relatively Low

(Source: Newman, 1988 and Gray, 1999).

Appendix 3.1

Structure of the River Basin Management Information System (RB-MIS)



(Source: DOE, Malaysia, 1990)

Appendix 3.2

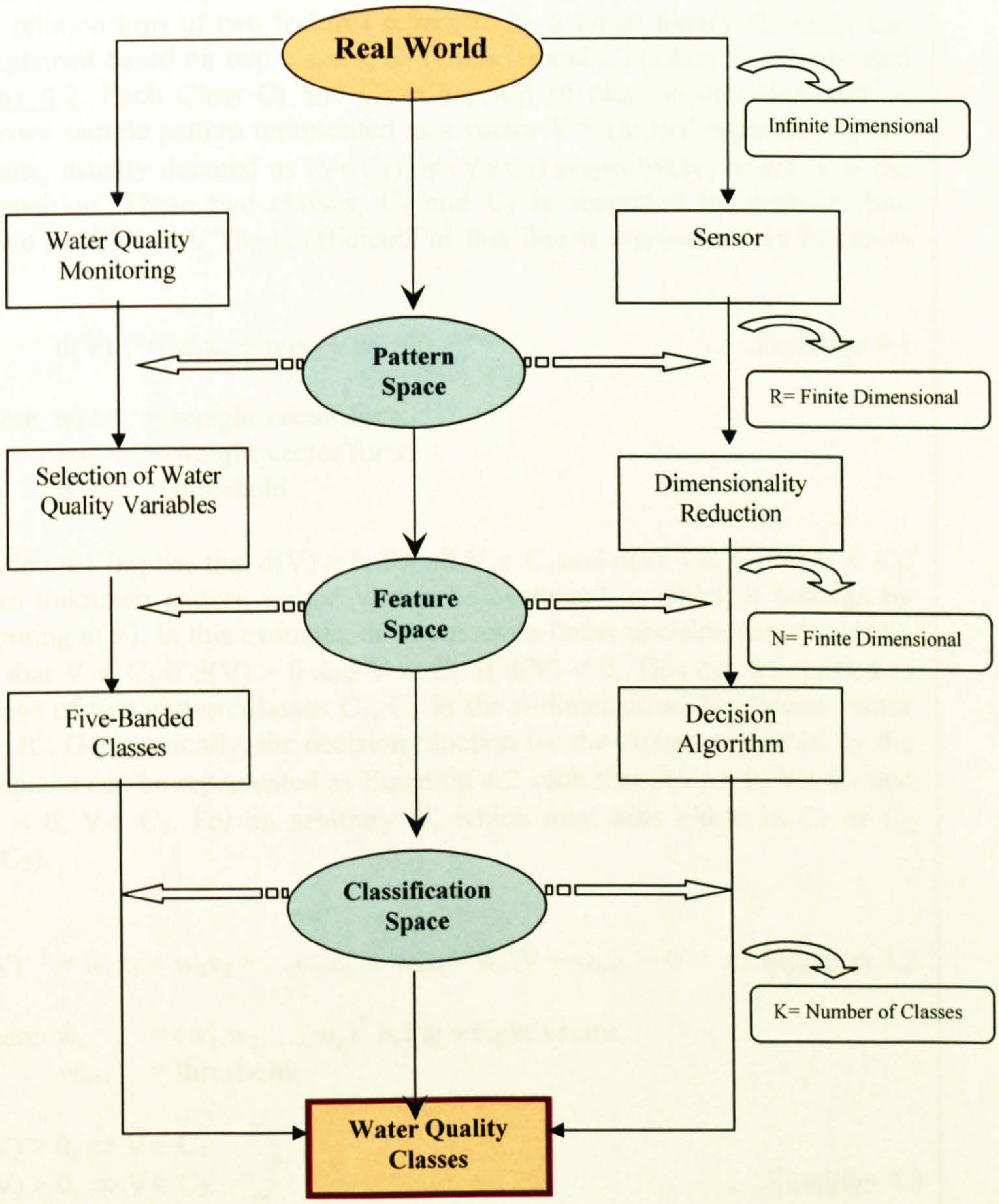
Sampling methods and laboratory techniques in Biological Classification Systems

Main Parameter	Sampling Method	Laboratory Analysis	Choices of Index
1. Bacteria: a. Total bacterial b. Total coliforms c. Escherichia coli d. Enterococcus	Grabbed samples using Standard method APHA (1992)	Standard Method APHA (1992): a. Method 9215 b. Method 9222B c. Method 9213D d. Method 9230C	Shannon-Weiner Index (1949)
2. Aquatic macrophytes: a. Periphyton b. Plankton	Grabbed samples using APHA (1992)	Standard Method APHA (1992): a. Method 10200F b. Method 10200F	Autrophic Index. Periphyton Biotic Index Shannon-Weiner Index (1949)
3. Benthic invertebrates	Eckman grab	Manual identification and counting	a. Family Biotic Index b. Biomonitoring Working Party Index c. Shannon-Weiner Index
4. Fish	Cast net	Manual identification and counting based on taxonomical references.	Index of Biotic Integrity

(Source: DOE, 1990)

Appendix 4.1

The concept of Pattern Recognition in water quality classification



(Source: Modified from Andrews, 1972; Schalkoff, 1992; Theodoridis and Koutroumbas, 1999)

The relationships of the two features separated by Linear Decision function

The relationships of two features separated by a linear binary classifier can be explained based on two classes, C_1 (Class 1) and C_2 (Class 2) as indicated in Box 4.2. Each Class C_1 and C_2 is a priori of class information and an unknown sample pattern represented as a vector $V = (x_1,x_2)^T$ separated by x_1-x_2 plane, usually denoted as ($V \in C_1$) or ($V \in C_2$) respectively, where T is the transposition. These two classes, C_1 and C_2 is separated by decision line denoted as d(V) = 0. The coefficients of this line is represented as Equation 4.1.

$$d(V) = w_1x_1 + w_2x_2 + w_3 = 0 \qquad \text{......Equation 4.1}$$

where w_1 = weight vector for x_1
w_2 = weight vector for x_2
w_3 = threshold

Equation 4.1 implies that $d(V) > 0$, for all $V \in C_1$ and $d(x) < 0$, for all $V \in C_2$. For an unknown pattern vector V, can be evaluated to which it belongs by computing d(V). In this example, d(V) possess a linear decision function of C_1 such that $V \in C_1$ if $d(V) > 0$ and $V \in C_2$ if $d(V) < 0$. This can be applied to the case of two pattern classes C_1, C_2 in the n-dimensional Euclidean vector space R^n. Geometrically, the decision function for the classes separated by the hyperplane can be represented as Equation 4.2 such that $d(V) > 0$, $V \in C_1$ and $d(V) < 0$, $V \in C_2$. For an arbitrary V, which may falls either in C_1 or C_2 ($C_1 \cup C_2$).

$$d(V) = w_1x_1 + w_2x_2 + \ldots w_nx_n + w_{n+1} = \hat{w}_o^T V + w_{n+1} = 0 \qquad \text{....Equation 4.2}$$

where $\hat{w}_o$ = $(w_1,w_2,\ldots,w_n)^T$ is the weight vector,
w_{n+1} = threshold

$$\left.\begin{array}{l} d(V) > 0, \Rightarrow V \in C_1 \\ d(V) > 0, \Rightarrow V \in C_2 \end{array}\right\} \qquad \text{....Equation 4.3}$$

(Source: Friedman and Kandel, 1999).

The Linear Decision functions with Absolute and Pairwise Separation

If for each class C_i has a linear decision function $d_i(V)$ such that $1 \le i \le m$, where $\hat{w}_i$ is the weight vector associated with $d_i(V)$, then absolute separation exist between $C_1, C_2, C_3, \ldots\ldots, C_m$ or $\{C_i\}^m{}_{i=1}$ are absolutely separable as represented in Equation 4.4. In an absolute separable condition, a pattern class $\{C_i\}^m{}_{i=1}$ with a linear decision functions $d_1(V), d_2(V), \ldots\ldots, d_m(V)$, and decision regions of $C_1, C_2, C_3, \ldots\ldots, C_m$ respectively, the decision region vector sets is represented as Equation 4.5. When there exist an overlapping of one or more classes, partial separation between pattern classes occur and linear decision function may still applies. This associated pattern classes is a pairwise separable. The decision function, d_{ij} for each pair of classes C_i and C_j is represented as Equation 4.6 for $j \neq i$. Thus, Equation 4.6 can be written as Equation 4.7 and an unknown pattern V can only be classified as C_i if it satisfies this Equation 4.7. In a pairwise separation condition with decision regions of $C_1, C_2, C_3, \ldots\ldots, C_m$ respectively, and separated by the linear decision functions $\{d_{ij}(V)\}^m{}_{i,j=1}$, the decision rule for the vector sets is represented as Equation 4.8.

$$d_i(V) = \hat{w}^T{}_i V = \begin{cases} > 0, & V \in C_i \\ < 0, & \text{otherwise} \end{cases} \qquad \ldots\text{Equation 4.4}$$

$$D_i \quad = \{ V \mid d_i(V) > 0; d_j(V) < 0, j \neq i \}, 1 \le i \le m, \ldots\text{Equation 4.5}$$

$$\left.\begin{array}{ll} d_i(V) & > 0 \text{ for all } V \in C_I \\ d_i(V) & < 0 \text{ for all } V \in C_j \end{array}\right\} \qquad \ldots\text{Equation 4.6}$$

$$d_{ij}(V) \;\; > 0 \text{ for all } j \neq i \qquad \ldots\text{Equation 4.7}$$

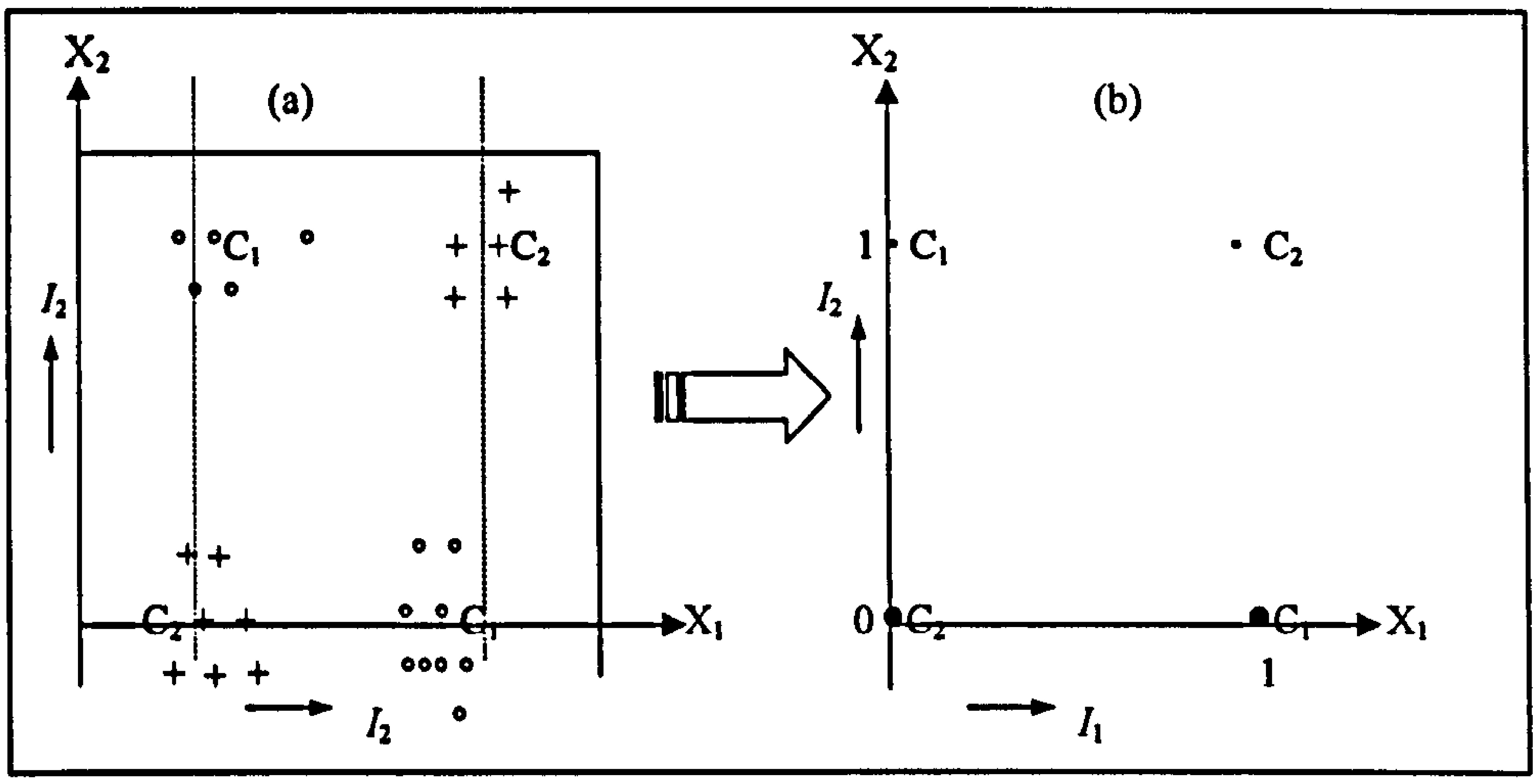
$$D_i \quad = \{ V \mid d_{ij}(V) > 0, j \neq i \}, 1 \le i \le m, \qquad \ldots\text{Equation 4.8}$$

(Source: Friedman and Kandel, 1999).

