# AN EVALUATION OF KEY PERFORMANCE INDICATORS FOR BEEF HERDS

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## Abstract

Key performance indicators (KPIs) can be used to monitor progress towards predefined targets. They are used widely across many industries, and although their use in the beef sector currently lags that in the dairy, pork and poultry sectors, it is growing with farmer appetite for data driven decision making. There is limited evidence behind many of the commonly suggested metrics however, and although they have typically been developed through evaluation of expert opinion, analysis of the associations between these metrics and overall enterprise success is lacking. There are several reasons for this; data can be more challenging to capture in more extensive systems (typical of beef suckler enterprises especially). Small herd sizes and a long production cycle also limits the quantity of data available, and the diversity of the sector presents challenges around data continuity. Beef enterprises may operate under tighter margins than other livestock enterprise types, so there may also be a financial barrier to data capture and analysis. Farmers are often unsure of how to make the best use of their data, so in addition to improving recording, there is also substantial value that could be added by making the best use of whatever data is available (such as legally required movement data).

This project used a combination of focus group discussion and a questionnaire to evaluate farmer and adviser opinion around performance metrics for beef herds. Six focus group meetings were held over 18 months and 140 responses from UK beef farms, including 107 suckler farms, were collected by questionnaire survey. This led to the development of a KPI 'toolkit' with calculation methods and definitions. In order to demonstrate the value of the metrics, regression analysis was carried out using data from a single beef finishing unit in the East Midlands. The dataset contained 16,248 animal records from 2010 to 2016. Predictors of daily liveweight gain (DLWG) and antibiotic treatments were investigated. Predictors of DLWG included purchase price, month of purchase, source of purchase, breed and age of animal, and whether the animals had been given any antibiotic treatments. Predictors of antibiotic treatment included age at purchase and weight for age at purchase.

Linear regression analysis of an AHDB Stocktake dataset containing 56 suckler and 36 grower/finisher farms between 2013 and 2015 was used to evaluate the associations between performance metrics in the KPI toolkit, and overall enterprise success (defined as net margin per cow bred for suckler herds and net margin per head of output for grower or finisher herds). Metrics such as age at first calving, scanning percentage, weaning weight and mortality rate were found to be significantly associated with net margin per cow bred in suckler units. In contrast, only financial metrics, such as feed cost per head, were found to be significantly associated with net margin per head of output in grower or finisher herds.

To further investigate the relationships between metrics and enterprise success, a stochastic simulation model was developed representing a suckler herd. This was used to generate data from 10,000 herds of 200 suckler cows which could then be analysed using multiple regression. The results of this were used to further influence the

structure of the KPI toolkit, and to provide example effect sizes for changes in performance. For example, a change in weaning weight per cow bred from the median (227kg) to the upper quartile (246kg) was associated with an increased net margin per cow bred of £19.96. Relationships between performance indicators and enterprise success such as these could be used to further assist beef farmers with data driven decision making.

A mixed methods approach has been used to evaluate KPIs for monitoring beef herd performance. Focus group discussions and surveys have been combined with both real herd data and simulated data, with the aim of evaluating not only what is possible to monitor and record on a regular basis, but also what is practical and useful. The close involvement of stakeholders has helped to ensure that outcomes are relevant to the beef industry and has facilitated knowledge transfer.

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# Chapter 1: Literature review

## 1.1 Introduction

Key performance indicators (KPIs) are used widely across many industries to inform decision-making and monitor efficiency of production. Financial margins in the beef industry are narrow, meaning that efficient production is important in achieving economic sustainability (AHDB Beef and Lamb, 2015). Increasing uncertainty over the future of subsidies in the UK agricultural sector places further emphasis on production efficiency, especially in the beef sector where subsidy has often been a key source of income (Riddell, 2005). In addition to financial pressures, there is increased interest in improving efficiency in order to reduce the environmental impact of farming, as with a growing world population it has been predicted that agricultural production will have to increase by 60% by 2050 (Alexandratos and Bruinsma, 2012). Growing consumer awareness around livestock production may also now require farmers to collect data and monitor performance; they may be required by retailers to monitor specific performance indicators, for example around antibiotic use or welfare standards, or they may elect to do so through voluntary schemes. Accurate data recording and monitoring of KPIs may be used to help improve efficiency of beef production in an economically and environmentally sustainable way, whilst maintaining the health and welfare of the livestock.

In this review, the function of KPIs and the purpose of benchmarking is initially examined. The use of KPIs in the beef industry in England and Ireland is evaluated and compared to that in other major beef producing countries. KPIs used in other sectors such as dairy, pork and poultry, are investigated and their potential application in beef enterprises considered. The majority of KPIs appearing in the literature in these areas fall into two main categories: those measuring fertility parameters, and those measuring financial parameters. In order to investigate KPIs that monitor different parts of the beef production system further literature is considered: Methods of monitoring growth rates and carcass classification are evaluated as these may be particularly applicable to grower/finisher enterprises, and herd health (for example infectious disease prevalence or incidence and antibiotic use) and cow longevity measures (for example cull and replacement rates) are investigated, as these appear to be underrepresented in the initial literature search considering their potential effects on production. Measures of environmental impact are also investigated due to the topical nature of the issue and the inherent link between production efficiency and environmental impact. Finally, aspects around the practicalities of data collection, including the use of electronic identification (EID) and automated data collection, as well as farmer attitudes towards evaluating performance through data analysis are explored.

## 1.2 Key performance indicators and benchmarking

Recording and monitoring performance data is an essential part of managing any business. A small number of easily calculable measures that can be used to predict overall business success are required; these are often termed key performance indicators. Once KPIs have been established they can be used to benchmark an enterprise, allowing data to be converted into knowledge.

### 1.2.1 Key performance indicators

KPIs can be defined as 'critical indicators of progress toward an intended result' (KPI.org, 2022). They are used in industry to check a system works, monitor effects of changes to a system, and to benchmark it either internally against itself, or against other systems. For example, they can be used to improve and monitor energy efficiency in a factory, allowing optimisation and improvement of production efficiency and supporting decision-making. By comparing energy consumption and production data, relationships between inputs and outputs can be evaluated (May et al., 2015). Evaluating the relationship between inputs and outputs is an important aspect of good KPIs as it provides information on how components of a system are related, and how changing one will affect another. KPIs are often output focussed, but in order to be able to draw better conclusions about the efficiency of a system, inputs should also be evaluated. KPIs can be described as business metrics that are used to evaluate the success of an organisation against key goals or critical success factors (CSFs). These CSFs will vary between organisations or systems, or in the case of farming, types of enterprise, and KPIs should be tailored appropriately.

KPIs are often calculated using historic data. This is due to the lag time that inherently occurs between an event, and that event being recorded and incorporated into a KPI. Manning et al. (2008) discuss the use of 'lead' and 'lag' KPIs in broiler production; lag indicators focus on more historic data, whilst lead indicators focus on current performance allowing any necessary interventions to be taken sooner (this is discussed in more detail in a following section about KPIs for the poultry sector). When determining new performance indicators, the following were suggested by Manning at al. (2008) as important considerations:

- They should be easily communicated to farmers
- They should incorporate traditional and familiar indicators as far as possible
- They should be measured and acted upon during the crop cycle i.e. not historic
- They should be analysed using a standard computer spreadsheet

These considerations are generic and relatively adaptable between sectors, for example KPIs across the sectors should be easy to communicate to farmers, and a component of this is the incorporation of familiar indicators. Although beef systems often will not operate an ‘all in all out’ system with a defined crop cycle, some KPIs can be measured during the cycle, for example daily liveweight gain (DLWG). The use of pregnancy diagnosis also allows monitoring of relatively current fertility status, and aspiring to monitor current performance through KPIs should be encouraged. However, there will always be some situations where historic performance is being analysed, particularly when monitoring fertility performance. Although it may not be possible to perform complex analysis using a standard computer spreadsheet, for KPIs to be used regularly and routinely, they should be easy for the farmer and advisor to interpret and understand, whether that be through a spreadsheet, herd management software, or benchmarking programmes. Standardisation is also important to allow comparisons to be made either between enterprises, or within an enterprise year on year. It could be argued that there are other characteristics that KPIs should have in addition to these, such as being reliable and objective.

### 1.2.2 Benchmarking

A benchmark can be defined as “something that serves as a standard by which others may be measured or judged”(Merriam-Webster, 2019). However, it can be more than just comparing data across similar enterprises, or monitoring data within an enterprise over time; it can include using that data to inform best practice and make effective changes. Manning et al. (2008) described it as ‘a method of converting process data to relevant process information from which process knowledge and understanding can be developed'. Through benchmarking, relationships between data and farming practices can be highlighted, thus allowing practices to be evaluated and changes instigated. Benchmarking can be described as internal or external, with internal benchmarking assessing the system against previous performance or key targets of the enterprise, and external benchmarking involving local, national or international comparison with similar enterprises (McDougall, 2012). The following challenges for implementing benchmarking strategies in the agricultural sector have been suggested by Ronan and Cleary (2000):

- Accreditation of sound benchmarking systems by the industry
- Appropriate context for use by farmers
- Lack of consistency between industries
- Limited farmer participation in programs
- Lack of information on how the use of benchmarking improves farm business performance

The diversity of the beef industry, with many different types of enterprise with varying goals, may be at least in part the source of these challenges; it makes defining a ‘blue-print’ set of performance indicators problematic. Lack of consistency is also a challenge, particularly with respect to data capture and analysis tools, as software providers understandably aim for their products to be significantly different to those of competitors. Challenges around farmer engagement and participation are likely to be largely a result of the other perceived barriers listed, and by offering solutions to some of these challenges farmers may feel more able to participate. Use of already recorded statutory data, such as movement data, may also be a way of engaging with farmers who currently do not record additional data or use data analysis to inform management decisions. Investigation of how use of KPIs and benchmarking improves farm business performance can also be challenging; data takes a relatively long time to collect from a beef system due to the long production cycle (compared to pigs and poultry for example), meaning that the potential for other factors to change during and between production cycles is great. Beef systems also tend to be more extensive than many dairy, pig or poultry systems, with cattle being handled less frequently and the practical challenges of data collection often being greater. The diversity of the beef industry, coupled with the lack of consistency in what data is recorded and in what format, makes collection of the large data sets required to account for these many confounding variables, an additional challenge. Collectively, these challenges result in a lack of information on how benchmarking and performance indicators are associated with enterprise performance.

### 1.2.3 The concept of a KPI toolkit

Data collection on farm is often time-consuming, and it is therefore important to identify what data is of most use, whilst being easy to record and monitor on a regular basis. Some KPIs incorporate multiple components of a system (and so require more data), whilst others measure more specific components. Both types of KPI are required to inform decision-making, but they will be used at different times, in different enterprises, to solve different problems. Therefore, a 'toolkit' approach to KPI use may be helpful, whereby appropriate metrics can be selected according to the current performance and aims of the enterprise. Within this toolkit, the KPIs may be structured into a 'hierarchy', with the use of 'comprehensive' KPIs to monitor overall farm success, and a selection of more specific KPIs used to investigate problems in more detail. This could then provide a decision-making pathway that can be used by both farmers and advisors when evaluating herd performance. The development of such a toolkit is discussed in more detail in Chapter 2.