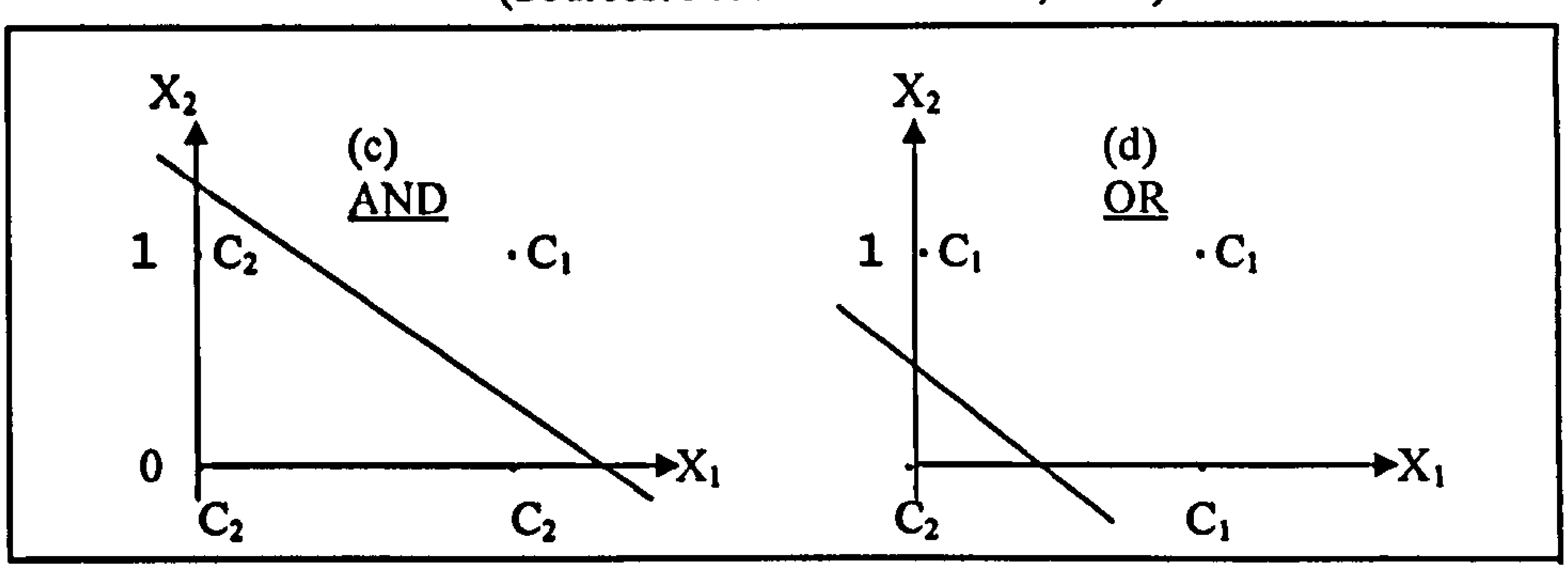
Appendix 4.4

Resolving XOR, AND and OR problems

With an input binary data $V = [x_1, x_2, x_3, \ldots\ldots, x_l]^T$, the output value is either in the form of 0 or 1 and V is then classified either into C_1 or C_2 as illustrated in Box 4.4a and 4.4b. Box 4.4a illustrates the distribution of the features both in C1 and C2 and the sign • in Box 4.4b represent its centre of gravity. The results of this XOR problem is be represented as in Table 4.4 which concluded that no single straight line can be drawn to separates this two classes in 2-dimensional pattern space. However, if the centres of gravity of the two classes are distributed as in Box 4.4c and Box 4.4d, then they can be separated by the two straight lines as linear classifiers. The situation in Box 4.4c is known as AND and Box 4.4d is known as OR and the result are shown in Box 4.4e.



Box 4.4(a) and (b) Two classes C_1 and C_2 describing the XOR problem (Sources: Modified from Pao, 1989)



Box 4.4(c) and (d) Two Classes C_1 and C_2 describing the AND and OR problems. (Source: Modified from Theodoridis and Koutroumbas, 1999)

X_1	X_2	XOR		AND		OR	
		Value	Class	Value	Class	Value	Class
0	0	0	C_2	0	C_2	0	C_2
0	1	1	C_1	0	C_2	1	C_1
1	0	1	C_1	0	C_2	1	C_1
1	1	0	C_2	1	C_1	1	C_1

Box 4.4e Classification based on two vectors X_1 and X_2
(Source: Modified from Theodoridis and Koutroumbas, 1999)

Two decision lines for resolving the XOR problem

XOR problem can be resolved when the two classes as indicated in Box 4.4b, Appendix 4.4, are separated by two possible decision lines, $d_1(V)$and $d_2(V)$ as represented in Figure 4.5. Both $d_1(V) = d_2(V) = 0$ and in pattern space are represented as $d_1(V) = d_2(V) >< 0$. However to resolve the XOR problem in hyperplanes involves two stages of calculations. Firstly, is to calculate the position of vector V with respect to each of the two decision lines and secondly is to combine the results from the first calculation and then to evaluate the position of V with respect to both lines either outside or inside of the two lines. Consequently, this is then view from slightly different perspective, which leads to generalisation of the problem. The first stage of calculations can be achieved with the applications of two perceptrons or neurons with inputs of x_1 and x_2 through an appropriate synaptic weights. In hyperplanes, the two lines are represented as $d_1(\bullet) = d_2(\bullet)$. The basic perceptron model is shown in Appendix 4.6.

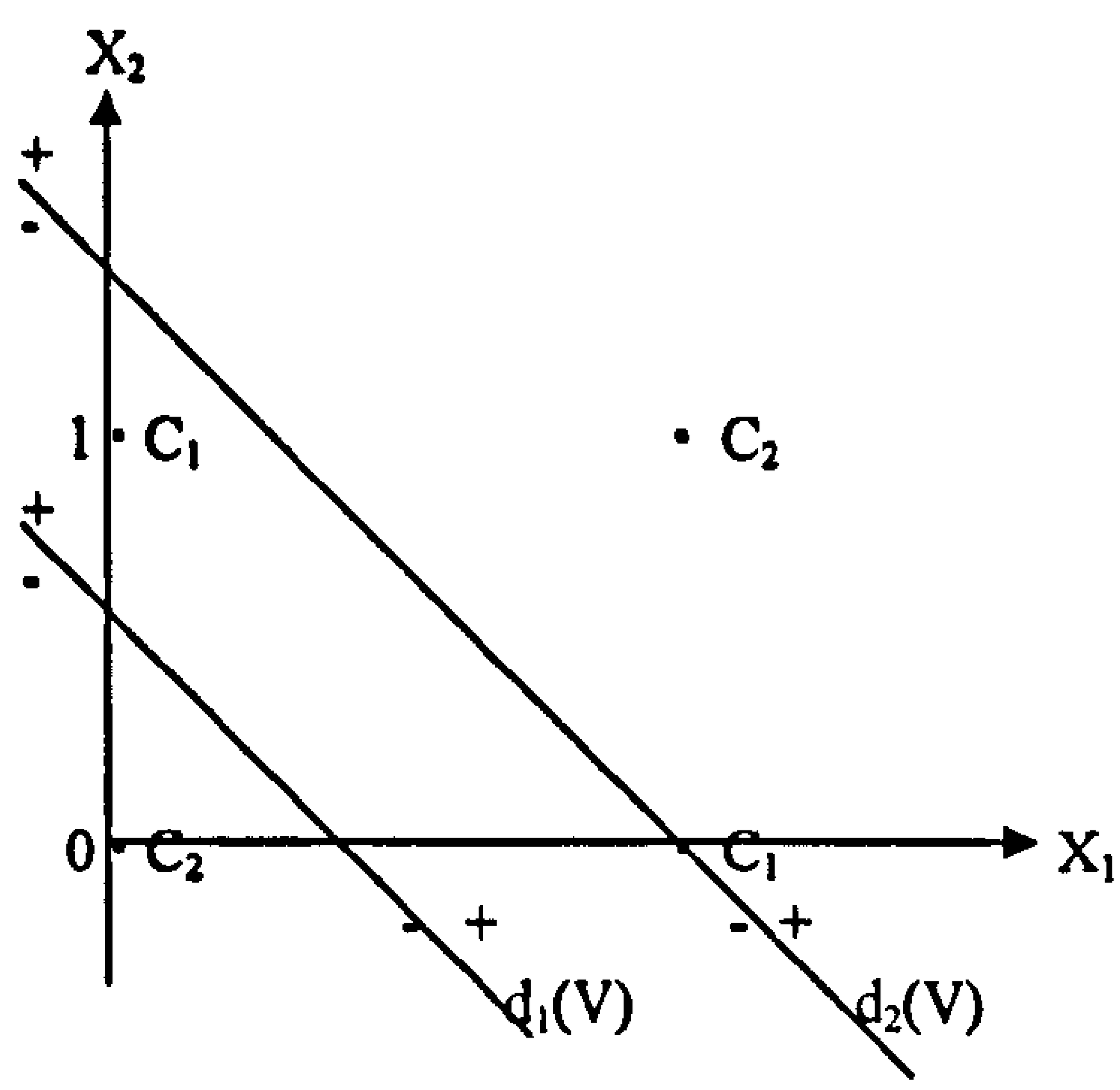


Figure 4.5

(Source: Theodoridis and Koutroumbas, 1999)

Basic model of Perceptron

In a basic perceptron model, the feature vectors, $X = [x_1,x_2,x_3......,x_l]$ are the inputs applied to the input nodes as in Box 4.6. Each of this feature is multiplied by the respective weights w_i, ($i = 1,2,3,....l$), which is known as synaptic weights (or synapes). The product of these features and synaptic weights are summed together with the threshold value, W_o. The output will pass through the nonlinear device that implements the activation function, f(•), which commonly used the step function [$f(x) = 1, x > 0$ and $f(x) = -1, x < 0$ or $f(x) = 1, x > 0$ and $f(x) = 0, x < 0$]. When two levels of step function is used, the values chosen are 0 and 1. An unknown feature vector, V can then be classified in one of the classes depending on the sign of the output. Consequently, this basic structure is the learning machine where their variables or inputs features can be updated by a learning algorithm in order to learn a specific task based on a set of training data (Haykin, 1999).

Based on Figure 4.5 (Appendix 4.5), the two decision lines are realised when two perceptrons with an inputs of x_1, x_2 and the respective synaptic weights are applied. Thus, the outputs are $Y_i = f(d_i(V))$, $i = 1,2$, where the activation function, f(•) is the step function with levels 0 and 1. The results that show the relative positions of the vector V with respect to each of the two lines are tabulated as Box 4.6a.