## 1.3 Beef production in the UK

The price paid per kg of beef in the UK is one of the highest in the world, and yet many herds fail to make a net profit (AHDB Beef and Lamb, 2022). Many farms appear viable in the short term as their returns cover their cash costs, but are unlikely to be viable in the long term, with non-cash costs such as depreciation, family labour, and return on owner-occupied land not being covered (AHDB Beef and Lamb, 2016b). The current challenges facing the beef industry in England are complex, with many factors contributing. The diversity of the beef sector, with limited integration of supply chains, has been cited as a major challenge for the industry. The retailing of imported beef has also been cited as a possible cause of reduced farm gate price. High costs of production (and sometimes a lack of knowledge of what these costs are) has been suggested to limit financial efficiency within the sector, coupled over the last few years with the uncertainty of the impact of the UK's exit from the European Union, and what the outcome may mean for the sector (Agri benchmark, 2018, AHDB, 2019, Drysdale, 2016, Pennock, 2015). However, inefficiencies at the farm level are something that can be monitored and potentially changed relatively quickly by an individual, as opposed to industry wide problems. Performance indicators are an integral part of monitoring those processes and of effecting change.

### 1.3.1 Beef KPIs used in the UK and Ireland

KPIs currently used in the beef industry in the UK and Ireland are largely focussed on suckler herds and tend to be fertility based. Some suckler herd KPIs have been established for many years; the current AHDB Beef & Lamb English suckler herd KPIs are based on those developed by SAC Consulting, who defined them using international data, research reviews and data from top performing herds (Riddell et al., 2013). During farmer discussion groups, production data was collected and a set of production targets was created (Caldow et al., 2007). These are illustrated along with reproductive targets for beef herds in Ireland suggested by Teagasc, the Agriculture and Food Development Authority in Ireland (Kenny and Diskin, 2014) (Table 1-1). Although presented as targets (i.e. the final goal), rather than KPIs (i.e. the metrics used to help achievement of the goal), they are useful for illustrating how different parameters can be measured. Hybu Cig Cymru (Meat Promotion Wales) provide examples of performance indicators including calf growth rate, kg of concentrate used per cow, kg of concentrate intake per calf, calving period length, barren cow rate, herd replacement rate, herd labour requirements, length of winter housing period and machinery costs per cow (Hybu Cig Cymru, 2012), and advise that the specific KPIs used should vary depending on the needs of the enterprise. This is an opinion echoed by Steven Sandison in his Nuffield Farming Scholarship Trust Report (Sandison, 2016), in which the difficulties in determining sector wide KPIs and targets are described. Farms across the UK and Ireland (as well as Canada, Norway and Sweden) were compared and a large variation in performance was identified. Even the best performing farms were often not achieving commonly quoted industry targets for some performance indicators (such as scanning percentage and weaning percentage), leading to the suggestion that targets should be reduced in order to make them more achievable. An alternative may be to have 'flexible' targets, or a target range that can be adjusted to reflect the enterprise type and current performance.

*Table 1-1: Comparison of beef suckler fertility key performance indicators used in England (AHDB KPIs) and Ireland (Teagasc targets)*

| Fertility Indicator | AHDB KPIs | Teagasc targets | Comments |
|---|---|---|---|
| **Calving Interval** | % of cows with calving interval below 370 days (target >90%) | 365-day calving to calving interval | This is an inherently historic measure of fertility, but a useful measure of fertility in year round calving systems. |
| **Culling / replacement rate** | Culling rate (<6%) | < 5% cows culled annually as barren | This is good to monitor but will be affected by many factors such as age of herd, target herd size and culling policy, so targets may be difficult to set. It is also important to differentiate between voluntary and involuntary culls where possible. |
| | Replacement rate (<13%) | Replacement rates 16 - 18% | |
| **Weaning rate** | Calves weaned per 100 cows/heifers put to bull (target >94) | % of cows calving to wean a calf (target >95%) | The AHDB KPI takes into account conception rates and abortion rates in addition to calf losses pre-weaning. It may be influenced by high twinning rate.<br>The Teagasc measure focuses on losses between birth and weaning. |
| **Calving period** | % calving in the first 3 weeks (target 65%) | % calving in the first 6 weeks (target 80%) | The AHDB KPI focuses on the first 3 weeks, whereas the Teagasc target focuses on the first 6 weeks.<br>Overall calving period could be affected by a very small number of cows with late (or early) calving dates. |
| | Calving period (target <12 weeks) | | |
| **Age at first calving** | | Heifers calving at 24 months | This is an important target to maximise productive lifetime. |
| **Calving rate** | Calves born alive per 100 cows/ heifers put to bull (target >95) | | This can be used alongside the weaning rate KPI to evaluate pre-weaning mortality rates. |
| **Calf growth and calving rate** | 200-day calf weight per cow/heifer put to bull | | This comprehensive KPI incorporates calf growth, calving rate and weaning rate. Targets can be difficult to set due to variation between breeds and will be influenced by creep feeding. |

## 1.4 KPIs used in other major beef producing countries

Although there are many differences between beef production systems in different areas of the world, the primary elements of an efficient cow are likely to remain the same worldwide. It has been suggested that an efficient cow is one that calves unassisted, weans a calf of 40 -50% her bodyweight, and returns in calf with minimal inputs, regardless of the farm system or country of production (Moyles, 2015). This conclusion is based on observations of various beef production systems worldwide. The way this is achieved will vary with production system and environmental conditions, however it is useful to consider beef KPIs used in other major beef producing countries. At the time of writing, the United States is the largest beef producer, closely followed by Brazil and then the EU (United States Department of Agriculture, 2018). Although not one of the top beef producers, Australia is the third largest exporter of beef worldwide (after India and Brazil), with New Zealand in fourth place.

### 1.4.1 The United States

The National Cattleman's Beef Association (NCBA) is an industry levy body for beef farmers in the USA. They provide a Standard Performance Analysis (SPA) spreadsheet which can be used to calculate financial outputs. Information such as value of assets, expenses, and cow production data is used to calculate financial parameters such as net income per cow and total net Income (Hamilton, 1996). NCBA funds the National Beef Quality Audit every 5 years in the USA. This is designed to monitor progress, highlight weaknesses and identify challenges to the beef industry as a whole. It involves producer surveys, data collection at beef packing plants, as well as information gathered by interview from all production and marketing sectors of the industry. The 2011 audit identified the top three challenges as food safety, eating satisfaction, and getting information to the consumer about how and where cattle are raised (Igo et al., 2013). One of the institutions involved in collecting and analysing data for the National Beef Quality Audit is Texas A&M AgriLife, a part of Texas A&M University. They proposed a set of KPIs and targets for beef cow-calf operations (Table 1-2). These were developed by analysis of herd data, including data from the beef cow-calf SPA (Bevers, 2015).

*Table 1-2: KPIs and targets for beef cow-calf operations proposed by Texas A&M University*

| KPI and target | Description of KPI and uses |
|---|---|
| **Pounds weaned per exposed female (target > 460 pounds)** | A comprehensive measure of production; it measures both weaning percentage and weaning weights and includes pregnancy rate and calving percentage. |
| **Revenue per breeding female (target >$950)** | Incorporates weaning weight and price obtained for cows culled and calves sold. It should also take into account the value of weaned calves that are kept as replacements. |
| **Nutrition base expense as a percent of total expenses (target 30-45%)** | Will include costs of purchasing feed, producing feed and maintaining grazing. |
| **Labour and management expense as a percent of total revenue (target <15%)** | Can be the most variable cost between herds due to the use of family labour. |
| **Operating expense as a percent of total revenue (target <75%)** | Includes all expenses except interest and depreciation. |
| **Net income ratio (target >5%)** | Proportion of total revenue that is retained as income. |
| **Cost per hundredweight of weaned calf (target <$170)** | Incorporates inputs and outputs and so is a measure of efficiency. It could also be classified as a comprehensive KPI as it incorporates multiple components of the system, i.e. fertility, weaning rates, growth rates and input costs. |
| **Current ratio (target >2)** | Reflects how much of a business's assets can be used to pay short-term debts and is therefore an indicator of how stable the business will be in the case of unforeseen events e.g. drought. This is useful for businesses that operate in a market that is inherently volatile and dependent on unpredictable factors such as the weather. |
| **Total investment per breeding female (target $7500 - $12500)** | Land is usually the main asset, but as it is now so valuable and the rate of return so low this KPI target assumes that some land was already purchased / inherited or that some is leased. |
| **Debt per breeding female (target <$500)** | Will vary between farms, but as the rate of return is generally low, the level of debt a business can cope with must also be low. |
| **Equity to asset ratio on market basis (target >50%)** | What percentage of the farm the owner owns. The opposite, i.e. the percentage owned by lenders, is the debt to asset ratio. |
| **Asset turnover ratio on cost basis (target >15%)** | Describes how well the assets of a business generate a turnover. 15% means that every $ of asset should generate at least $0.15. This is a low value but reflects the rate of return for 'ranch' farms. |
| **Rate of return on assets on market basis (target >1.5%)** | Describes how well the assets of a business generate a net income. The target is low due to the nature of the industry. |

These KPIs are far more financially focussed than the industry standard KPIs used in England. Although monitoring of financial parameters is obviously of great importance in any business, use of physical production parameters to enable informed decision-making at the individual cow and herd level is also key; often the producer will have far more control over physical production than input costs and output prices. KPIs such as 'cost/hundredweight of weaned calf' and 'revenue/breeding female' link physical to financial measures and incorporate system inputs and outputs. 'Pounds weaned/exposed female' is also a good example of a comprehensive KPI which incorporates many aspects of the production system.

One of the major differences between beef production in the USA and in England is the use of implants and growth promoters to enhance production in the USA. A meta-analysis conducted by Wileman et al. (2009) used a breakeven model to determine the financial benefits of modern technologies such as steroid implants and antimicrobial metaphylaxis in beef cattle production. They calculated that organically reared animals would require a \$0.62/kg premium to compensate for the lower efficiency. There is however increasing resistance to the use of performance enhancing technologies such as growth promoters in the USA. Branded beef programmes have been developed, many of which ban the use of such technologies. As consumer demand for beef produced without the use of hormones grows, interest in improving efficiency in other ways increases (Wagner et al., 2014).

### 1.4.2 Australia

Meat and Livestock Australia is a levy funded organisation delivering research, marketing, and development strategies to livestock farmers in Australia. They have produced a cost of production (COP) calculator allowing farmers to calculate various parameters and benchmark themselves against others in the region. A report by Hoffman Beef Consulting Pty Ltd used the output from COP calculations to develop regional benchmarks for three KPIs: COP, kg beef produced/ha and kg beef produced/ha/100mm rainfall. It appears that these KPIs were chosen as they were deemed to be important by farmers in the benchmarking group that provided the data. Kg of beef produced and COP were found to be strong indicators of profitability, highlighting the importance of cost control. As rainfall is a limiting factor in arid regions of Australia, productivity efficiency can be measured in terms of mm rainfall.

### 1.4.3 New Zealand

Subsides in New Zealand were removed in 1984, and it has been suggested that this has increased technological uptake amongst farmers in order to drive efficiency (Ross and Edwards, 2012). Although New Zealand production systems tend to be quite different to English ones, often with far more emphasis placed on grazing and the benefit of economies of scale, useful comparisons can be drawn when considering KPIs.

Beef and Lamb New Zealand (an organisation responsible for promotion of beef and lamb in New Zealand and jointly funded by farmers, retailers and processors), defines beef cow efficiency as ‘net return per kilo of feed consumed’. It can be measured in a number of ways which have been ordered by accuracy and ease of measurement (Figure 1-1) (Morris and Smeaton, 2005). As accuracy of the metric increases, ease of measurement decreases. This highlights the need for compromise when developing KPIs that are practical to be monitored routinely whilst also accurately monitoring performance.

| EFFICIENCY MEASURE | ACCURACY | EASE OF MEASUREMENT |
|---|---|---|
| 1. Kg calf wean weight/kg cow weight at weaning | Less | Easiest |
| 2. Kg calf wean weight/ kg cow mating weight | | |
| 3. Kg dry matter (DM) intake/year/kg calf wean weight | | |
| 4. MJ ME intake/year/kg calf wean weight | | |
| 5. Cents gross margin/unit of intake*/year | More | Hardest |

***Figure 1-1: New Zealand beef efficiency measures*** *(*intake refers to intake of cow and her suckled calf over a 12-month period)*

Massey University’s cow efficiency project has been investigating productivity and efficiency of beef cattle. In their studies they measure efficiency as kg of calf weaned/kg of cow or kg of food intake annually. Therefore, efficiency can be improved by either increasing calf weaning weights, decreasing cow size, or both. In a recent study they showed that efficiency and productivity of individual cows increases with increased milking ability and decreasing size (Law et al., 2013).

### 1.4.4 Brazil

Brazil has a wealth of agricultural resources and is the largest beef exporter in the world (United States Department of Agriculture, 2018). Although traditionally grass-based systems predominated, feedlot type enterprises are now becoming more common. As Brazil’s political and economic situation has stabilised, its beef industry is growing and becoming more organised and integrated, with many of the large feedlots being owned by packing plants. As the industry is intensifying and moving from grass-based systems to feedlot enterprises, the length of the production cycle has decreased (Thompson, 2008). The move from natural pasture to cultivated pasture is also increasing efficiency, and this has been indicated by a reduction in methane emissions/kg animal (Millen et al., 2011). The cost of production in Brazil has been estimated to be 60% less than in Australia and 50% less than in the USA. This, coupled with an abundance of natural resources and a large available workforce, has made Brazil a big player in the world beef market (Somwaru and Valdes, 2004).

A Brazilian study, aiming to create a performance indicator system for a beef enterprise including breeding, calf rearing, finishing and sire production, listed strategic goals and critical processes and devised indicators to monitor these (Rosado Júnior and Lobato, 2010). Goals included increasing trading volume, producing cattle to meet market requirements, and improving skills of operational personnel. Indicators used were designed to address these goals, and included gross margin/ha, productivity (kg/ha/year), % of cattle marketed according to the customers' specifications, and training hours per employee. These indicators were grouped according to the balanced score card (BSC) which aims to represent all aspects of a business by grouping indicators into financial, internal processes, customer, and learning/development sections (Table 1-3). This ensures that the indicators selected are as comprehensive as possible. By using this methodical approach, a bespoke collection of performance indicators was devised which applied directly to the goals of the enterprise. This bespoke approach lends itself to beef enterprises which can display considerable variation

The different KPIs used worldwide reflect the different landscapes, climates, and production systems found. The KPIs suggested in literature from the USA focus on financial measures; this may be due in part to the lack of subsidies, or to the fact that larger farms can be viewed as investment opportunities, and so this sort of information is required for investment portfolios. In Australia, where rainfall is often a limiting factor, efficiency can be measured in terms of mm of rain, a measure that would be of little use in England. In New Zealand, the removal of subsides over 30 years ago may have created an agricultural industry more focussed on monitoring efficiency and as a result have a selection of efficiency measures ordered by accuracy and ease of monitoring. In Brazil, with a developing beef industry, efficiency is increasing with intensification and a very integrated supply chain means that enterprise KPIs cover internal as well as customer satisfaction indicators.

***Table 1-3: Beef enterprise performance indicators grouped according to a balanced score card**. This aims to represent all aspects of a business by grouping indicators into financial, internal processes, customer and learning/development sections (Rosado Júnior and Lobato, 2010).*

| Category | Indicator | Uses |
|---|---|---|
| **Financial** | Gross margin/ha | Monitors financial performance |
| | Gross margin/sire | Supports decision to expand sire production |
| **Internal Processes** | Soil fertility | Monitors basic substrate for feed production |
| | % of cattle marketed in niche markets | Monitors success of production |
| | Productivity (Kg/ha/year) | Monitors finisher /sire production |
| | Cow BCS (calving and weaning) | Predicts reproductive performance allowing timely corrections. |
| | Pregnancy rate (% cows/heifers mated that are pregnant) | Monitors reproductive performance |
| | Weaning rate (% calves weaned/cows or heifers mated) | Monitors reproductive and calf rearing performance |
| | Herd mortality rate | Monitors herd health |
| | Sire target rate at 6, 18 and 24 months of age. | Monitors production of sires and calves. |
| | Awards in breed contests | Affects brand marketing profitability |
| **Customer** | % cattle marketed to customer's spec. | Monitors success of production |
| | Satisfaction of sire customers | Monitors success of sire production |
| | % retention of sire customers | Affects brand consolidation |
| | % new sire customers | Affects brand consolidation |
| **Learning/ development** | Training hours/employee | Monitors personal development of staff |
| | Days absent | Monitors occupational health |

## 1.5 Use of KPIs in the dairy, pork and poultry sectors

Use of KPIs in the dairy, pork and poultry sectors has tended to be more widespread than in the beef industry. Reasons for this may include greater intensification of these sectors necessitating, and in some cases enabling, data recording and KPI use. More intensification tends to mean more direct contact with stock, for example indoor feeding versus grazing, or service via AI rather than natural service. There may be greater stock numbers and higher disease incidence (although not necessarily), and so more data to record. Greater use of technology may enable more data capture, for example automated systems. In addition, the benefits of data analysis and KPI use may be more apparent with greater stock numbers, and so the motivation to collect and record data may be greater. In the dairy sector the relative ease of data access and recording (for example milk recording of dairy herds) may also play a role, as may the need for more day-to-day monitoring of individual animals, for example yield monitoring. Benchmarking and target development is likely to be easier when a more uniform product is being produced; pig and poultry systems will generally display more breed uniformity within herds/flocks. The shorter production cycle of pork and poultry will also allow larger amounts of data to be generated faster which may encourage KPI use.

### 1.5.1 Dairy

Over recent years' volatile milk prices have forced UK dairy farmers to carefully monitor business performance and production efficiency, and as a result many have become familiar with using financial and physical KPIs on a regular basis. Software is available allowing farmers and advisors to analyse data which can often be presented in a very user-friendly way. Trends can be monitored, changes in performance identified quickly, and problems investigated. Milk recording companies, such as National Milk Records (NMR), gather huge amounts of data for analysis, allowing dairy farmers to monitor their performance and benchmark their progress against similar farms. The University of Reading, in conjunction with NMR, produces a yearly KPI report that uses data from 500 herds. Various health and fertility parameters are calculated and targets are set. The target is the level achieved (or bettered) by 25% of herds in the study (Hanks and Kossaibati, 2021). Many of the performance indicators calculated monitor mastitis levels and milk quality, parameters that are not applicable to the beef herd. Fertility measures however, such as age at first calving and calving interval, may be applicable. Although this allows benchmarking against other herds and monitoring of physical performance, it is not associated with any financial output.

#### *1.5.1.1 Linking dairy production parameters to financial parameters*

In the USA the Profit Opportunity AnalyserSM™ (POA) has been developed with the aim of extending the use of milk recording data to include financial parameters. It is designed to identify areas of the system where there is most opportunity for financial improvement, whilst requiring very little extra input information (net milk price per hundredweight, replacement value per animal, cull cow value per animal, calf value [estimated value at 3 weeks of age] and annual interest rate [current rate of borrowed capital]). This is done by splitting the herd into seven management areas (turnover, reproductive cows, reproductive heifers, udder health, transition and dry periods, genetics, and production), and ranking each herd in each individual category. The 'profit opportunity' or economic potential in each area is measured against the 80th percentile for similar herds in each management category (Giacomini, 2009). This allows farmers to make herd management decisions based on financial as well as physical data. In a similar way, Teagasc have developed the 'Dairy Scorecard' which links production measures to financial output. It focuses on four main areas of a dairy business, namely grass, cow, yield, and cost, and uses data collected in these areas to calculate a net profit per hectare (O'Dwyer, 2014). Linking physical performance with financial output in beef enterprises in a similar way could be beneficial for monitoring beef herd performance. Use of a 'scorecard' for production monitoring in this way is similar to the balanced scorecard previously described in section 1.4.4, where indicators measuring different aspects of business performance were grouped together. This ensured comprehensive monitoring of the entire business, whilst allowing a bespoke set of indicators to be selected (Rosado Júnior and Lobato, 2010).

Due to the complexity of the dairy herd system, coupled with the long interval between calvings and the volatile dairy market, it is often difficult to collect sufficient 'real herd' data for studies linking dairy herd performance to financial success; collecting data from enough herds over a sufficient period of time, whilst minimising additional 'noise' from confounding factors, can be problematic. The same can be said of studies into beef herd performance, and this can hamper investigation of KPIs. For example, it can be challenging to link financial indicators (such as net margin) to physical indicators (such as growth rate) as beef and feed prices are constantly changing. Simulation models can be used to analyse the effect of a particular variable on an outcome whilst keeping all others constant, and so help to overcome these problems (Kristensen et al., 2008). For example, Lof et al., (2012) used a stochastic simulation model to evaluate how reproductive performance indicators varied in dairy herds with different reproductive performance. By examining how well the various reproductive indicators could discriminate between the different levels of herd reproductive performance, they were able to define a single best performance indicator for estimating reproductive performance. They also accounted for management decisions such as voluntary waiting period (VWP) and looked at parameters that would reflect the whole herd rather than just animals that had been served (e.g. calving interval or calving to conception interval). They found that the percentage of cows in the herd pregnant at the end of the VWP plus 30 days was the single best performance indicator. Similar methods could be used to investigate KPIs that have the greatest influence on beef enterprise success.

#### *1.5.1.2 Predictive KPIs*

When assessing fertility KPIs in the dairy herd it has been suggested that predictive KPIs would be a useful tool, i.e. those that could predict reproductive failure, rather than focussing on historic events. For dairy herds, using risk factors of poor fertility such as metabolic disease, lameness or infectious disease have been suggested as ways of doing this (Smith et al., 2014). In a similar proactive approach, KPIs have been investigated that can be monitored as part of an 'Early Warning System' for welfare incidents on farm, allowing problems to be identified earlier and resolved quicker than with traditional reactive approaches (Kelly et al., 2011). Such predictive KPIs are an extension of the concept of 'lead KPIs' mentioned previously, and may be a useful tool in performance monitoring and preventative management. Predictive analytics, such as predictive modelling and machine learning, are being used to aid management of dairy herds, for example to predict calving (Borchers et al., 2017), or to predict conception success (Hempstalk et al., 2015, Fenlon et al., 2017). Such precision farming could, where data is available, be used in beef systems to develop and evaluate predictive KPIs.

#### *1.5.1.3 Transferring dairy herd KPIs to the beef herd*

Many common dairy herd KPIs are based around milk production and fertility (although health and longevity measures feature too). Of these, fertility performance indicators, such as age at first calving and calving interval, are often most relevant to beef herds, although milk yield is also important for calf growth. Block calving dairy herds may use performance indicators to monitor the calving period, for example the percent calving in the first 3 weeks or the total calving period length, both of which are very relevant to block calving beef herds. In addition to fertility performance indicators, disease incidence rates are commonly used in dairy herds to monitor health, and these can also be easily transferred for use in the beef herd. The use of such performance indicators is discussed in the herd health KPIs section (section 1.8).

### 1.5.2 Pork

Although useful to draw comparisons between KPIs used in the dairy industry and potential KPIs for the beef industry, arguably the pig sector is a closer comparison with the focus being on reproduction and growth rather than milk production. The higher number of available animals and the shorter gestation period of pigs means that large quantities of data can be generated quickly. The pig industry has also been under pressure for several years to lower costs of production in line with most of Europe. This caused pig farmers to look to KPIs to improve efficiency some time ago.