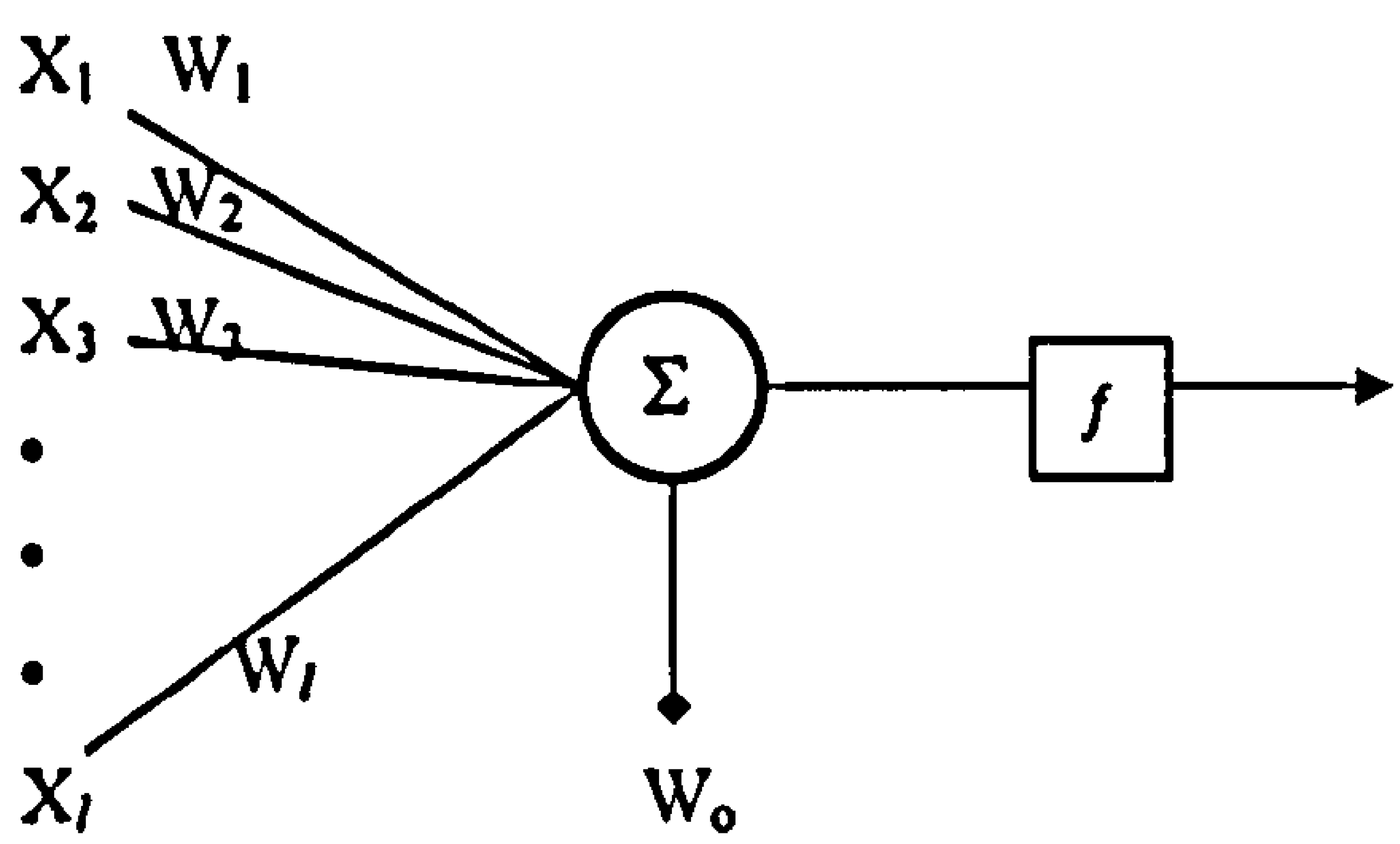


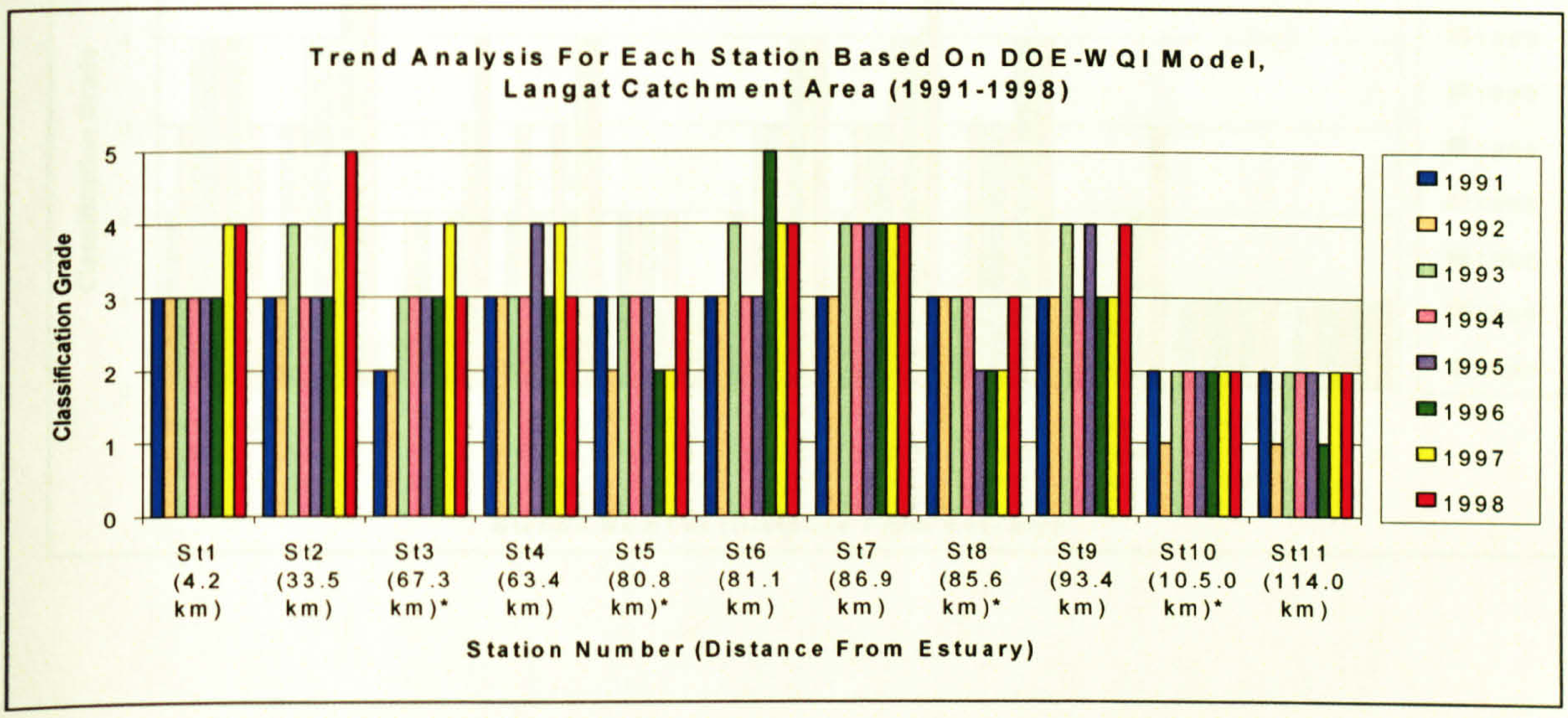
Figure 4.6

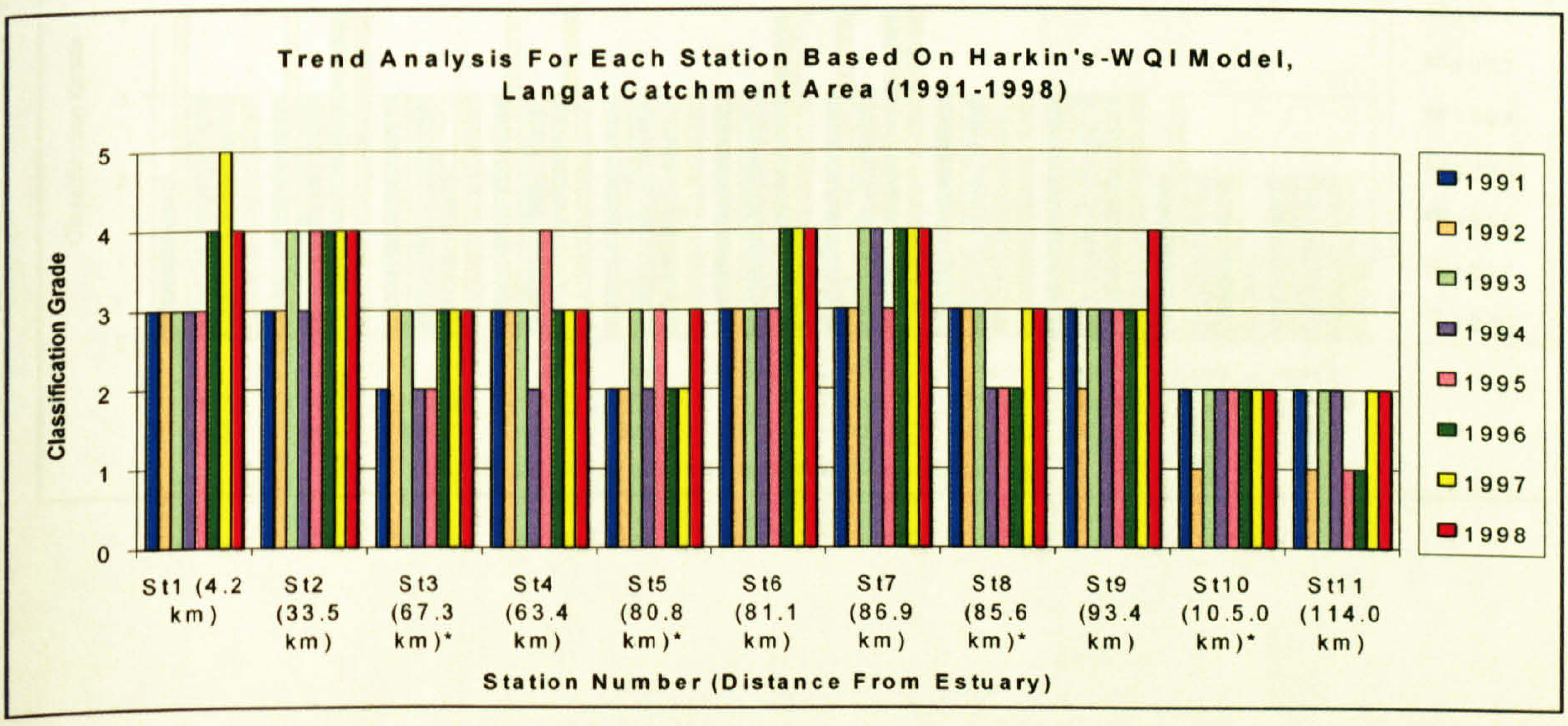
(Source: Haykin, 1999)

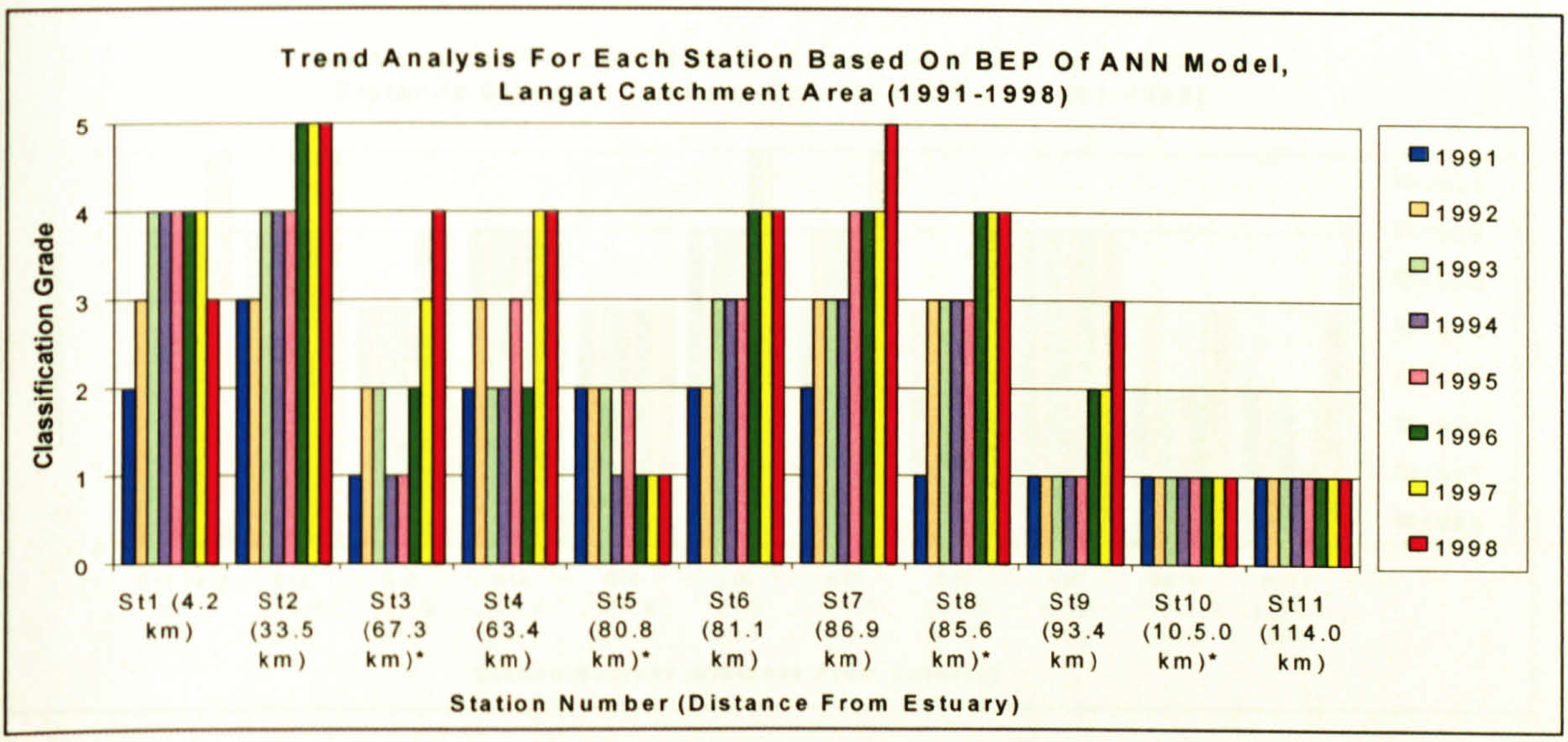
First Stage				Second Stage
X_1	X_2	Y_1	Y_2	Class
0	0	0(-)	0(-)	C_2 (0)
0	1	1(+)	0(-)	C_1 (1)
1	0	1(+)	0(-)	C_1 (1)
1	1	1(+)	1(+)	C_2 (0)

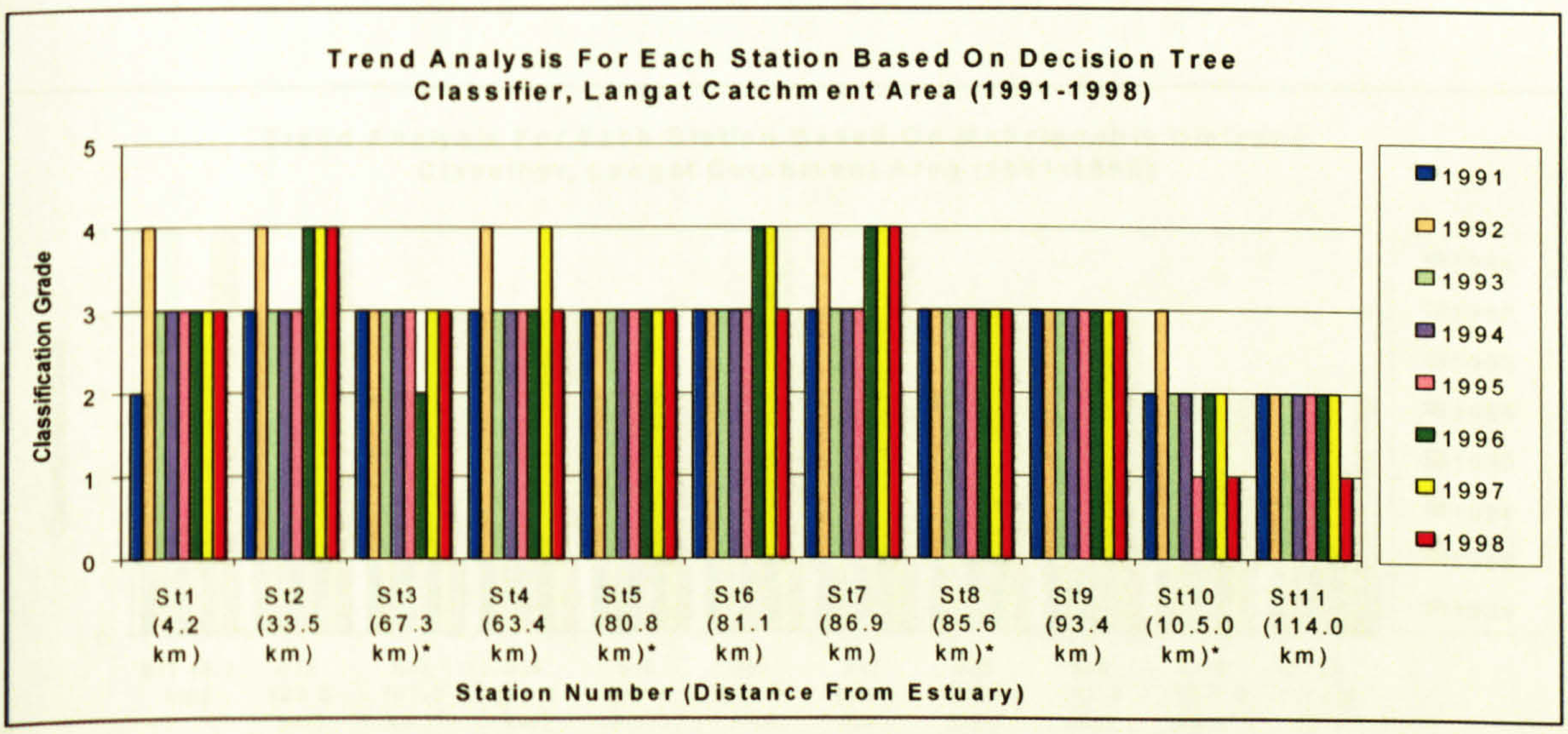
Box 4.6a Classification based on two vectors X_1 and X_2
(Sources: Pao, 1989; Graupe, 1997; Theodoridis and Koutroumbas, 1999)