#### *1.5.2.1 Pork KPI hierarchy*

Performance of breeding herds is often ranked by pigs weaned/sow/year (AHDB Pork, 2016). This is a good example of a 'comprehensive' KPI which incorporates most of the production system including fertility, litter size and mortality rates. In order to investigate causes of a low number of pigs weaned/sow/year however, other more specific parameters would be required, for example farrowing rate, litters/sow/year and pre-weaning mortality rate. Beyond these more specific KPIs, further areas for investigation are suggested, for example heat detection and infectious disease rates. This highlights how different levels of KPIs (a KPI hierarchy) can be used when assessing herd performance (Figure 1-2)

#### *1.5.2.2 Pork rearing and finishing KPIs*

Pig rearing and finishing units use KPIs focussing on areas other than fertility which are useful when considering KPIs for grower/finisher beef units. These include mortality rate, feed conversion ratio (FCR), daily live weight gain (DLWG), weight of pig produced, average carcass weight and feeding days/pig (AHDB Pork). Average carcass weight and feeding days/pig, although of use in the pork sector with a uniform system and little variation between individual animals, may be of less use in a beef system if a variety of animal type (breed, age, etc.) exists. Mortality rate, FCR and DLWG may be more directly applicable to beef grower/finisher units if this is the case.

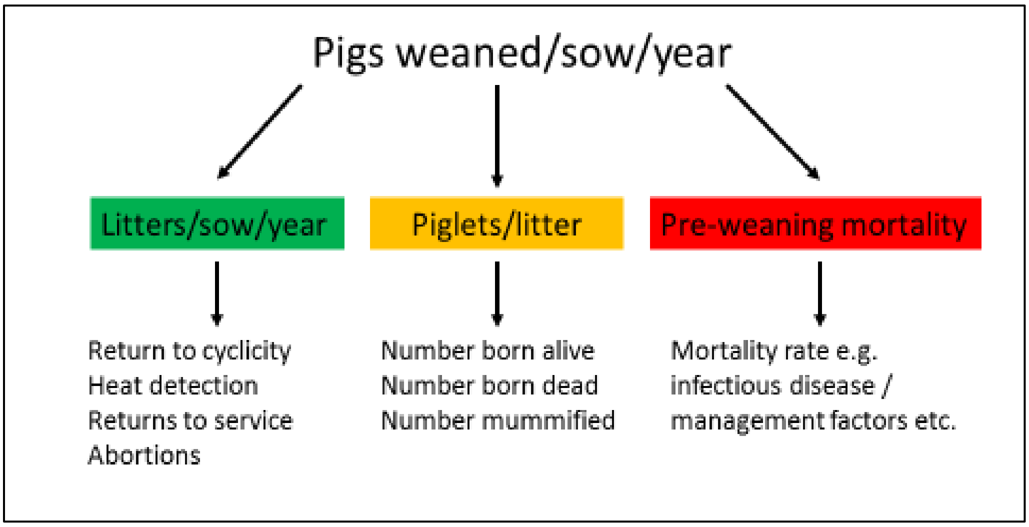


*Figure 1-2: **Suggested KPIs for pig enterprises** organised in a hierarchical structure with one comprehensive KPI, three more specific performance indicators, and areas for further investigation suggested. This shows how different levels of KPIs can be used when assessing herd performance.*

#### *1.5.2.3 Linking pork production parameters to financial parameters*

A Canadian pork benchmarking study used net income (or net profit)/pig produced (including family labour expense) as their measure of farm success. Although productivity was found to be very similar between farms, the biggest difference between the top and bottom half of farms was in cost control i.e. the top half of farms had lower expenses (Marchand and Duffy, 2013). The importance of incorporating financial parameters into performance monitoring of pig herds has also been highlighted (Bilbrey, 2012b). Here it was suggested that although farmers were often more willing to benchmark production measures, financial information was also crucial as the best production performance does not always correlate with the best financial performance. The benefits of benchmarking were also emphasised by highlighting the fact that it was the most profitable swine producers that benchmarked their cost and performance (Bilbrey, 2012a). This illustrates how metrics can be categorised as financial metrics (those measuring financial aspects of enterprise performance, such as cost of production) or production metrics (those measuring physical aspects of enterprise performance, such as growth rates or mortality rates).

### 1.5.3 Poultry

Another example of a very uniform system with more extensive use of KPIs is broiler poultry production. In a similar way to the pork sector, the focus is on growth with meat being the final product. As fertility is not important in broiler poultry production, KPIs used in this sector may be particularly applicable to grower/finisher beef enterprises.

### 1.5.3.1 'Intra-crop' and 'Inter-crop' performance indicators

Manning et al. (2008) suggested a collection of KPIs for poultry meat production (Table 1-4). In this collection a distinction has been made between measuring current problems (intra-crop performance indicators) and measuring problems at slaughter or between batches (inter-crop performance indicators), which can only then be used to make changes to the next production cycle. This is a similar concept to the 'lead and lag' KPIs mentioned previously and could be particularly useful to consider in relation to beef grower/finisher enterprises. Financial parameters and additional performance indicators, mainly associated with utility use, have also been identified

***Table 1-4: Suggested poultry meat production performance indicators*** *with those considered particularly relevant to grower/finisher herds highlighted in bold*

| Inter-crop performance indicators | Cost driven indicators | Intra-crop performance indicators | Additional performance indicators. |
|---|---|---|---|
| **Total mortality (%)** | **Financial returns/kg live weight** | Daily mortality (%) | Total water consumed (L/bird/cycle) and (L/$m^2$) |
| **Total leg culls (%)** | Financial returns/$m^2$ | Weekly weight gain (g) | Electricity usage (kWh/bird) and (kWh/kg live weight) |
| **Feed conversion rate (FCR)** | Financial returns/$m^2$/week | Growth (%) | Gas usage (KWh/bird) and (KWh/kg live weight) |
| **Average bird weight (Kg)** | | **Coefficient of variation** | Feed usage (Kg/bird): water consumption (L/bird) ratio. |
| **European production efficiency factor (EPEF)** | | Ventilation rate ($m^3$/hr/kg) | Total energy usage (kWh/bird) and (kWh/kg live weight) |
| **Bird place efficiency (kg/$m^2$/week)** | | Air humidity (%) | |
| **Veterinary medicine use (kg/1000 birds)** | | Daily min/max temperature (°C) | |

### 1.5.3.2 Poultry KPIs applicable to grower/finisher beef enterprises

Of the KPIs listed in the table, several are particularly worth considering with respect to use in grower/finisher herds, these are highlighted in the table:

- **Mortality rate** can be used to demonstrate trends in mortality rates, for example between seasons or age groups.
- **Feed conversion rate (FCR)** is a measure of feed efficiency which is important from an environmental and financial point of view. If used to inform breeding decisions however, there is a danger that it can select for bigger, less efficient cows.

- **Coefficient of variation** is a measure of uniformity which may be of use when trying to produce a uniform carcass, however it involves regular weighing which may prove too time-consuming for many beef producers.
- **Financial returns/kg live weight** incorporates both growth rates and financial output, although does not take into account input costs.
- **Veterinary medicine use** is recorded as kg/1000 birds. This may be a useful measure, however different drug dose rates may make it difficult to interpret. Measuring use by month would give an indication of seasonal patterns and differentiating between drugs used and the condition treated may also be of use.
- **Bird place efficiency** combines growth rates with stocking density and so is a KPI suited to systems where space is a limiting factor, such as some indoor finishing units.
- **The European production efficiency factor (EPEF)** is an industry wide performance indicator which incorporates growth rate (g/day), survival rate (%) and FCR as illustrated below. The idea of this is to act as a comprehensive KPI which can be used to monitor any adverse or beneficial management changes on a unit. A similar production efficiency factor has been proposed in the US (the PEF) where condemnations are taken into account and calorie conversion is used instead of FCR. In a study comparing a poultry unit's PEF with its cost of production (COP) (cents/pound live weight), it was found that the two were moderately inversely related but that this was not statistically significant. This suggests that there are factors other than performance affecting COP, and so ranking units by COP alone is not fully reflective of efficiency (Shane, 2016). An indicator such as this may be of use for grower/finisher units (although FCR can be challenging to measure).

$$EPEF = \frac{Average\ daily\ gain\ x\ survival\ rate}{Feed\ conversion\ rate}$$

*Figure 1-3: European Production Efficiency Factor (EPEF)*

Although it is useful to consider KPIs used in other sectors, there are significant differences between these sectors and the beef industry which means direct extrapolation should be done with caution. The beef industry is very diverse; with multiple different enterprise types and breed types blanket targets are difficult to develop and benchmarking between enterprises can be challenging. This was highlighted by an Italian paper looking at the performance of intensively managed feedlot cattle, which used average daily gain (ADG in Kg/day) and net sale gain (NSG in €) per head, per day, and per kg gain, to monitor performance (Gallo et al., 2014). They found that the 'highest performing' cattle varied depending on which metric was used, and that there was considerable variation between breeds.

## 1.6 Financial benefits of KPI use

The aim of using KPIs is to allow an enterprise to achieve its goals. Although these will vary to some extent between enterprises, particularly between suckler and finisher enterprises, a common target will often be the ability to generate a net profit. The financial implications of poor performance have been estimated recently by Teagasc: With the current reproductive performance of Irish suckler herds, it was calculated that every day beyond the 365 day calving interval target was costing €2.20/cow/day and that delaying age at first calving from 24 to 36 months reduced net margin/hectare by 50% (Kenny and Diskin, 2014). Even in a small herd these sums will add up to considerable losses. Studies linking KPIs to financial performance are limited, likely due to the challenges around collecting sufficient data, and the many confounding factors affecting the financial performance of a beef enterprise.

### 1.6.1 Assessing the relationship between production and financial parameters

Bio-economic farm models have been used to study financial implications of making changes to complex farm animal production systems and can incorporate genetic, production, and economic data. Roughsedge et al. (2003a) used a bio-economic model to evaluate the effects of changing breeds and mating systems used in an enterprise. Within the model, an 'animal model' generates weekly performance data, a 'population dynamics model' predicts the number of animals in each class, and an 'economic model' combines the two whilst incorporating financial information. The study was used to investigate replacement policy. It found that, in this enterprise, keeping homebred replacements rather than buying in heifers resulted in a small decrease in profitability in the first year, but an increase in profitability thereafter. A similar study, looking at effects of alternative replacement breeding strategies, demonstrated that cow efficiency (measured as either weight weaned/100kg cow mated or food cost/kg weaned/cow mated) was highly correlated with profitability (Roughsedge et al., 2003b). It also identified cow size, age at first calving, reproductive success and replacement rate as major maternal traits contributing to the profitability of beef enterprises in the UK.

Economic selection indexes have been developed to assist in selecting animals to meet a breeding objective (Roughsedge et al., 2005). During development, economic values were defined for breeding traits previously shown to influence farm profitability using a combination of industry data, mathematical modelling, and results of previous studies. These economic values estimated the saving made by decreasing the calving interval by one week to be £4.41/cow, increasing weaning weight by 10kg was estimated to increase profit by £6.50/calf, and increasing carcass conformation by one classification was estimated to increase profit by £7 per head.

Although financial parameters are important to monitor in any business, they are not always a farmer's main motivator. In their paper looking into dairy farmers' motivations towards lameness control, Leach et al. (2010) found that dairy farmers were motivated more by pride in a healthy herd than by economic factors. They also found that different farmers had different motivators, for example those with greater public access to their land were more concerned about public perception. When engaging with farmers about data collection and performance monitoring it is important to understand their motivations. This will allow appropriate performance indicators to be selected and realistic targets to be set.

Cattle KPIs considered so far have largely focussed on fertility and/or financial parameters and tend to be of relevance mainly to suckler herds. In order to investigate KPIs that may be more applicable to grower/finisher units, and to consider in greater depth parts of the beef production system not already examined, ways of monitoring the following parameters were investigated: growth and carcass conformation (as this may be particularly applicable to grower/finisher enterprises), herd health status (including longevity, prevalence of infectious diseases and antibiotic use), and the environmental impact of an enterprise. Methods of engaging with farmers around data use and the implications of automated data capture and EID systems are also considered.

## 1.7 Growth and carcass KPIs

Feed costs are the largest variable cost associated with beef production, accounting for around 50% of total variable costs (AHDB Beef and Lamb, 2016a). More efficient beef animals are therefore of financial and environmental benefit. Metrics measuring feed intake and utilisation can be challenging to measure in a commercial setting, but are important metrics to consider measuring both input and output.

### 1.7.1 Feed conversion ratio and feed efficiency

Feed conversion ratio (FCR) is often used as a KPI of feeding efficiency, as mentioned with respect to pork and poultry KPIs. It is the ratio between dry matter intake (DMI) and weight gain with a lower number indicating better efficiency. It does not however differentiate between feed used for maintenance and feed used for growth. Therefore, if we monitor FCR alone, and use it to inform breeding decisions (for maternal sires), there is a danger of selecting for bigger cows rather than efficient cows. These animals are likely to use more energy for maintenance and so cost more to feed (they will also however provide a bigger cull income).

Other measures have been suggested to better measure feed efficiency for incorporation into genetic evaluations, such as Net Feed Efficiency (NFE). This scales DMI to animal size, growth rate, and carcass fatness, allowing the most efficient animals to be identified without adversely affecting carcass characteristics or growth rate. It is expressed in terms of kg DMI/day and negative values are preferable. A trial in Stabiliser cattle in the UK showed that the most efficient bull was 25% more efficient, consumed 13% less feed and cost £25 less to feed over a 12-week period. Steers also showed a similar trend (Hyslop, 2014). Although NFE is being used as a breeding tool, rather than a KPI, it is of use to consider the difference between this measure of feed efficiency and FCR, which is a commonly quoted KPI.

Recently it has been suggested that in bulls there may be an inverse relationship between feed efficiency and fertility; more feed efficient bulls have been shown to have decreased sperm motility and increased morphological abnormalities (Fontoura et al., 2015). This highlights problems associated with focussing on individual indicators and illustrates the need for both comprehensive KPIs to monitor the whole system, and more specific measures to identify individual problems.

### 1.7.2 Carcass classification

Classifying carcasses is a topical issue in the beef industry, with specifications increasing in complexity and sometimes changing at short notice. Visual inspection of animals has always been used to decide on breeding animals, and breeding combinations. With the development of estimated breeding values and molecular breeding values this can now go one step further. Genetic tests are available to identify cattle with certain genes and work is being done to link this to phenotypic outcome, and more importantly financial outcome. Thompson et al. (2015) showed that increasing the genetic potential for yield alone in an animal was not beneficial to overall carcass quality as it had a negative effect on quality classification. Improving genetic potential for yield and marbling however was more reliable in improving overall carcass quality. This highlights the dangers of focussing on one aspect of production at the expense of others. Although not widely used currently, carcass quality KPIs may be of use in beef finisher enterprises, particularly with high levels of cattle routinely not meeting specification (AHDB Beef and Lamb, 2019a).

## 1.8 Herd health KPIs

The efficiency and productivity of a herd is likely to be influenced by the health of the animals in that herd. This, linked with increasing consumer interest in the welfare of farmed animals, means that monitoring herd health is important both from a production and a public perception point of view. Increasingly farm assurance schemes are making such monitoring mandatory, however there is often little consistency between schemes as to what data is monitored and how. Measures of cow longevity are discussed as a way of monitoring herd health, and the effects on productivity of specific infectious diseases are reviewed. Methods for measuring antibiotic usage are also discussed, as this is an area where increased monitoring in the future is likely.

### 1.8.1 Measures of cow longevity in suckler herds

Producing or purchasing replacement animals for the suckler herd incurs a cost (economic and environmental), and so optimising cow longevity can increase efficiency of production. However, maintaining an older herd with lower culling and replacement rates can decrease the speed of genetic advancement of the herd, as well as reducing productivity through retaining potentially less productive cows. As when using any performance indicator to monitor herd performance, targets should be based on current performance and enterprise targets.

#### 1.8.1.1 Culling rates

Targets for culling rates are difficult to define; some degree of culling is necessary to maintain a productive herd, but high levels of culling can indicate poor cattle welfare. Culling rates in beef cows have been estimated to be 19.2% using national cattle movement data from the Cattle Tracing System (CTS) (Gates, 2013). Of these 25.4% died on farm, 16.5% were sold to another herd for breeding, and 58% went for slaughter. A similar study using data from the Irish National Cattle Movement Monitoring System (CMMS) calculated a culling rate of 18% for the Irish national beef herd (Maher, 2008). Culling will be influenced by many factors, for example feed price, cull cow value, and availability or cost of replacement heifers (Vosough Ahmadi et al., 2017). A cow that is not in calf will not generate any output for a year, but the decision whether to cull her or not will depend on the cost of keeping her against the cost of a replacement. Likewise, although culling may be required to maintain the desired calving period, the economic advantages of early calving within the calving period may not be sufficient to justify the costs of increased culling (Vosough Ahmadi et al., 2017).

Simulation models have been used to try to determine 'optimal' culling rates in different scenarios. What is optimal, as with any performance indicator, depends on the targets of the enterprise. For example, if cow productivity (measured as number of calves/cow life year) is to be optimised, this is likely to increase with age. However, beef quality and so cull price are likely to decrease with cow age (Oishi et al., 2011). This study highlighted that the optimal culling strategy for an enterprise varied depending on whether better biological or economic efficiency was the target. It also showed that cull cow beef quality was a significant factor in determining the optimal culling parity, as was calf sale price (i.e. as calf price falls, retaining them as replacements becomes more attractive and optimal culling parity decreases). Likewise, when cull cow price is high, increasing culling rates can improve financial returns (Turner et al., 2013).

It is important to make a distinction between voluntary and involuntary culling; voluntary culls are a management decision based on the productivity of the cow compared to potential replacement animals, whereas involuntary culls are animals that are no longer productive due to infertility, injury or disease. Often this information is not recorded, but in the dairy herd, culling rates in the first 100 days of lactation can be used as an indicator of involuntary cull rate as it is unlikely that animals would be selected for culling voluntarily during this time (Salfer, 2017). A comparable metric in the suckler herd could be culling rate pre-weaning. Optimum voluntary culling rate has been shown to be sensitive to market prices, body condition score (BCS) of cows, cull cow prices and replacement prices (Vosough Ahmadi et al., 2017). Interestingly, this study showed that BCS did not affect involuntary culling rates (BCS may be expected to decrease with causes of involuntary culling such as lameness or disease), although animals with a higher BCS were more likely to be culled voluntarily, likely due to their potential for a higher cull value.

As well as distinguishing between voluntary and involuntary culls, reasons for culling need to be recorded for the data to be used to inform effective management changes. These categories need to be consistent to allow internal benchmarking year on year, as well as benchmarking between enterprises. Cows will often be culled for a variety of reasons, so determining the main reason can sometimes be challenging. Once the main cause of involuntary culling on an enterprise has been determined, further analysis may be required in order to make effective management changes. This is illustrated well in the following diagram, taken from a University of Minnesota Extension Service publication about decreasing cull rates in dairy herds (Salfer, 2017).

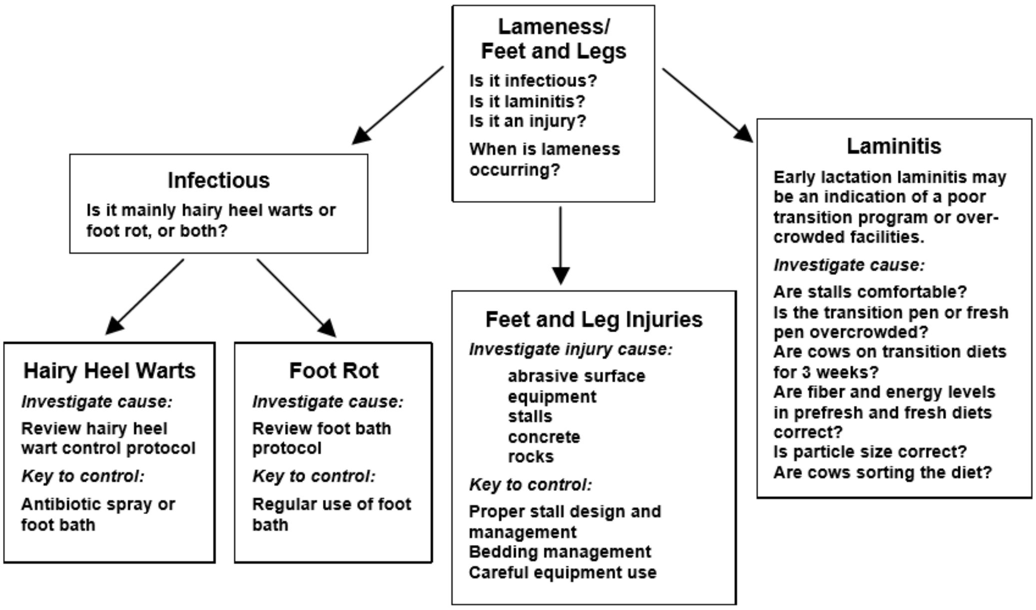


***Figure 1-4: Flow diagram illustrating information required to further investigate high levels of cullingdue to lameness in a dairy herd*** *(Salfer, 2017).*

### 1.8.1.2 Replacement rates

Replacement and culling policies help to determine the age of the herd, and so affect its efficiency and productivity. The effects of these policies can often take many years to become apparent, and so can be difficult to analyse without historic data. External factors, such as climate, infectious disease status, and market prices can also affect replacement rates, as well as deliberate management decisions. This is the type of complex system that lends itself to stochastic modelling. A simulation model of a suckler herd has been used to assess the effects of various replacement policies on the stability of herd productivity (Romera et al., 2006). Measures of herd productivity and stability used were 'sold animals' (animals/year), 'liveweight sold' (kg/ha/year), 'total number of cows' and 'replacement heifers' (animals/year). Three replacement policies were compared over a fifty-year period, the first keeping as many replacement heifers as required to maintain target herd size after culls (due to infertility and age), the second kept a constant number of replacements each year, the third limited the number of animals that could be culled due to age (defined as >10 breeding seasons), and replacements were kept to maintain target herd size. The differences in the herd productivity measures were small, but the third policy appeared to show the most stability in herd age structure.

#### *1.8.1.3 Other measures of cow longevity*

Other measures of longevity used in the dairy sector include lifetime milk/cow/day (kg) and age at exit from the herd (years) (Hanks and Kossaibati, 2021). Age at exit from the breeding herd could be used for the suckler herd, and calves produced per cow life year is a comparable metric to lifetime milk/cow/day. Another metric suggested to measure longevity is percent calving success, calculated as 100 x (number of calves/years in herd-2) (Saxton et al., 2017). This is a similar metric to calves/life year but expressed as a percentage and using breeding years (assuming age at first calving is 2) as the denominator. As number of breeding years, as opposed to years of life, is the denominator, this will not decrease as the cow ages (assuming she has a calf every year) so is less useful to measure longevity.

The percent of cows reaching a specified time point, for example third lactation, has also been suggested as an indicator of longevity in the dairy herd (Rushen, 2013), and could be modified to the percent calving for a third time (or reaching 48 months of age in a herd calving heifers at 2) in a suckler herd. 'Stayability' is another term often used when measuring longevity, and has been defined as a measure of the probability of an animal remaining in the herd until a specified time point, i.e. the probability that the cow survives to a specific age, calves again, or weans another calf (Jamrozik and Miller, 2013). These have been used to define estimates of expected progeny differences (EPDs) but are more involved to calculate and less appropriate for monitoring individual herd performance.