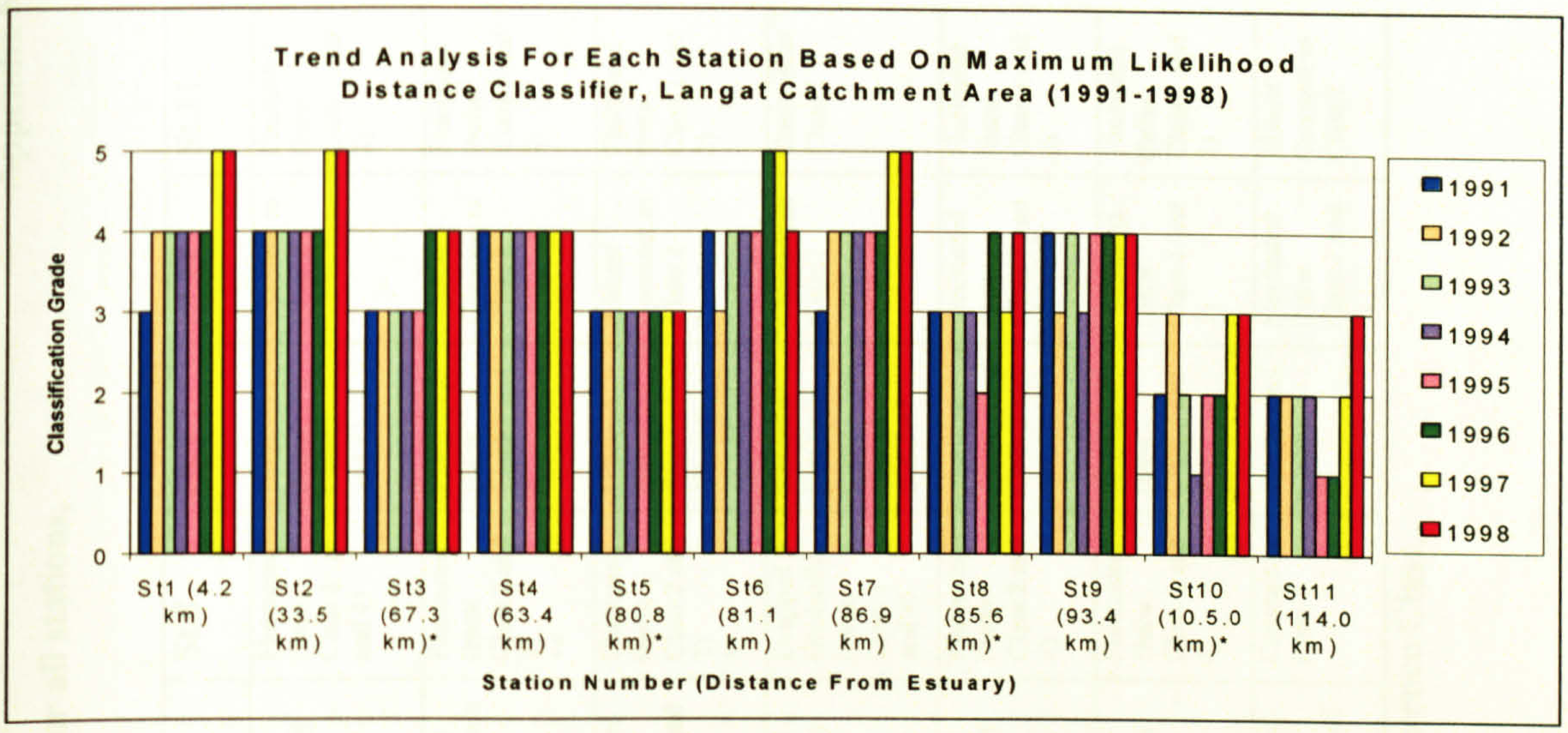
Trends analysis for the six models

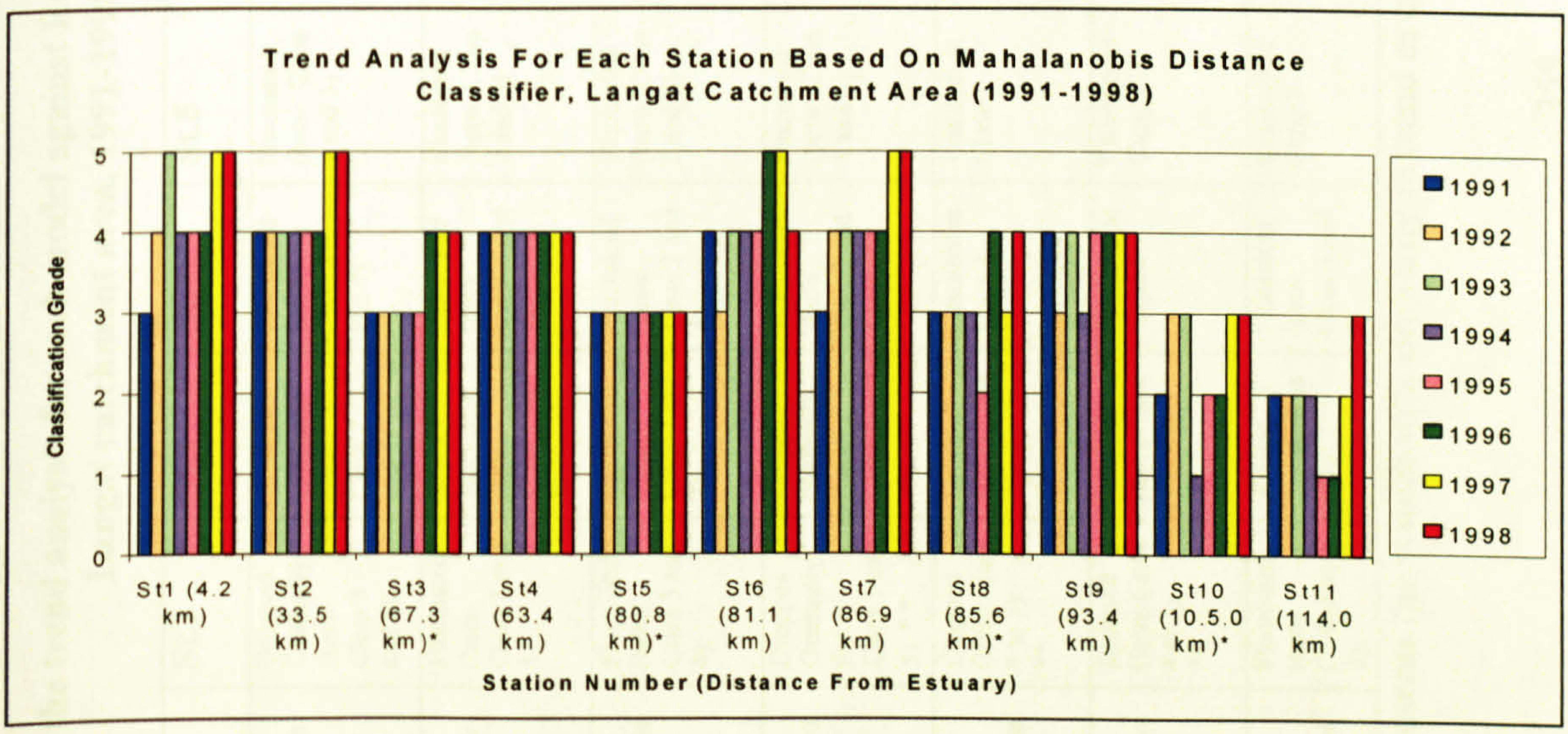





Trend Analysis For Each Station Based On BEP Of ANN Model, Langat Catchment Area (1991-1998)
Classification Grade
5
4
3
2
1
0
St1 (4.2 km)
St2 (33.5 km)
St3 (67.3 km)*
St4 (63.4 km)
St5 (80.8 km)*
St6 (81.1 km)
St7 (86.9 km)
St8 (85.6 km)*
St9 (93.4 km)
St10 (10.5.0 km)*
St11 (114.0 km)
Station Number (Distance From Estuary)
1991
1992
1993
1994
1995
1996
1997
1998


Trend Analysis For Each Station Based On Decision Tree Classifier, Langat Catchment Area (1991-1998)
Classification Grade
5
4
3
2
1
0
St1 (4.2 km)
St2 (33.5 km)
St3 (67.3 km)*
St4 (63.4 km)
St5 (80.8 km)*
St6 (81.1 km)
St7 (86.9 km)
St8 (85.6 km)*
St9 (93.4 km)
St10 (10.5.0 km)*
St11 (114.0 km)
Station Number (Distance From Estuary)
1991
1992
1993
1994
1995
1996
1997
1998


Trend Analysis For Each Station Based On Maximum Likelihood Distance Classifier, Langat Catchment Area (1991-1998)
Classification Grade
5
4
3
2
1
0
St1 (4.2 km)
St2 (33.5 km)
St3 (67.3 km)*
St4 (63.4 km)
St5 (80.8 km)*
St6 (81.1 km)
St7 (86.9 km)
St8 (85.6 km)*
St9 (93.4 km)
St10 (10.5.0 km)*
St11 (114.0 km)
Station Number (Distance From Estuary)
1991
1992
1993
1994
1995
1996
1997
1998


Trend Analysis For Each Station Based On Mahalanobis Distance Classifier, Langat Catchment Area (1991-1998)
Classification Grade
5
4
3
2
1
0
St1 (4.2 km)
St2 (33.5 km)
St3 (67.3 km)*
St4 (63.4 km)
St5 (80.8 km)*
St6 (81.1 km)
St7 (86.9 km)
St8 (85.6 km)*
St9 (93.4 km)
St10 (10.5.0 km)*
St11 (114.0 km)
Station Number (Distance From Estuary)
1991
1992
1993
1994
1995
1996
1997
1998

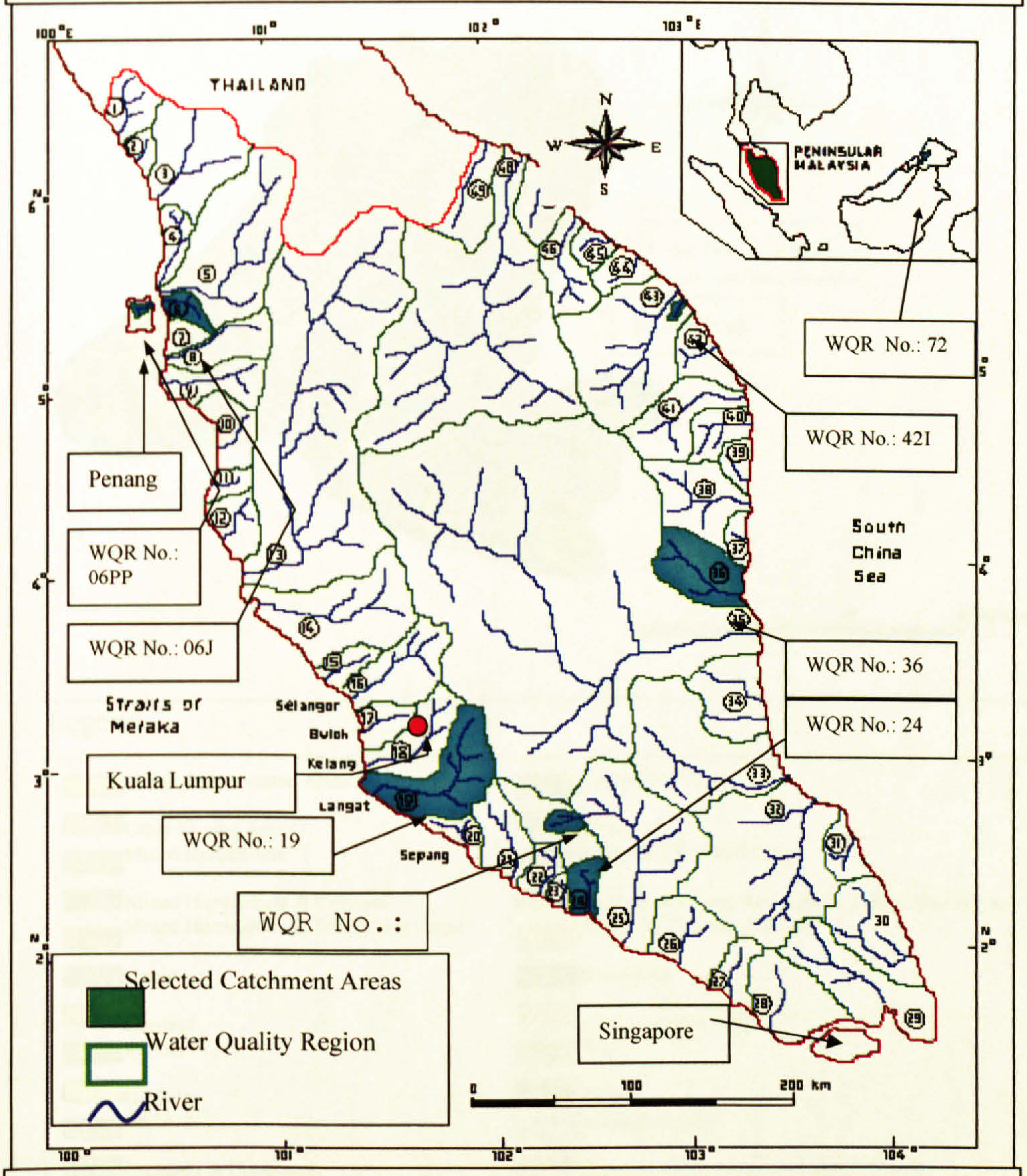
Summary of the trend analysis for each model against Reference Class for all stations, Langat catchment area, 1991-1998