Lifetime production of a suckler cow depends on age at first calving, age at exit from the herd, and the number of calves weaned in between. Age at first calving and age at exit can be monitored using an average (mean or median), but ideally the distribution should also be evaluated. A study from the University of Florida using US Department of Agriculture (USDA) data found that 15% of reported culls from the beef herd were cows under 5 years of age, and that these culls were mainly for reproductive reasons. 32% of culls were cows of 5 to 9 years of age, and the reason for culling in this age group was more varied. Cows over 10 years of age accounted for 53% of all reported culls (Hersom et al., 2015). In this study, the two most common reasons for culling were 'pregnancy status' and 'age/bad teeth'.

Distinguishing between voluntary and involuntary culls is important in analysing cull data effectively, but it can be difficult as the distinction is often subjective. Recording a reason (or reasons) for each cull also allows this data to be better used to inform decision-making. Culling rates are affected by many factors such as target herd size and infectious disease status, as well as many external factors such as market values and feed prices. This makes them challenging to use to monitor herd health if used in isolation. Other more comprehensive measures of cow longevity, such as calves produced/cow life year, may be more appropriate indicators of overall herd health.

### 1.8.2 Infectious disease KPIs

As herds increase in size and cattle move longer distances, the control of infectious diseases becomes both more difficult and more important. There are various disease eradication schemes worldwide, some compulsory and some voluntary, and many farmers are keen to gain certified free accreditation status for specific diseases. This could provide data that would enable further investigation of how disease infection status impacts farm success, and how it might be incorporated into a KPI. Three infectious diseases of importance to beef enterprises are considered: Bovine Viral Diarrhoea (BVD), pneumonia and Johne’s Disease (although the same monitoring principles could be applied to other infectious diseases). How they each affect herd performance, and how monitoring them could be incorporated into specific KPIs is discussed.

#### *1.8.2.1 Bovine Viral Diarrhoea (BVD)*

BVD is an infectious disease of cattle causing infertility and abortion in adult cattle, as well as immunosuppression in calves which can predispose them to other infections. If a cow is infected during the first few months of gestation, her calf may become persistently infected (a ‘PI’ calf) and will shed the virus for the rest of its life. The calf may have stunted growth or be more susceptible to disease, or it may appear normal. If a female PI reaches maturity and produces calves they will also be PIs, which can contribute to persistence of the virus in the herd. It has been shown that calf mortality rates are 1.35% higher in seropositive beef herds, and that seropositive beef herds are likely to have increased levels of culling, which it was suggested could be due to infertility (Gates et al., 2013). However, the extent to which BVD impacts herd performance can be highly variable. A study in the US found that 3% of randomly selected herds contained at least one persistently infected (PI) animal, and that most of these were the result of acute infection during gestation. The proportion of cows pregnant the following autumn in herds with PI animals was also 5% lower than non PI herds (Wittum et al., 2001). When looking at how BVD infection affects grower/finisher performance, a study in the US found no statistically significant differences in morbidity, mortality, ADG or DMI between pens of animals containing at least one PI animal and pens containing no PI animals. ADG and DMI did however show a trend of being better in pens with no PI animals (Booker et al., 2008). As BVD appears to mainly affect calf mortality rates and fertility, seroprevalence could be used as a specific performance indicator to further investigate herd fertility or calf mortality problems.

#### *1.8.2.2 Pneumonia*

Pneumonia in calves can be caused by a variety of agents, and often more than one is involved in a case; the term Bovine Respiratory Disease (BRD) complex is therefore commonly used. Calves showing clinical signs of pneumonia are often only the tip of the iceberg, however subclinical BRD (i.e. calves that show no clinical signs of disease but have some damage to their lungs) can also affect performance. This was illustrated in a study from the USA which showed that rates of 'sick' animals from a unit did not correlate with the rates of sub clinically infected animals identified at slaughter. Cattle with subclinical BRD were also shown to have decreased ADG, and a 20% subclinical rate was estimated to cost approx. $20/finished animal (Griffin, 2014). In a second study, it was suggested that BRD may result in poorer feed conversion, however there was insufficient disease challenge during the study to draw statistically significant conclusions. Trends did indicate however that ADG was lower in affected animals and that FCR was higher. This is to be expected as pyrexia is known to cause poor feed conversion (Jim et al., 1993). In their paper looking at how the number of treatments an animal received (for pneumonia and other diseases) affected ADG and carcase quality, Reinhardt et al. (2012) found that increasing number of treatments decreased ADG, final body weight, and carcase classification. A pneumonia incidence KPI (e.g. animals treated/100 calves/year) could therefore be used as a specific performance indicator to investigate poor growth.

#### *1.8.2.3 Johne's Disease*

Johne's Disease is caused by *Mycobacterium avium subspecies paratuberculosis* (MAP), a mycobacterium very similar to the one which causes bovine tuberculosis (bTB). Calves are infected at a young age from adult cattle, but then have a latent infection for a number of years before starting to shed the bacteria in adult life. This shedding is sporadic initially and occurs before there are any clinical signs making infected animals difficult to identify. To further hinder identification of infected animals, diagnostic tests used are often low in sensitivity (particularly early on in infection) and some are further complicated by cross reaction with the tuberculin intradermal skin test (used for bTB testing). Control measures include testing and culling individual animals and trying to break the cycle of infection by taking calves away from dams immediately after birth ('calf snatching'). Johne's Disease has been reported to cost £17/beef animal/year in the UK (Gunn et al., 2004). In their review of the economic cost of paratuberculosis in cattle, Garcia and Shalloo (2015) report that 205 day adjusted weaning weights were also considerably less for calves from positive cows (Bhattarai et al., 2013), although the impact of the disease on fertility appeared variable. The review concludes that closing infection routes is crucial to control of

Johne's Disease, and that test and cull strategies alone are not sufficient or economically viable, mainly due to low sensitivity of diagnostic tests. In dairy herds, closing the Johne's infection route often involves removing calves from their dams at birth, which is largely impractical in suckler herds. Bennett et al. (2010) designed an economic decision support tool for Johne's control in suckler herds in the UK. They found that the most financially beneficial control option was improving management i.e. improving calf hygiene and having a designated clean calving area. Testing and culling was found to have a negative financial return over 10 years in this scenario. The impact Johne's Disease has on the beef herd through reduced growth rates, and possibly fertility, suggest that seroprevalence could be used as a specific performance indicator to further investigate poor growth rates or reduced fertility.

#### *1.8.2.4 Monitoring infectious disease*

The impact of infectious diseases on herd health and performance can be significant, and as beef enterprises increase in size, control of infectious diseases becomes less focussed on individual animals and more focussed on populations. Measures such as morbidity rate, mortality rate, case fatality rate, re-treatment rate, non-performer incidence, and health and disease cost have been suggested as metrics to monitor infectious disease levels in feedlots (Corbin and Griffin, 2006). They are defined as follows:

- **Morbidity rate** – the number of animals that become diseased during a time period divided by the number of animals at risk (i.e. the group size). This could be monitored over various time periods, for example between groups or seasonally as required. It could also be analysed further, for example by disease type (e.g. BRD/lameness etc.), or by source or age of animal.

- **Mortality rate** – the number of animals that die during a time period (adjusted for time at risk if necessary) divided by the number of animals at risk (i.e. the group size). This could also be further monitored as described above.

- **Case fatality rate** – the number of animals with a specific disease that die of that disease during a time period, divided by the total number of animals with that disease over the time period.

- **Re-treatment rate** – the number of animals requiring a second treatment for the same disease divided by the number of animals treated for that disease during a time period. This can be used to monitor treatment efficacy.

- **Non-performer incidence –** number of animals that are salvaged due to poor performance or chronic disease during a time period divided by the group size over that time period.

- **Health and disease cost –** can be monitored as treatment cost/animal treated for a disease to evaluate the economic cost of each disease, or as treatment cost/head to compare different groups of cattle. Total health and disease costs (which can include processing costs and the value of animals that have died) can be expressed as a percentage of total cost of production per head or per unit weight.

### 1.8.3 KPIs to measure antibiotic usage

The need to monitor antibiotic usage in livestock is clear amid concerns around development of antimicrobial resistance and the setting of national targets. Significant progress has been made, with the sales of antibiotics used to treat food producing animals halving since 2014 (RUMA, 2020). However, there is more work to be done, and some specific considerations to be made when applying some of the metrics to the beef sector. In the UK, antibiotic use is measured nationally using mg/PCU (population correction unit). PCU are used when analysing antimicrobial sales data to account for the variation in animal populations over time (imports, exports etc). It represents the estimated weight at treatment and the estimated number of animals eligible for treatment over a 12-month period. Overall sales of product for use in food producing species can then be presented as mg/PCU enabling year on year comparison. In beef enterprises, PCU is calculated using the number of animals slaughtered, (whereas live animals are taken into account in dairy enterprises) (European Medicines Agency, 2016). If used to monitor antibiotic usage at individual farm level, animals not going to slaughter (for example suckler cows) will not be included in the estimated number of animals eligible for treatment, risking an over estimation of antimicrobial usage. Conversely, in a finishing enterprise where cattle may only stay on a unit for a short period of time, the number of cattle slaughtered may be much higher than the number eligible for treatment at a given time, leading to an underestimation of antimicrobial usage.

The Cattle Health and Welfare Group (CHAWG) has developed an industry standard for measuring and monitoring antibiotic use on beef farms in the UK (CHAWG, 2020). The report discusses many of the challenges associated with measuring antimicrobial use of beef farms and suggests a number of metrics for use in different situations. The metrics are either based on the mass of the animals (mg antibiotic/kg animal) or the number of animals (% of the herd treated or the % of days animals are receiving treatment), and can be split to represent treatments in specific age groups of animal. The mass-based metrics use a set of standardised weights to calculate a whole herd weight in a similar way to PCU calculation, but more applicable to an individual farm. They do not however give an indication of the number of animals treated (the mass of antibiotic required for one adult will be the same as for several calves for example). This is when either evaluating antimicrobial use in a subset of animals (e.g. calves) is useful, or using animal number-based metrics in conjunction with mass-based metrics (such as % of herd treated per year). Varying herd size can also be a challenge in beef herds, so use of an average herd size is suggested in the CHAWG report. Ideally, this would involve adding together the herd size on each day of the year, and dividing by 365 (making 'cattle-years at risk' the denominator). This may be difficult to calculate from readily available data however, so an alternative of recording herd size once a month and dividing the sum of these by 12 was suggested in the report.

There is a concern that measuring mg of antibiotic used has the potential to promote use of antibiotics with lower dose rates, a characteristic of many of the high priority critically important antibiotics (HP-CIAs) which should only be used as a last resort. An alternative approach could be to use defined daily doses (DDD), which are used to define the average maintenance dose per day for a drug used for its main indication, and are used to standardise dose rates and monitor veterinary antibiotic use at a national and international level (European Medicines Agency, 2015). The Netherlands Veterinary Medicine Authority (SDa) uses a similar principle to monitor antibiotic usage at individual farm level, using a Defined Daily Dose Animal Farm ($DDDA_F$) (Heederik et al., 2014). The number of kilograms of animal that could be treated with the amount of antibiotics used by a farm is calculated, and this number is divided by the average number of kilograms of animal present on that farm in the year concerned (expressed in DDDA/animal year or 1000 animal days). Although more representative of responsible antibiotic use, this is quite involved to calculate. As use of HP-CIAs is low in the beef sector, and use of this class of antibiotics can be examined in isolation using the metrics suggested by CHAWG, it is hoped that any increased use of HP CIAs would be unlikely and visible with the metrics suggested.

## 1.9 Environmental KPIs

Consumer interest in farming methods has been increasing in recent years with concerns around the environmental impact of food production. This is a complex issue, and beyond the scope of this review to cover in detail, but the development of metrics for measuring and monitoring environmental impact is relevant.

There are many ways of measuring environmental impact, but often greenhouse gas (GHG) emissions are a focus due to the methane produced by ruminants (Hyland et al., 2017). GHGs tend to be converted into $CO_2$ equivalents for monitoring, which standardises them according to their global warming potential (GWP). However, methane breaks down relatively quickly and so its overall contribution to global warming is short lived. A new metric, GWP*, has been suggested which incorporates this, and would reduce the recorded GHG emissions for beef farms (Allen et al., 2018). Interestingly, this is likely to have the largest effect on systems with relatively high methane production, which would include more extensive grass-based systems. It may also focus attention on farms from reducing methane emissions from cattle to reducing fossil fuel use, or other sources of GHGs such as manure management (Capper, 2020). In a study of beef production in the US carbon emission ($CO_2$ equivalent/kg carcass weight), fossil fuel energy use (MJ/kg carcass weight), blue water use (L/kg carcass weight) and reactive nitrogen loss (gN/kg carcass weight) were all recorded to indicate environmental impact (Rotz et al., 2019). With a variety of different measures, the environmental impact of a system may vary depending on which metric, or combination of metrics, is used. For example, Modernel et al. (2013) showed that as beef systems intensify they perform better in terms of greenhouse gas (GHG) emissions, but worse in terms of energy consumption and soil erosion rate.

As improving efficiency tends to reduce environmental impact, it should also be considered that any performance indicator that improves production efficiency could potentially be classed as an environmental KPI (Capper, 2020). A simulation model predicting the GHG emissions with different levels of production and management systems, using an optimised diet, highlights how production and GHG are connected (White et al., 2015). Scenarios investigated included shortening the calving window (calving period) from 60-80 days, using expected progeny differences (EPD) to improve herd genetics and weaning early at 5 months rather than 7 months. The effect of twinning in cows was also investigated. The inputs for the model were based on average US production and the various scenarios were compared to a baseline based on a low cost (but nutritionally complete) diet. In addition to GHG emissions, the model looked at the effect of changes on land use and water use, all measured per kg of HCW (hundred carcass weight) beef produced. Decreasing the calving window from 60-80 days resulted in a 3.2% reduction in all three environmental impact parameters. Early weaning resulted in an 8.5% reduction in all parameters, twinning a 9.2% reduction, and use of EPDs an 11.1 or 11.3% reduction (referring to AI or natural service respectively).

The term ‘sustainable intensification’ has been used to describe this increase in production and consequent reduction in measures of environmental impact (Hyland et al., 2017). As well as being environmentally and economically sustainable though, they must also be acceptable to the consumer. When discussing sustainability, the three sustainability pillars are often referred to; environmental impact, economic viability and social acceptability. White and Capper (2013) assessed these three aspects in beef production systems, with varying levels of efficiency, in order to evaluate sustainability of the systems. Cow-calf, stocker/backgrounder (including calf rearing and store systems) and feedlot systems were all represented in the deterministic simulation model. Three scenarios were used in which the beef enterprise either had representative average US production level, 15% increase in average daily gain (ADG), or 15% increase in finishing weight (FW). Environmental impact was measured using feed consumption, land use, water use, greenhouse gas emissions and nitrogen and phosphorus excretion. Economic viability was assessed using income over variable costs (IOVC). Social acceptability was assessed using customers’ ‘willingness to pay’ as an estimate of consumers’ desire to purchase beef. In all cases improved efficiency resulted in reduced environmental impact. When efficiency was improved through management practices that were not socially acceptable however, both the social acceptability and economic viability were compromised. The concept of feeding cattle food that could be used to feed people is a commonly cited aspect of production that does not appeal to consumers. Metrics that include the potential value of cattle feed to people (i.e. whether they are 'human-edible' or not) have been suggested as a way of assessing overall environmental efficiency of food (Wilkinson, 2011). FCR were calculated on an edible input:output basis for various meat production systems, and grass-based beef and lamb production was found to be more efficient (had a lower FCR) than pig or poultry meat production using this metric. Apart from milk and upland suckler beef however, all edible feed protein:edible animal protein FCRs were >1, although it was suggested that the use of by-products in place of cereals and soya may help to counteract this.

Regardless of which metrics are used, focussing on an individual measure of environmental impact has the inherent risk of increasing impact in other areas. The most environmentally efficient system for a farm will depend on the resources available, as well as other external factors such as local culture and climate. Therefore, having a blanket 'one size fits all' approach to defining an environmentally sustainable system is unlikely to be successful.

## 1.10 Key issues around data in beef enterprises

### 1.10.1 Engaging with farmers to improve data capture and analysis

In order for any of these aspects of performance to be monitored, data must be collected and analysed. This will usually involve investment of time (and sometimes money) by the farmer, often involving an external person such as a vet or consultant too, and so a degree of commitment is required. Understanding farmer motivations and attitudes to risk is important in engaging with them around recording and using data to make informed management decisions, and in assessing the likelihood of technology uptake (Greiner et al., 2009). Record keeping is often seen by farmers as a way of complying with regulation, rather than a way of collecting data for analysis to inform decision making (Escobar and Buller, 2014). In the UK, statutory data is often not recorded and presented in a way that allows farmers to easily make best use of it for analysis (Escobar, 2018). However, many aspects of performance such as fertility and mortality rates can be investigated to some extent using statutory movement data, and this could provide a way of increasing the amount of data available for performance monitoring. Use of such data may present a way of engaging with farmers who currently do not performance record, and this 'base-line' level of data could be built on over time, as required by the enterprise.

It has been suggested that vets tend to adopt a paternalistic approach to consultations, rather than a mutualistic approach (Bard et al., 2017). This can lead to farmer motivations being assumed rather than discussed, and a consequent lack of engagement from farmers. Instrumental support (i.e. offering solutions) is often provided, rather than emotional support (i.e. investigating farmers feelings and perceptions), which is also likely to lead to less emotional engagement. Decision making is often not a rational process, and has an emotional element (O'Kane et al., 2017). Decisions are also rarely made based on one factor (Escobar and Buller, 2014), and relying on economic arguments alone can often fail to result in behavioural change (Reyher et al., 2017). Factors such as professional pride, concern for the environment or welfare of an animal, and social and community engagement may also play a part (Escobar and Buller, 2014). It is therefore important to engage in discussion with farmers about what they want to achieve with their data.

Allowing farmers to develop their own plans, goals and performance indicators may be beneficial in allowing them to take ownership of a situation, and so increase motivation. It will also help to ensure that indicators are relevant to an enterprise (Duval et al., 2016). High levels of adoption and behavioural change are also associated with schemes that use or build on existing practices (Escobar and Buller, 2014). Scientists (or vets) and farmers may use data differently, and so may have different priorities when collecting data. For example, scientists may be more interested in comparing many herds whereas farmers are likely to be more interested primarily in their own data. In a study where organic dairy farmers were asked to accept or reject a list of performance indicators drawn up by scientists, and suggest alternatives for rejected indicators, it was found that farmer suggestions tended to be more specific to their particular farm (Duval et al., 2016). This highlights the need for performance indicators to be adaptable in order to address specific needs of a given enterprise at a particular time, and for the opportunity of discussion with the farmer when selecting performance indicators.

### 1.10.2 Automated data collection

As discussed in the previous section, one of the main challenges with using performance indicators to monitor herd performance is capturing the required data. A 'catch 22' situation exists where demonstrating the benefits of data analysis to inform decision-making is challenging where the data is not available, and so as a result encouraging farmers to capture and use data can also be a challenge when there is a limited evidence base. Data capture can be time consuming and expensive, so methods of automated data capture may be a way of increasing data use amongst beef farmers.

Automated methods of data capture exist within the dairy industry. For example, behaviour meters record lying times as well as activity of individual cows for heat detection purposes, and walk-over weigh cells can be positioned (for example at the parlour exit) to record cow weights. Automated body condition scoring of dairy cows is also being developed (Azzaro et al., 2011). Cow body shape is evaluated by measuring the difference of an individual cow from the 'average'. 23 anatomical points were used around which angles were calculated to evaluate body shape. The often more extensive nature of beef enterprises, with greater time spent at grass and less handling of cattle, plus the greater variety of beef breeds (often within the same herd), and the reduced uniformity between beef cows, may make some of this technology more challenging to apply to beef herds.

Automation of many processes and an increased need for traceability has resulted in a growing use of EID within the cattle industry, in the form of ear tags, ruminal boluses or microchips. Boluses and microchips tend to be preferred by research institutions as there is less chance of loss and fraud, however industry tends to prefer ear tags due to their ease of application (Huber, 2004, Eggers et al., 2009). As well as facilitating data collection and management on farm, they may also aid exchange of data between businesses, and feedback of data from abattoirs. The use of EID in sheep became compulsory in the UK in 2010 (for all animals born after 31st December 2009 and not slaughtered before 12 months of age) and its use in cattle is mandatory in several countries worldwide. In Denmark the use of EID in all cattle became mandatory in 2010, with the aims of helping to eradicate infectious diseases and improve herd management, food safety and farm economics. It has been estimated to save the Danish cattle industry €11 million/year through time saved (Hansen, 2010). EID is also mandatory in Australia, Botswana, Canada and Uruguay (Passantino, 2013), but there are many countries in the world with a large number of cattle and no animal identification system (electronic or not), including China, India and Russia (Bowling et al., 2008). Financial restrictions appear to be a major perceived barrier to uptake of EID; a study in Welsh sheep flocks where the acquisition of EID was subsidised and farmers' experiences to using the technology were recorded, found that over 70% of participants would not have started using EID without the financial incentive provided by the study. Other than economic constraints, farmers also had a perception that EID was too complicated for them to use, although the training element of the project appeared to solve this problem in the majority of participants (Hybu Cig Cymru, 2015). In Scotland the situation seems similar, with barriers to EID uptake in sheep flocks mainly reported as being financial (Morgan-Davies and Lambe, 2015), and suggestions made to increase uptake such as provision of training, simplification of software, financial assistance and demonstration of value added by EID.

Automated data collection allows capture of large data sets, often termed 'big data'. When this data is used to inform not only management decisions on an individual farm, but also business decisions in wider agricultural industry, the question arises as to who owns the data, and therefore how it should be used. This data may be of value not only to the farmer, but also to other businesses, to be used in product development for example (Dyer, 2016). With a rise in the capture and use of 'big data' within the livestock industry, this is likely to be an area of discussion within the sector for some time (Hudson et al., 2018).

### 1.10.3 Developing KPIs for beef enterprises

Examples of performance indicators that could be used to monitor productivity in the beef herd have been suggested throughout this review. Data behind their development however is lacking, as is determination of which metrics are most relevant to enterprise success. There may be several reasons for this: detailed physical and financial data is required for a large number of herds over a number of years, which requires engaged farmers and data compatibility. The beef production cycle tends to be longer than other sectors (e.g. pork and poultry), with numbers of animals on units much smaller, increasing the length of time over which data has to be available. Beef systems are often more extensive than dairy, poultry and pork, making data capture more difficult, expensive and time consuming. In addition, farms are complex systems with many confounding variables which can make data difficult to interpret. Simulation models can be used to overcome these problems, for example Lof et al., (2012) used a stochastic simulation model to evaluate how reproductive performance indicators varied in herds with different reproductive performance (as previously discussed in the dairy KPI section). This allowed determination of the best metric to use to measure reproductive performance. Similar techniques could be used in order to assess different measures of beef herd performance.