Model	St.1	St.2	St.3	St.4	St.5	St.6	St.7	St.8	St.9	St.10	St.11
Reference Class	Dropped (from Class 3 to 4)	Dropped Gradually (betw. Class 3 and 5)	Dropped Gradually (from Class 2 and 4)	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 2 and 3)	Fluctuated (betw. Class 3 and 5)	Dropped Gradually (betw. Class 3 and 5)	Fluctuated (betw. Class 2 and 4)	Dropped (from Class 3 and 4)	Constant as Class 2	Fluctuated (betw. Class 1 and 2).
DOE-WQI	Dropped (from Class 3 to 4) **	Fluctuated (betw. Class 3 and 5)	Slightly Fluctuated (betw. Class 2 and 4)	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 2 and 3)	Fluctuated (betw. Class 3 and 5) **	Dropped (from Class 3 to 4)	Fluctuated (betw. Class 2 and 3) **	Fluctuated (betw. Class 3 and 4)	Almost Constant as Class 2	Fluctuated (betw. Class 1 and 2)
Harkins-WQI	Fluctuated (betw. Class 3 and 5)	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 2 and 3)	Fluctuated (betw. Class 2 and 4)	Fluctuated (betw. Class 2 and 3)	Dropped (betw. Class 3 and 4)	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 2 and 3) **	Dropped Gradually (betw. Class 2 and 4)	Almost Constant as Class 2	Fluctuated (betw. Class 1 and 2)
BEP of ANN	Fluctuated (betw. Class 2 and 4)	Dropped Gradually (betw. Class 3 and 5) **	Dropped Gradually (betw. Class 1 and 4)	Fluctuated (betw. Class2 and 4) **	Fluctuated (betw. Class 1 and 2)	Dropped Gradually (betw. Class 2 and 4)	Dropped Gradually (betw. Class 2 and 5)**	Dropped Gradually (betw. Class 1 and 4)	Dropped Gradually (betw. Class 1 and 3)**	Constant as Class 1 **	Constant as Class 1
MLDC	Dropped Gradually (betw. Class 3 and 5)	Dropped (from Class 4 to 5) **	Dropped (from Class 3 to 4) **	Constant as Class 4	Constant as Class 3	Fluctuated (betw. Class 3 and 5)	Dropped Gradually (betw. Class 3 and 5)**	Fluctuated (betw. Class 2 and 4)	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 1 and 3)	Fluctuated (betw. Class 1 and 3)
MDC	Fluctuated (betw. Class 3 and 5)	Dropped (from Class 4 to 5) **	Dropped (from Class 3 to 4) **	Constant as Class 4	Constant as Class 3	Fluctuated (betw. Class 3 and 5)	Dropped Gradually (betw. Class 3 and 5)**	Fluctuated (betw. Class 2 and 4)	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 1 and 3)	Fluctuated (betw. Class 1 and 3)
DT	Slightly Fluctuated (betw. Class 2 and 4)	Fluctuated (betw. Class 3 and 4)	Almost Constant as Class 3	Fluctuated (betw. Class 3 and 4)	Constant as Class 3	Fluctuated (betw. Class 3 and 4)	Fluctuated (betw. Class 3 and 4)	Constant as Class 3	Constant as Class 3	Fluctuated (betw. Class 1 and 3)	Almost Constant as Class 2.

Note: ** represents the station with similarity in trend as compared to Reference Class.

Appendix 6.1

The Water Quality Region showing the eight selected catchment areas



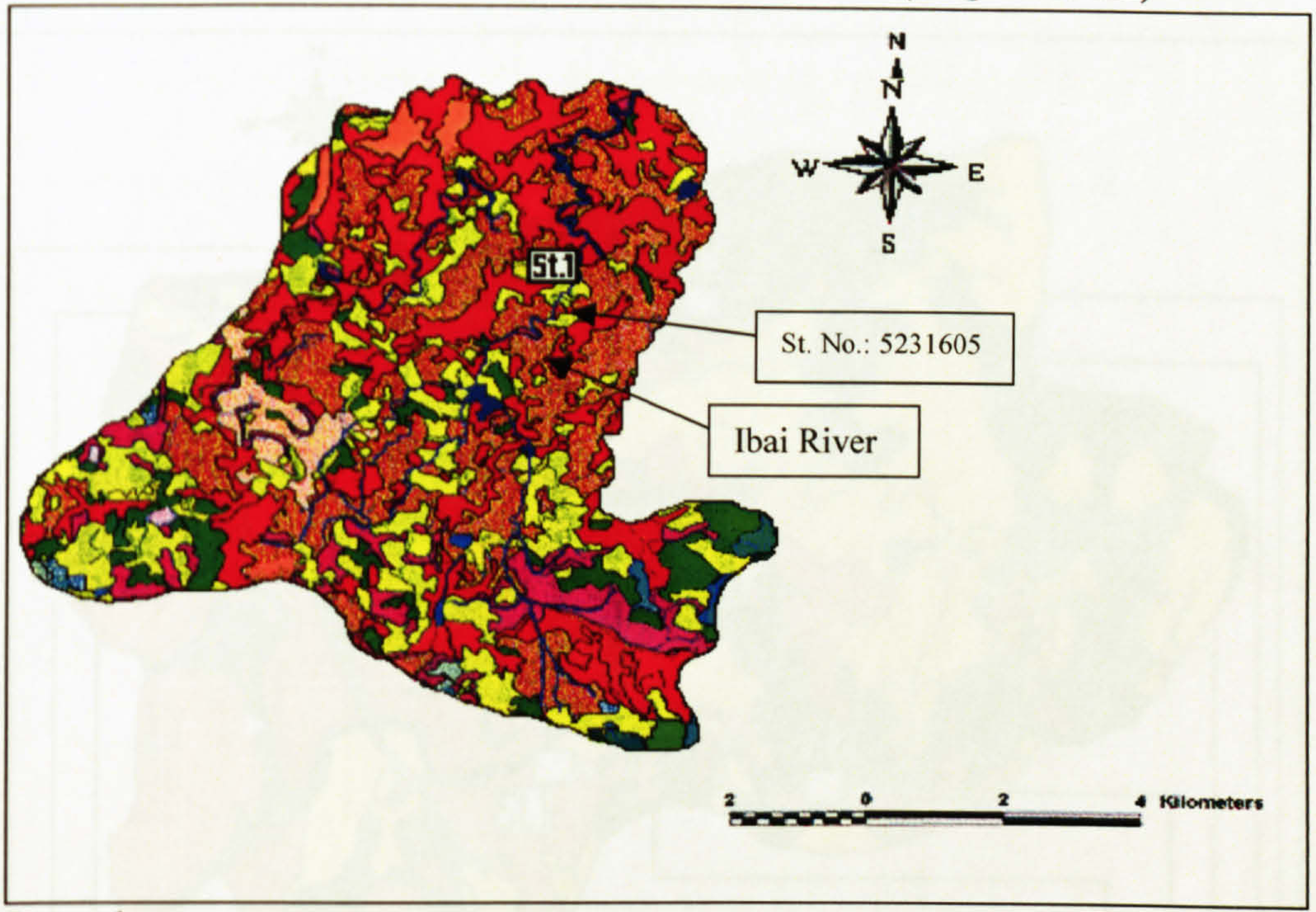
The distribution of land use of the eight selected catchment areas are as follows:

1)	WQR No.: 42I	-	Ibai Catchment Area	Appendix 6.1A
2)	WQR No.: 06J	-	Juru Catchment Area	Appendix 6.1B
3)	WQR No.: 24	-	Kesang Catchment Area	Appendix 6.1C
4)	WQR No.: 36	-	Kuantan Catchment Area	Appendix 6.1D
5)	WQR No.: 19	-	Langat Catchment Area	Figure 5.7
6)	WQR No.: 72	-	Padas Catchment Area	Appendix 6.1E
7)	WQR No.: 06PP	-	Pinang Catchment Area	Appendix 6.1F
8)	WQR No.: 35B	-	Serting Catchment Area	Appendix 6.1G

(Details see Appendix 6.2)

Appendix 6.1A

Land use distribution, Ibai catchment area (WQR No. 42I)



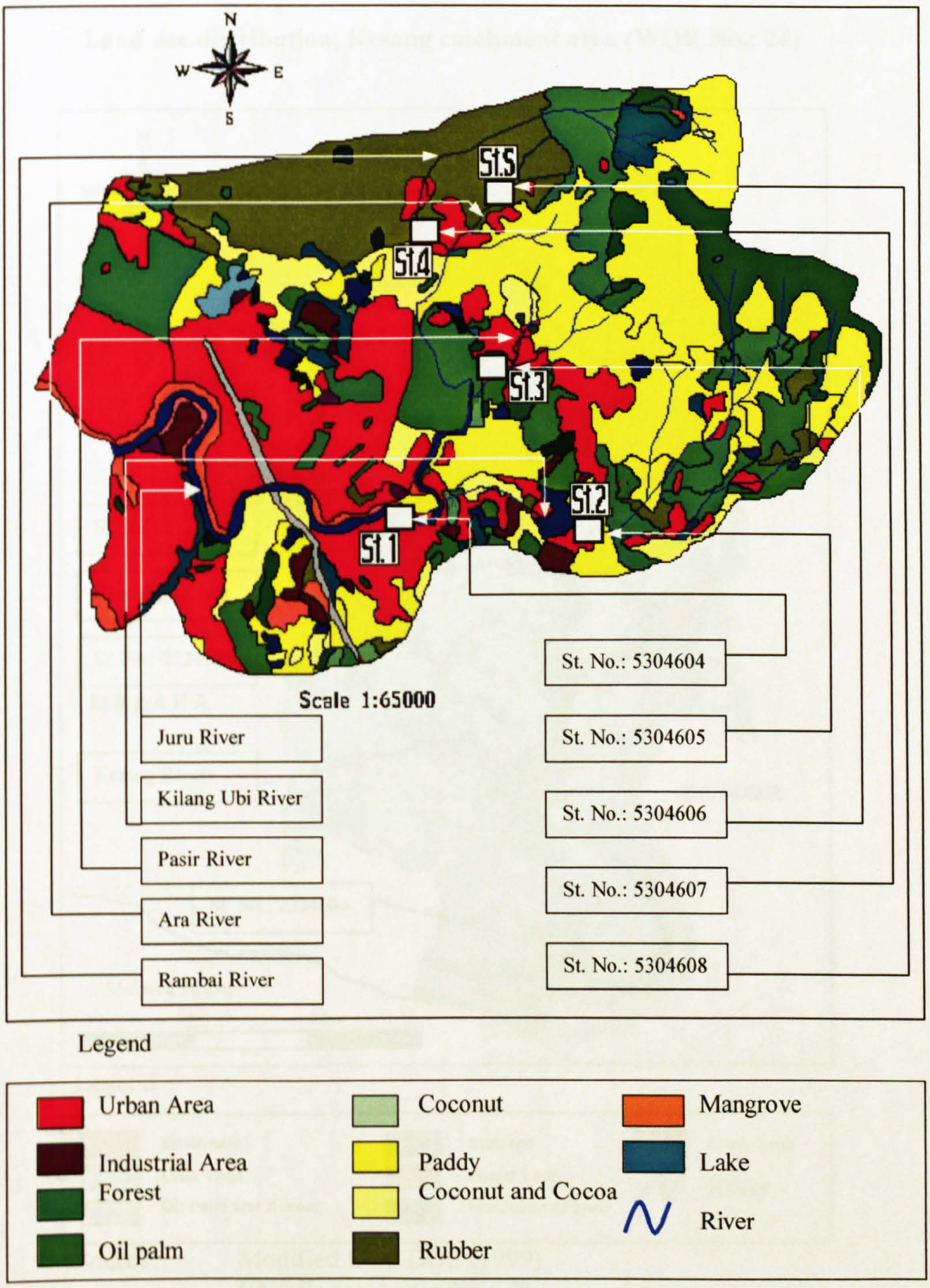
Legend

- Urban & Associated Areas
- Other Mining Areas
- Mixed Horticulture
- Mixed Horticulture & Coconut
- Mixed Horticulture & Diversified Crops
- Cocoa
- Coconut
- Rubber
- Oil Palm
- Orchards
- Orchards & Grasslands
- River
- Diversified Crops
- Paddy
- Paddy & Diversifed Crops
- Paddy & Swamps, Marshlands & Wetland Forests
- Improved Permanent Pasture
- Grasslands
- Newly Cleared Land
- Forest
- Scrub
- Scrub & Rubber
- Swamps, Marshlands & Wetland Forests
- Unused Land

Source: Modified from DOE (1994, 1999).
(Details see Appendix 6.2)

Appendix 6.1B

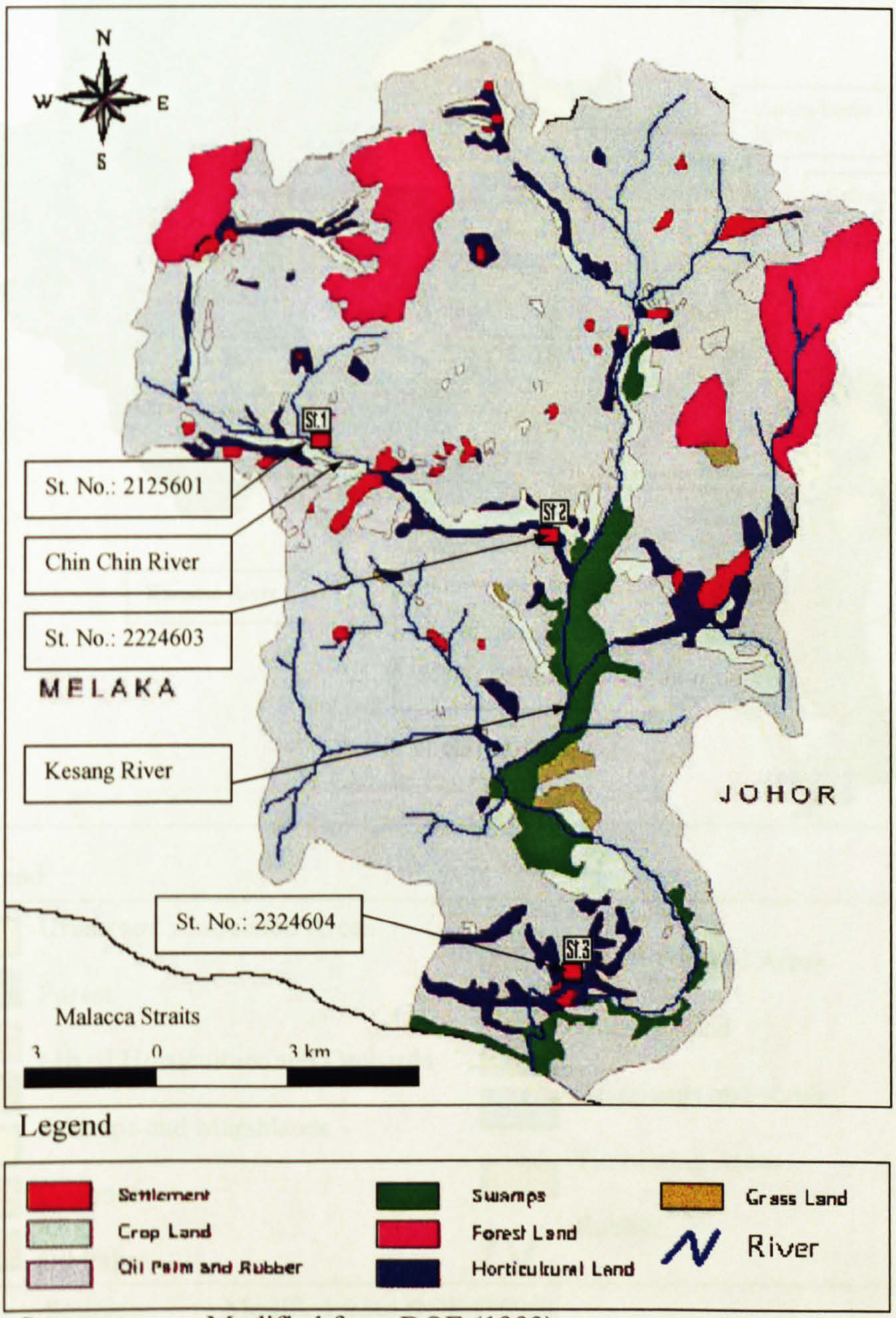
Land Use Distribution, Juru Catchment Area (WQR No.: 06J)



Sources: Modified from DOE (1994, 1999)
Details see Appendix 6.2

Appendix 6.1C

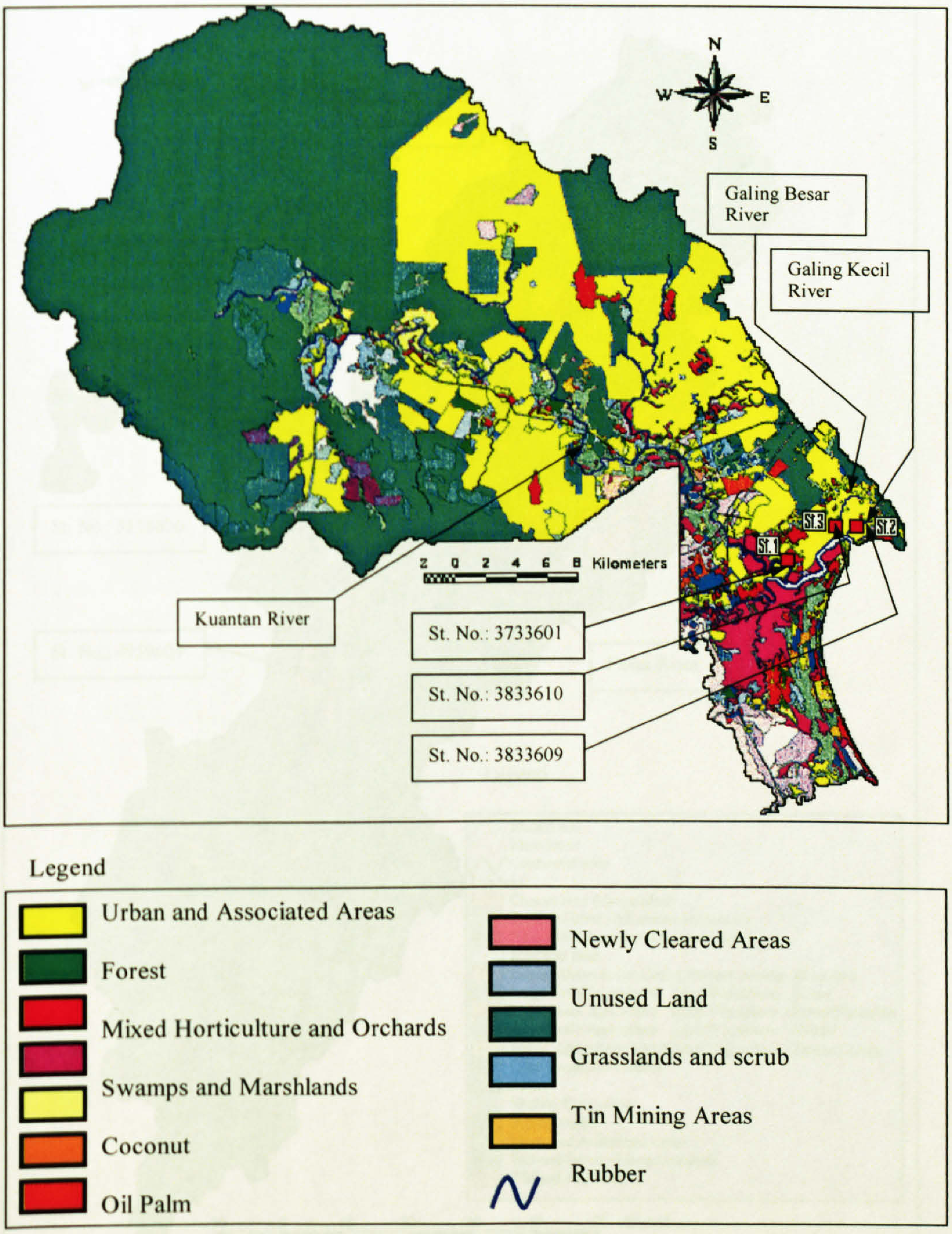
Land use distribution, Kesang catchment area (WQR No.: 24)



Source: Modified from DOE (1999)
(Details see Appendix 6.2)

Appendix 6.1D

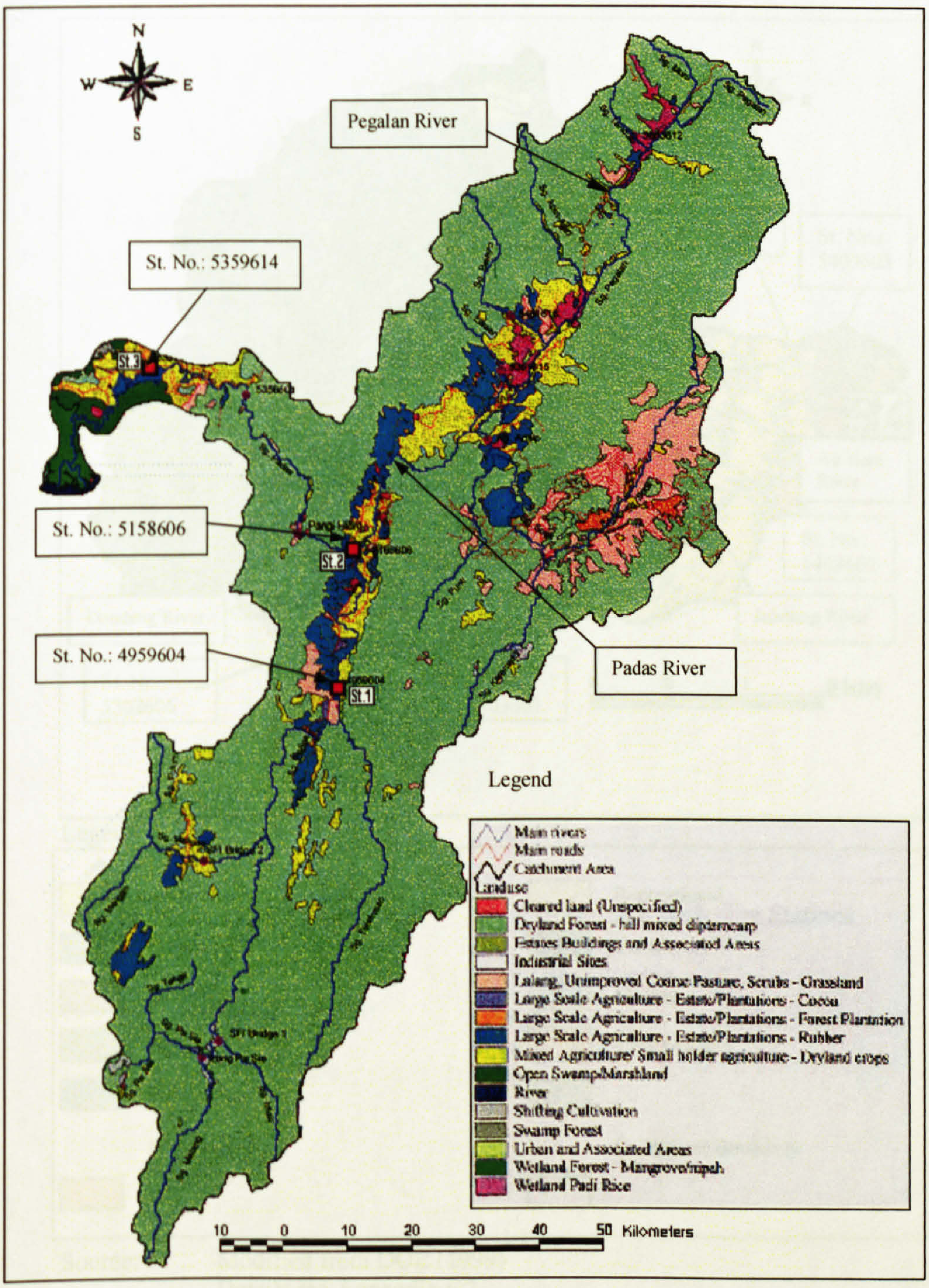
Land use distribution, Kuantan catchment area (WQR No.: 36)



Source: Modified from DOE (1999).
Details see Appendix 6.2

Appendix 6.1E

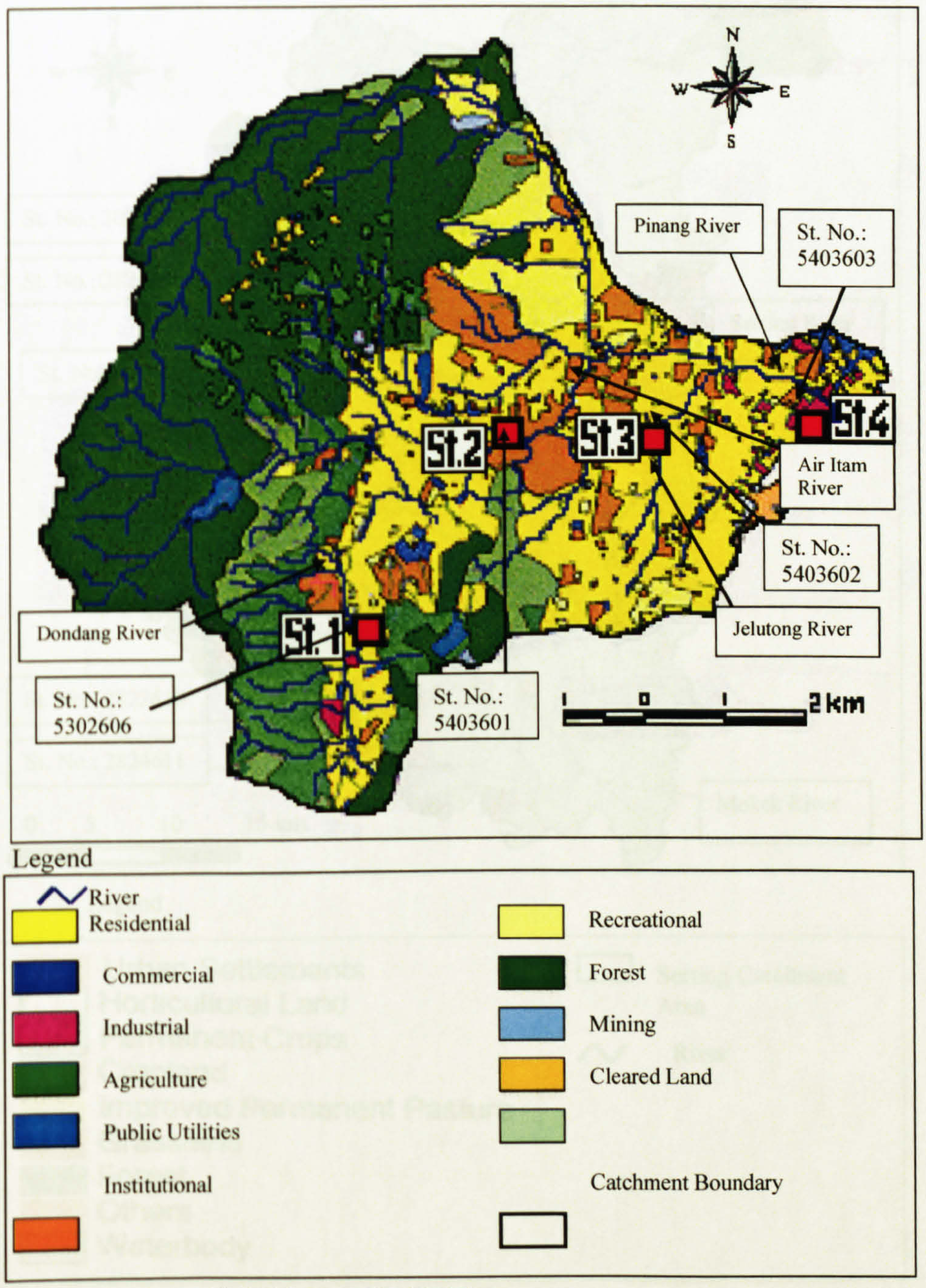
Land use distribution, Padas catchment area (WQR No.: 72)



Sources: Modified from DOE (1999)
Details see Appendix 6.2

Appendix 6.1F

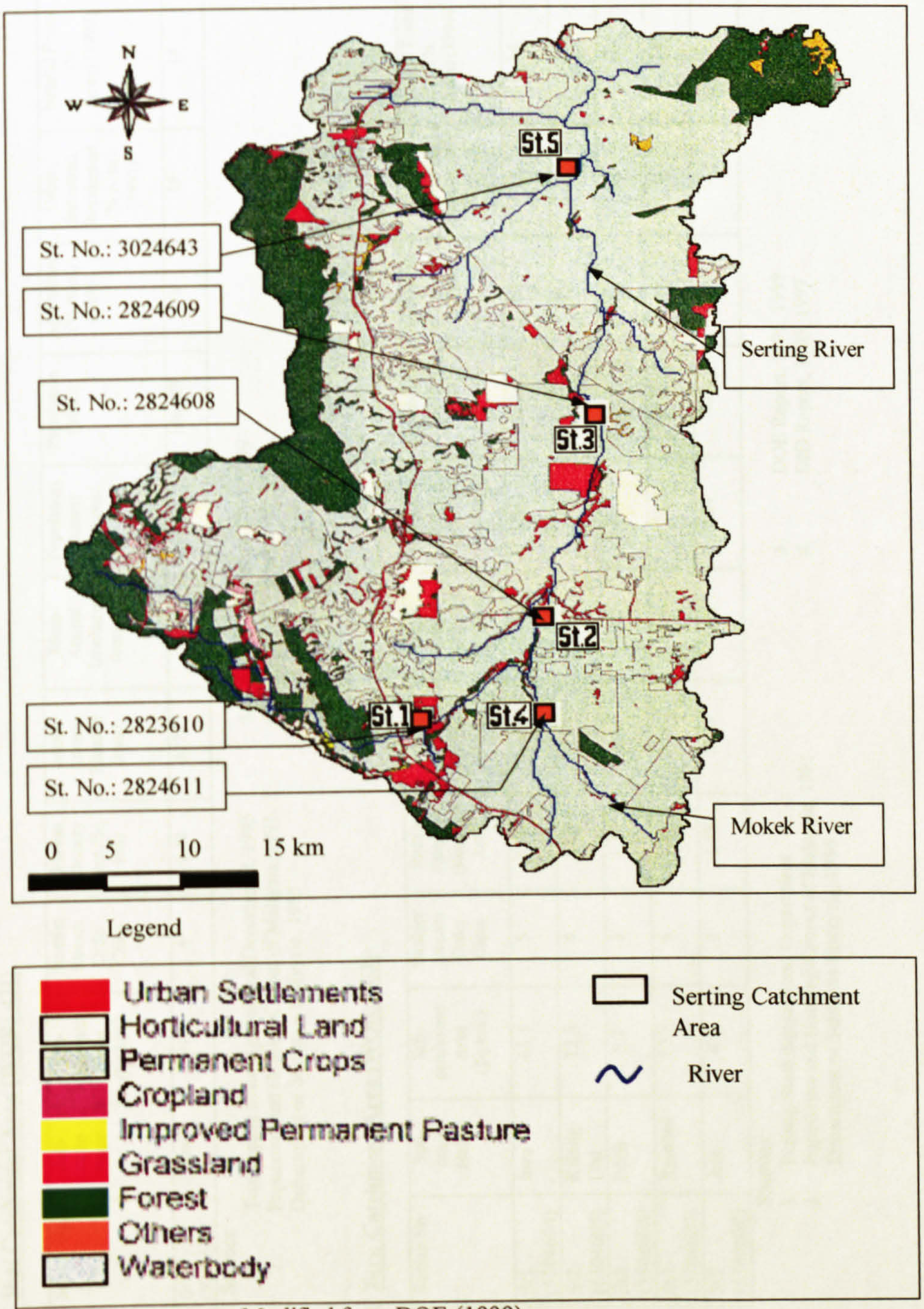
Land use distribution, Pinang catchment area (WQR No.: 06PP)



Source: Modified from DOE (1999)
Details see Appendix 6.2

Appendix 6.1G

Land use distribution, Serting catchment area (WQR No.: 35B)



Source: Modified from DOE (1999)
Details see Appendix 6.2

Appendix 6.2

The land use and hydrological features for the selected eight catchment areas

A. Ibai Catchment Area (WQR: 42I)

Station No.	Sub-basin Name	Sub-catchment Area (Sq.km.)	Strahler Stream Order Class	Stream Density (km./Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St1 (5231615)	Ibai	91	4	1.12	3125	1.76	1444	146,608	71	15	14

Sources:
1. Terengganu State Agricultural Department, 1995
2. Population and Housing Census of Malaysia, 1991 Department of Statistics Malaysia, 1995
3. DOE Report, 1995, 1999
4. DID Report, 1995, 1997

B. Juru Catchment Area (WQR: 06J)

Station No.	Sub-basin Name	Sub-catchment Area (Sq.km.)	Strahler Stream Order Class	Stream Density (km./Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (19950
St1 (5304604)	Juru	63.1	5	0.49	1844	12.56	1794	120740	61	25	14
St2 (5304605)	Kilang Ubi	12.5	4	1.68	1844	0.25	119	1585	79	8	12
St3 (5304606)	Pasir	5.3	3	1.33	1844	0.06	120	672	85	12	3
St4 (5304607)	Rambai	12.5	4	1.44	1844	0.26	151.3	2016	82	6	12
St5 (5304608)	Ara	4.0	4	1.78	1844	0.03	134	569	91	5	4

Sources:
1. Penang State Agricultural Department
2. Population and Housing Census of Malaysia, 1991 Department of Statistics Malaysia, 1995
3. DOE Report, 1995, 1999
4. DID Report, 1995, 1997

C. Kesang Catchment Area (WQR: 24)

Station No.	Sub-basin Name	Sub-catchment Area	Strahler Stream Order Class	Stream Density (km/Sq. km)	Mean Annual Rainfall (mm)[a]	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St1 (2125601)	Kesang	636.4	6	1.59	2000	21.3	172.0	118833	60	15	25
St2 (2224603)	Chin Chin	168.0	5	2.31	2000	1.61	51.2	9339	87	5	8
St3 (2324604)	Chin Chin	112.0	5	2.50	2000	1.68	135.7	16499	85	5	10

Sources:

1. Melaka State Agricultural Department
2. Johor State Agricultural Department
3. Population and Housing Census of Malaysia, 1991
   Department of Statistics Malaysia, 1995
4. DOE Report, 1999
5. DID Report, 1997
6. [a] Robiah Bani et al (1988)
7. Johor State Agricultural Information

D. Kuantan Catchment Area (WQR: 36)

Station No.	Sub-basin Name	Sub-catchment Area (Sq.km.)	Strahler Stream Order Class	Stream Density (km/Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.) (1995)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St1 (3733601)	Kuantan	1138	7	4 97	3000	15	226.8	289174	28	21	51
St2 (3833609)	Galing Kecil	25	5	2.24	3000	0.28	226.8	6338	3	86	11
St3 (3833610)	Galing Besar	37.5	5	2.39	3000	0.44	1636	9529	8	88	4

Sources:

1. Kuantan Structure Plan
2. Population and Housing Census of Malaysia, 1991
   Department of Statistics Malaysia, 1995
3. DOE Water Quality Report 1999
4. DID Report, 1997

E. Langat Catchment Area (WQR: 19)

Station No.	Sub-basin Name	Sub-catchment Area	Strahler Stream Order Class	Stream Density (km./Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.) (1995)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St3 (2817616)	Batang Labu	241.8	4	3.19	2455	3.41	70.5	18909	82	5	13
St5 (2817648)	Semenyih	577.3	6	2.93	2565	3.62	144.5	92529	41	15	44
St9 (3017612)	Middle Langat	273.3	6	3.32	2675	6.36	292.5	88670	45	20	35
St10 (3118645)	Lui	101.5	5	2.38	2565	1.74	23.6	2657	12	3	85
St11 (3118647)	Upper Langat	215.3	5	3.23	2675	2.51	7.4	1767	8	2	90

Sources:

1. Hulu Langat District Structure Plan
2. Seremban District Structure Plan
3. Population Census 1991
4. DID Report 1997
5. Selangor State Agriculture Department
6. Negeri Sembilan State Agriculture Department
7. DOE Water Quality Report 1998/99

F. Padas Catchment Area (WQR: 72)

Station No.	Sub-basin Name	Sub-catchment Area (sq. km)	Strahler Stream Order Class	Stream Density (km./Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.) (1995)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St1 (4959604)	Kemabong	3139.1	5	0.64	2250	327.7	2.0	7135	8	4	88
St2 (5158606)	Tenom	7945.4	6	0.53	2250	327.7	5.6	50565	12	8	80
St3 (5359614)	Beaufort	8482.0	6	0.54	2250	327.7	5.7	54944	12	9	79

Sources:

1. DOE Report, Sungai Padas, 1999
2. Population and Housing Census of Malaysia, 1991 (Sabah), Department of Statistics Malaysia, 1995.
3. DID Report, 1997

G. Pinang Catchment Area (WQR: 06PP)

Station No.	Sub-basin Name	Sub-catchment Area (Sq.km.)	Strahler Stream Order Class	Stream Density (km./Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.) (1995)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St1 (5302606)	Dondang	4.7	3	1.91	2200	0.02	3799.1	19005	63	29	8
St2 (5403601)	Air Itam	14.5	5	2.31	2200	0.28	2078.8	32172	14	33	53
St3 (5403602)	Jelutong	5.9	5	0.53	2200	0.08	7421.9	46389	1	99	0
St4 (5403603)	Pinang	51.0	6	0.81	2200	3.5	7421.9	403439	11	48	41

Sources:

1. Penang State Agricultural Department
2. Population and Housing Census of Malaysia, 1991
   Department of Statistics Malaysia, 1995
3. DOE Report, 1999
4. DID Report, 1997
5. Penang State Agricultural Information

H. Serting Catchment Area (WQR: 35)

Station No.	Sub-basin Name	Sub-catchment Area (Sq km.)	Strahler Stream Order Class	Stream Density (km./Sq. km)	Mean Annual Rainfall (mm)	Mean Annual Discharge (cumec)	Population Density (persons/ Sq. km.) (1995)	Population (1995)	Agriculture (% Area) (1995)	Urban, Industrial, Residential (% Area) (1995)	Natural Forest (% Area) (1995)
St1 (2823610)	Serting	129.3	5	3.64	1875	1.67	146	20394	15	12	73
St2 (2824608)	Serting	261.3	5	2.00	1875	7.21	235	66338	50	15	35
St3 (2824609)	Serting	572.5	6	2.18	1875	30.40	210	129880	62	12	26
St4 (2824611)	Mokek	45.4	4	1.41	1875	0.63	260	12752	52	8	40
St5 (3024643)	Serting	838.4	6	1.13	1875	35.11	211	191109	64	9	27

Sources:

1. Negeri Sembilan State Agricultural Department
2. Population and Housing Census of Malaysia, 1991
   Department of Statistics Malaysia, 1995
3. DOE Report, 1999
4. DID Report, 1997
5. Negeri Sembilan State Agricultural Information

Appendix 6.3

The water quality sampling frequency for the eight catchment areas

Catchment	WQR	St. No.	River	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
1. Ibai	421	1. 5231605 (St1)	Ibai	-	4	4	4	3	3	2	4	4	4
2. Juru	06J	2. 5304604(St1)	Juru	6	6	6	4	5	6	6	6	6	6
		3. 5304605(St2)	Kiland Ubi	6	5	6	4	5	6	6	6	6	6
		4. 5304606(St3)	Pasir	6	5	6	4	5	6	6	6	6	6
		5. 5304607(St4)	Rambai	6	5	6	4	5	6	6	6	6	6
		6. 5304608(St5)	Ara	6	5	6	4	5	6	6	6	6	6
3. Kesang	24	7. 2125601(St1)	Kesang	3	4	5	5	4	4	3	4	4	4
		8. 2224603(St2)	Chin Chin	3	4	5	4	4	4	3	4	4	4
		9. 2324604(St3)	Chin Chin	3	4	5	5	4	4	3	4	4	4
4.Kuantan	36	10. 3733601(St1)	Kuantan	3	4	5	5	4	3	3	5	5	5
		11. 3833609(St2)	Galing Kecil	3	4	5	5	4	4	3	5	5	5
		12. 3833610(St3)	Galing Besar	3	4	5	5	4	4	3	5	5	5
5. Langat	19	13. 2817616(St3)	Batang Labu	-	5	6	6	5	3	3	4	3	5
		14. 2817648(St5)	Semenyih	-	5	6	6	5	3	3	4	3	5
		15. 3017612(St9)	Langat	-	5	6	6	4	3	3	4	3	5
		16. 3118645(St10)	Lui	-	5	3	6	4	3	3	4	3	5
		17. 3118647(St11)	Langat	-	5	5	6	4	3	3	4	3	3
6. Padas	72	18. 4959604(St1)	Padas	5	3	5	6	5	4	5	6	7	6
		19. 5158606(St2)	Pegalan	5	3	5	6	5	4	5	6	7	6
		20. 5359614(St3)	Padas	5	3	5	5	6	5	5	5	6	6
7. Pinang	06PP	21. 5302606(St1)	Dondang	-	-	-	6	4	6	5	6	6	6
		22. 5403601(St2)	Air Itam	-	-	-	5	4	6	5	6	6	6
		23. 5403602(St3)	Jelutong	-	-	-	5	4	6	5	6	6	6
		24. 5403603(St4)	Pinang	-	-	-	5	4	6	5	6	6	6
8. Serting	35	25. 2823610(St1)	Serting	4	4	5	4	1	2	3	3	4	3
		26. 2824608(St2)	Serting	4	4	5	5	1	2	3	3	3	3
		27. 2824609(St3)	Serting	4	4	4	4	1	3	3	3	3	3
		28. 2824611(St4)	Mokek	4	4	5	4	1	3	3	3	4	3
		29. 3024643(St5)	Serting	5	4	5	4	2	3	3	5	5	3

Source: Data were supplied by the DOE, Malaysia

Notes: - not monitored

Appendix 6.4

The classification results based on the DOE-WQI and the BEP of ANN model for the eight catchment areas

Catchment Name	No. of Sub-Catchment	Station No.	DOE-WQI Classification										BEP of ANN Classification									
			1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
(A) Ibai	1	5231605(St1)	-	4	3	3	3	3	3	3	3	3	-	4	2	2	3	4	2	3	3	4
(B) Juru	2	5304604(St1)	4	4	4	4	3	4	4	4	4	4	4	4	4	3	3	4	4	3	4	4
	3	5304605(St2)	4	4	4	4	4	4	4	4	4	4	4	5	4	5	4	4	5	5	4	5
	4	5304606(St3)	4	4	4	5	4	4	4	5	4	4	4	5	5	5	4	5	5	5	4	5
	5	5304607(St4)	4	4	4	5	4	4	4	4	4	4	4	5	5	5	4	4	5	5	4	5
	6	5304608(St5)	4	4	5	5	5	4	5	4	4	4	4	5	5	4	5	5	5	5	4	4
(C) Kesang	7	2125601(St1)	2	3	3	2	2	2	3	3	3	3	3	3	3	2	2	2	2	4	2	3
	8	2224603(St2)	2	2	2	3	2	2	3	3	3	3	1	2	2	2	2	3	1	3	3	2
	9	2324604(St3)	2	3	2	2	2	3	3	3	2	2	1	3	2	2	1	3	1	3	3	1
(D) Kuantan	10	3733601(St1)	2	2	2	3	2	3	2	3	3	2	2	2	2	2	2	2	2	4	2	2
	11	3833609(St2)	2	3	3	3	2	3	2	4	4	3	3	4	3	3	3	4	4	3	5	4
	12	3833610(St3)	3	2	3	3	3	3	3	4	4	4	4	3	4	4	4	5	5	3	5	4
(E) Langat	13	2817616(St3)	-	2	2	3	2	2	3	3	4	3	-	1	2	2	2	2	2	2	4	3
	14	2817648(St5)	-	2	2	3	2	3	2	2	3	2	-	2	2	2	2	2	2	2	2	1
	15	3017612(St9)	-	3	3	3	3	3	3	3	4	3	-	2	2	2	2	2	1	2	3	1
	16	3118645(St10)	-	2	1	2	2	2	2	2	2	2	-	1	1	2	1	1	1	2	2	1
	17	3118647(St11)	-	2	1	2	2	2	1	2	2	1	-	1	1	1	1	1	1	1	1	1
(F) Padas	18	4959604(St1)	2	2	2	2	2	2	2	2	2	3	1	1	1	1	2	1	2	2	1	1
	19	5158606(St2)	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	2	2	1	1
	20	5359614(St3)	2	2	2	2	2	2	2	2	2	3	1	1	1	1	1	1	1	1	2	1
(G) Pinang	21	5302606(St1)	-	-	-	5	5	5	4	4	3	4	-	-	-	5	5	5	4	3	3	3
	22	5403601(St2)	-	-	-	4	4	4	4	4	4	4	-	-	-	5	5	5	5	5	4	5
	23	5403602(St3)	-	-	-	5	5	5	4	5	5	5	-	-	-	5	5	5	5	5	5	5
	24	5403603(St4)	-	-	-	5	4	4	5	4	4	4	-	-	-	5	4	5	5	4	5	5
(H) Serting	25	2823610(St1)	3	3	3	4	3	3	3	3	3	3	5	4	4	4	3	2	4	4	3	3
	26	2824608(St2)	2	3	3	3	3	2	3	3	3	3	4	4	3	2	2	1	3	3	3	2
	27	2824609(St3)	3	3	3	3	3	2	3	3	2	3	4	4	3	2	3	1	3	2	2	2
	28	2824611(St4)	3	3	3	3	3	2	3	3	3	3	4	4	4	3	3	2	3	4	3	2
	29	3024643(St5)	3	3	2	2	2	2	2	2	3	3	3	3	3	3	3	3	2	3	4	3

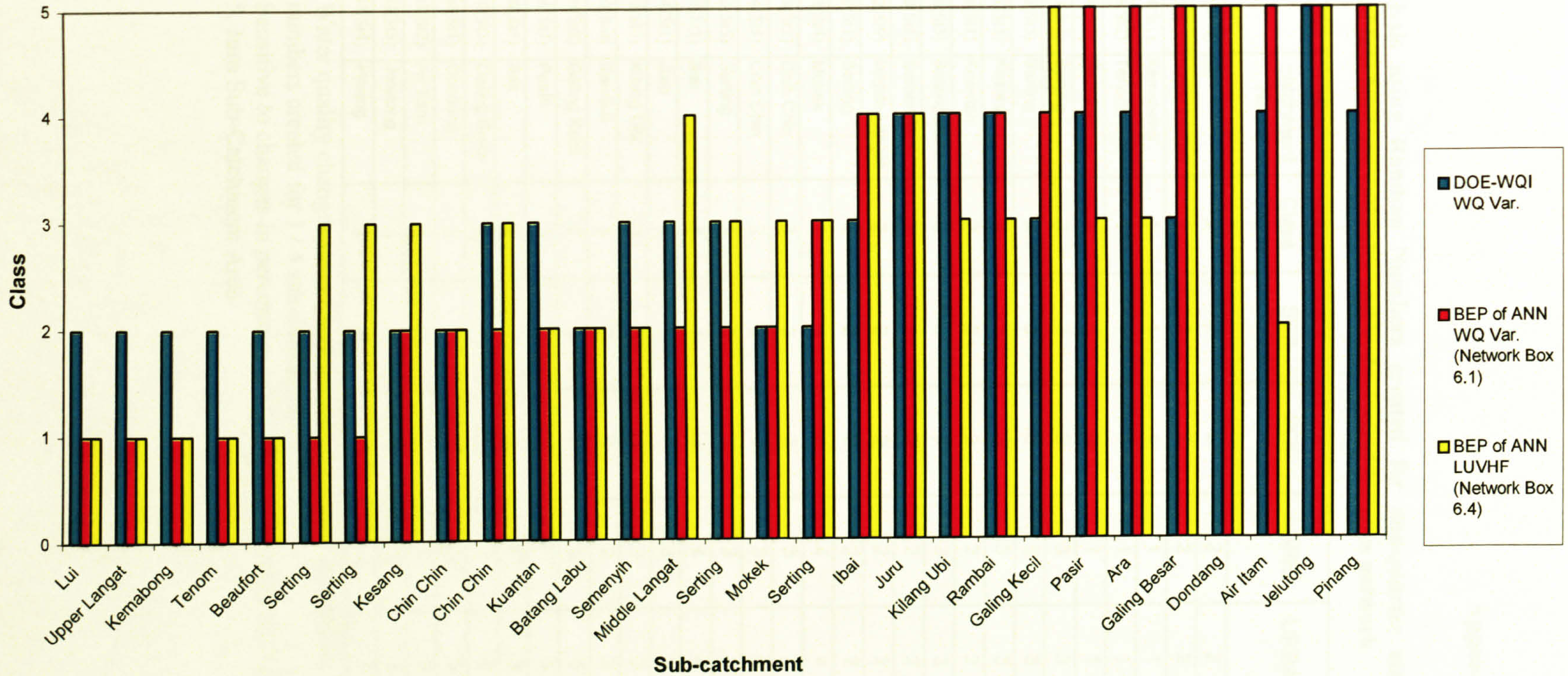
Appendix 6.5

The water quality classification results based on the DOE-WQI and the BEP Of ANN model

River Basin	Station No.	Sub-catchment Name	Sub-catchment Area(Sq.km)	Strahler Stream Order	Stream Density	Mean Ann. Rainfall(mm)	Mean Ann. Disch. (Cu.)	Pop. Density (1995)	Population (1995)	Agric. (% Area, 1995)	Urban, Ind., Res.(% Area, 1995)	Natural Forest (%Area, 1995)	Water DOE-WQI	Quality BEP of ANN
Ibai	5231605(St1)	Ibai	91	4	1.12	3125	1.76	1444	146608	71	15	14	3	4
Juru	5304604(St1)	Juru	63.1	5	0.49	1843.9	12.56	1794	120740	61	25	14	4	4
Juru	5304605(St2)	Kilang Ubi	12.49	4	1.68	1843.9	0.25	119	1585	79	8	12	4	4
Juru	5304606(St3)	Pasir	5.25	3	1.33	1843.9	0.055	120	672	85	12	3	4	5
Juru	5304607(St4)	Rambai	12.49	4	1.44	1843.9	0.26	151.3	2016	82	6	12	4	4
Juru	5304608(St5)	Ara	3.98	4	1.78	1843.9	0.031	134	569	91	5	4	4	5
Kesang	2125601(St1)	Kesang	636.4	6	1.59	2000	21.3	172	118833	60	15	25	2	2
Kesang	2224603(St2)	Chin Chin	168	5	2.31	2000	1.607	51.2	9339	87	5	8	2	3
Kesang	2324604(St3)	Chin Chin	112	5	2.5	2000	1.677	135.7	16499	85	5	10	3	3
Kuantan	3733601(St1)	Kuantan	1138	7	4.97	3000	15	226.8	289174	28	21	51	3	2
Kuantan	3833609(St2)	Galing Kecil	24.9	5	2.24	3000	0.28	226.8	6338	3	86	11	3	4
Kuantan	3833610(St3)	Galing Besar	37.5	5	2.39	3000	0.44	1636	9529	8	88	4	3	5
Langat	2817616(St3)	Batang Labu	241.8	4	3.19	2455	3.414	70.5	18909	82	5	13	2	2
Langat	2817648(St5)	Semenyih	577.3	6	2.93	2565	3.616	144.5	92529	41	15	44	3	2
Langat	3017612(St9)	Middle Langat	273.3	6	3.32	2675	6.364	292.5	88670	45	20	35	3	2
Langat	3118645(St10)	Lui	101.5	5	2.38	2565	1.736	23.6	2657	12	3	85	2	1
Langat	3118647(St11)	Upper Langat	215.3	5	3.23	2675	2.513	7.4	1767	8	2	90	2	1
Padas	4959604(St1)	Kemabong	3139.1	5	0.636	2250	327.7	2.0	7135	8	4	88	2	1
Padas	5158606(St2)	Tenom	7945.4	6	0.531	2250	327.7	5.6	50565	12	8	80	2	1
Padas	5359614(St3)	Beaufort	8482	6	0.544	2250	327.7	5.7	54944	12	9	79	2	1
Pinang	5302606(St1)	Dondang	4.69	3	1.91	2200	0.02	3799.12	19005	63	29	8	5	5
Pinang	5403601(St2)	Air Itam	14.51	5	2.31	2200	0.28	2078.8	32172	14	33	53	4	5
Pinang	5403602(St3)	Jelutong	5.86	5	0.53	2200	0.076	7421.9	46389	1	99	0	5	5
Pinang	5403603(St4)	Pinang	50.97	6	0.81	2200	3.495	7421.9	403439	11	48	41	4	5
Serting	2823610(St1)	Serting	129.3	5	3.64	1875	1.674	146	20394	15	12	73	3	2
Serting	2824608(St2)	Serting	261.3	5	2	1875	7.209	235	66338	50	15	35	2	1
Serting	2824609(St3)	Serting	572.5	6	2.18	1875	30.401	210	129880	62	12	26	2	1
Serting	2824611(St4)	Mokek	45.4	4	1.41	1875	0.629	260	12752	52	8	40	2	2
Serting	3024643(St5)	Serting	838.4	6	1.13	1875	35.113	211	191109	64	9	27	2	3

Appendix 6.6

Trend analysis for Table 6.11



Appendix 6.7

Sensitivity analysis using Random Numbers created for one-quarter standard deviation applied into land use variables and hydrological features network

River Basin	Station No.	Sub-catchment Name	Original Class Grade	SCA	POP	AGRIC	URBAN	FOR
Langat	3118645(St10)	Lui	2	2	2	2	2	2
Langat	3118647(St11)	Upper Langat	2	2	2	2	2	2
Padas	4959604(St1)	Kemabong	1	1	1	1	1	1
Padas	5158606(St2)	Tenom	1	1	1	1	1	1
Padas	5359614(St3)	Beaufort	1	1	1	1	1	1
Serting	2824608(St2)	Serting	3	3	3	3	3	3
Serting	2824609(St3)	Serting	3	3	3	3	3	3
Kesang	2125601(St1)	Kesang	3	3	3	3	3	3
Kuantan	3733601(St1)	Kuantan	2	2	2	2	2	2
Langat	2817616(St3)	Batang Labu	3	3	3	3	3	3
Langat	2817648(St5)	Semenyih	2	2	2	2	2	2
Langat	3017612(St9)	Middle Langat	2	2	2	2	2	2
Serting	2823610(St1)	Serting	2	2	2	2	2	2
Serting	2824611(St4)	Mokek	4	4	4	4	4	4
Kesang	2224603(St2)	Chin Chin	3	3	3	3	3	3
Kesang	2324604(St3)	Chin Chin	3	3	3	3	3	3
Serting	3024643(St5)	Serting	3	3	3	3	3	3
Ibai	5231605(St1)	Ibai	4	4	4	4	4	4
Juru	5304604(St1)	Juru	3	3	3	3	3	3
Juru	5304605(St2)	Kilang Ubi	3	3	3	3	3	3
Juru	5304607(St4)	Rambai	3	3	3	3	3	3
Kuantan	3833609(St2)	Galing Kecil	5	5	5	5	5	5
Juru	5304606(St3)	Pasir	3	3	3	4**	3	3
Juru	5304608(St5)	Ara	3	3	3	4**	3	3
Kuantan	3833610(St3)	Galing Besar	5	5	5	5	5	5
Pinang	5302606(St1)	Dondang	5	5	5	5	5	5
Pinang	5403601(St2)	Air Itam	2	2	2	2	2	2
Pinang	5403602(St3)	Jelutong	5	5	5	5	5	5
Pinang	5403603(St4)	Pinang	5	5	5	5	5	5

Note: ** Water quality changes from Class 3 to Class 4 based on random numbers created for 1 / 4 standard deviation.
Sensitive to changes in percentage of Agriculture area for St. 3 and St. 5, Juru Sub-Catchment Area.

Appendix 7.1

The summary of the research methodology