## 1.11 Conclusions

Investigating KPIs used in other livestock sectors, those used in beef enterprises outside the UK, and indicators specific to an area of production has allowed several conclusions to be drawn:

- KPIs used worldwide largely focus on suckler herds. KPIs for grower/finisher enterprises are less widely available, however by also investigating KPIs used in other sectors a collection of suggestions has been generated (Table 1-5).
- KPIs used in beef enterprises abroad often include financial parameters, whereas those used in England tend to focus on physical parameters. Within the financial parameters, cost of production (and especially fixed costs) are commonly considered to be key drivers of net margin. Although farmers may often be more willing to benchmark production measures, financial information is also important as the best production performance does not always correlate with the best financial performance.
- Although considering dairy KPIs may be of use for fertility parameters, in general KPIs used in pork and poultry production are more relevant to beef systems.
- Making KPIs relevant to individual enterprises is critical, i.e. they need to be adaptable. A way of achieving this may be to use comprehensive KPIs to monitor overall performance, and a ‘toolkit’ of more specific KPIs to investigate specific problems.

- Feed efficiency is an important component of production efficiency, however there can be problems if using FCR to inform breeding decisions as it has the potential to select for larger dams.
- Infectious disease can reduce performance and is important from an economic and welfare point of view. It is an area of production where few KPIs currently exist, however the increasing interest in gaining accreditation free status of certain diseases, leading to increasing testing for these diseases, may provide data for development of KPIs in this area. Such KPIs could be used in conjunction with other health related KPIs such as culling rates, mortality rates, and antibiotic usage.
- Environmental KPIs are important to measure with the aim of reducing the impact of farming on the environment, however they can also be a useful measure of efficiency.
- To aid farmer engagement and motivation with data collection and analysis, a dialogue should be opened with the farmer in which targets and motivations are discussed. Use of data that already exists, such as statutory movement data, could be used as a way of engaging with farmers who do not currently data record.
- There appears to be limited evidence behind many of the KPIs currently used to monitor beef herd production. Decisions regarding appropriate indicators are often made through discussion with benchmarking groups, or are based on what data is available. Stochastic simulation modelling provides a method of evaluating these metrics, without the need for large amounts of detailed 'real herd' data. It is anticipated that this evaluation will help farmers to focus on recording and analysing the data that is most relevant to their enterprise.

## 1.12 Aims and objectives

The aim of this project was to evaluate key performance indicators for English beef herds, producing a practical and relevant list of metrics and illustrating the association of these with enterprise success. The first objective was to explore what performance indicators are commonly used by beef farmers, whether metrics from other countries or sectors could be adapted for use in the English beef sector, and what the perceived challenges are around monitoring herd performance. The second objective was to analyse the associations between these metrics and overall enterprise success, using both data collected from farms and data generated in a simulation model. The combination of these objectives would lead to a collection of KPIs developed through stakeholder consultation and data analysis.

*Table 1-5: **Suggested beef grower and finisher KPIs**, generated through investigation of metrics used to monitor performance in a variety of livestock sectors.*

| KPI | Sector | Comments | Reference(s) |
|---|---|---|---|
| **Mortality %** | Pig, poultry and cattle | Can be used to investigate seasonal trends/monitor mortality within different groups of cattle. | (AHDB Pork)<br>(Manning et al., 2008)<br>(Corbin and Griffin, 2006) |
| **Feed conversion ratio** | Pig, poultry and cattle | Measure of feed efficiency and important from a financial and environmental point of view. When used to inform breeding decisions it can select for big cows. | (AHDB Pork)<br>(Manning et al., 2008)<br>(Jim et al., 1993) |
| **Daily liveweight gain (kg/day)** | Pig<br>Cattle | Useful measure of growth of an individual or group of animals over a period of time.<br>Does not incorporate any financial (or input) information. | (AHDB Pork)<br>(Sherwin et al., 2016) |
| **Net income/pig produced** | Pig | Financial parameter. | (Marchand and Duffy, 2013) |
| **Bird place efficiency (kg/m$^2$/week)** | Poultry | Useful in enterprises where space is limiting factor.<br>Not linked to financial parameters. | (Manning et al., 2008) |
| **European production efficiency factor (EPEF)** | Poultry | Incorporates growth rate, survival rate and FCR. Comprehensive KPI that is used industry wide for poultry benchmarking. | (Manning et al., 2008) |
| **Veterinary medicines (kg/1000 birds)** | Poultry | Used monthly would give an indication of seasonal patterns, but can be affected by size of animals treated and dose rate of drugs used. Incorporating drugs used and conditions treated may be of use. | (Manning et al., 2008) |
| **Financial return (£) /bird or kg live weight.** | Poultry | Incorporates both growth and financial output. Does not take into account input costs. | (Manning et al., 2008) |
| **Coefficient of variation** | Poultry | Measure of uniformity – useful if aiming to produce uniform carcasses. | (Manning et al., 2008) |
| **Net sale gain (€/head or day or Kg)** | Cattle | Incorporates financial input and output and can be expressed per head, day or Kg. Could be used to help make decisions on when to sell cattle. | (Gallo et al., 2014) |
| **Gross margin (£) / unit of intake / year** | Cattle | Measures inputs and outputs.<br>May be challenging to calculate. | (Morris and Smeaton, 2005) |
| **Gross margin (£) / ha** | Cattle | May be of use in grass based systems.<br>Calculating area of grazing may be challenging. | (Rosado Júnior and Lobato, 2010) |
| **Productivity (kg/ha/year)** | Cattle | May be of use in grass based systems.<br>Does not incorporate financial parameters. | (Rosado Júnior and Lobato, 2010) |
| **% marketed at customers' spec.** | Cattle | Measures success of providing what customer wants. | (Rosado Júnior and Lobato, 2010) |
| **Morbidity rate** | Cattle | May be more indicative of disease levels than mortality rate. | (Corbin and Griffin, 2006) |
| **Re-treatment/non-responder rate** | Cattle | Indicator of effectiveness of treatments and disease level. | (Corbin and Griffin, 2006) |
| **Non-performer incidence (animals salvaged due to poor performance)** | Cattle | Could be used as a health indicator. | (Corbin and Griffin, 2006) |
| **Health and disease cost** | Cattle | Measures financial cost of health status and disease levels. | (Corbin and Griffin, 2006) |

# Chapter 2: The beef KPI technical advisory group

## 2.1 Background

Following a review of the existing literature (Chapter 1), a technical advisory group (TAG) was created in order to further evaluate KPIs used in beef herds in England. This was funded by The Agriculture and Horticulture Development Board (AHDB), a statutory levy board funded by farmers. The literature review highlighted that the use of performance indicators to monitor production in the beef sector has tended to be more limited than in the dairy, pork and poultry sectors. Although uptake is increasing, it was felt that there was limited evidence behind the performance indicators currently advocated in the sector, and how they influence overall enterprise success. Further investigation around the practicalities of data recording on farm, and how this can be achieved routinely and reliably, was considered warranted.

## 2.2 Introduction

As summarised in Chapter 1, there are many varied performance indicators used by beef farmers and advisors to help inform management decisions on farm, often with slightly different definitions and methods of calculation. Although this may aid successful herd management in some instances, inconsistencies mean there is the potential for confusion and misinterpretation of data, leading to poor herd management decision making. Challenges around data capture in beef herds means that evidence around which performance indicators are best associated with overall enterprise success is limited, with current advised metrics often decided through farmer discussion groups (Caldow et al., 2007). Further exploration of consensus on which performance indicators are of most use in informing herd management decisions, and how these can best be calculated, was therefore one of the main aims of this project. Data required to calculate KPIs must also be practical to capture routinely and reliably, whilst reflecting the goals of the enterprise. Therefore, collating farmer and advisor opinion on practicality aspects of data capture and using performance indicators to inform decision making was also important to the project.

Collecting opinion through discussion with groups of experts has been used extensively to reach a consensus in a variety of veterinary and non-veterinary situations (Phythian et al., 2011, Delbecq et al., 1975, National Institute of Health, 1990, World Health Organisation, 2014). Where face-to-face discussion between experts is not required, or is not possible for example due to geographical constraints, the Delphi method may be used (World Health Organisation, 2014, Delbecq et al., 1975). This involves distributing questionnaires which are filled out by participants independently. Summaries of the outcomes are then distributed along with further iterations of the questionnaire, allowing participants to be aware of the ranges of opinion voiced, but not facilitating discussion. Where face-to-face discussion is possible and appropriate, techniques such as the nominal group technique (NGT) may be used (Delbecq et al., 1975, World Health Organisation, 2014). This involves small group meetings which are designed to encourage discussion and participation from all group members. The process involves an initial independent phase allowing participants to generate their own ideas, followed by feeding back the ideas to the group members and discussion. Mathematical voting techniques may be used to reach a consensus, for example by ranking the ideas.

Some organisations have developed their own techniques for reaching a consensus amongst a group of experts. For example, the consensus methodology of NIH, which uses a conference style meeting approach (National Institute of Health, 1990). This involves a pre-meeting consultation (for example a questionnaire) followed by focus group discussions, and enables idea generation and open discussion. The final step involves post-meeting distribution of outcomes, allowing participants to comment independently or confirm agreement. This method requires that the term “expert” be clearly defined, and that the group comprises a good balance of members in terms of occupation and expertise. It has been used successfully in a veterinary context to reach a consensus opinion on welfare indicators for sheep (Phythian et al., 2011).

As well as these formal methods for reaching consensus, unstructured, open discussion may also be used (although the risk of missing contributions from quieter members of the group, or dominance of louder members, is greater with this technique). Combinations of these various techniques may also be employed, often termed “hybrid approaches” (World Health Organisation, 2014).

Groups of experts that come together to advise organisations are sometimes referred to as Technical Advisory Groups (TAGs), and are commonly used in human health organisations (World Health Organisation, 2013, World Health Organisation, 2017), but also other sectors such as finance (FRC (Financial Reporting Council), 2013). Their objectives can include reviewing technical and scientific information, identifying problems and potential solutions, making recommendations, reviewing progress towards a goal and identifying innovations or opportunities.

The aim of this project was to evaluate performance indicators for use in beef herds, and a TAG would be co-ordinated to guide the project and ensure outputs were relevant and practical for both farmers and beef herd advisors. More specifically this would include:

- Advising farmers and advisors on issues around data collection and KPIs.
- Guiding the academic team so that data would be analysed and interpreted appropriately.
- Identifying barriers to data collection and suggesting possible solutions.
- Evaluating new ways of collecting, analysing, and interpreting data.

The TAG would consist of both beef farmers and advisors, as well as AHDB scientists and University of Nottingham academics. The above aims would be achieved through regular discussion around aspects of beef herd monitoring, and through a combination of the consensus reaching methods previously discussed. A list of appropriate KPIs for beef herds would be generated, which could then be correlated with overall “farm success”, as defined by the TAG. In addition to this, it was envisaged that the TAG would provide farm ‘case-studies’ and industry messages to promote the recording of data and use of KPIs. In summary, the TAG would provide a foundation on which to base the data analysis and data modelling used later in the project to further investigate the relationships between performance indicators and overall enterprise success.

## 2.3 Aims

The aim of this part of the project was to co-ordinate a TAG and conduct focus group meetings exploring KPI use in beef herds. Opinions were sought on challenges and benefits of data capture and use, methods of displaying data, and appropriate metrics for monitoring beef herd performance.

## 2.4 Methods and results

### 2.4.1 Co-ordination of the technical advisory group

Identification of potential TAG members was carried out in collaboration with AHDB, with the aim of including members whose expertise and experience encompassed key roles (such as farmers, consultants, vets, the levy body and academics) and enterprise types (suckler, grower, finisher, intensive, extensive etc.) within the constraints of a manageable group size and the budget of the project. The TAG consisted of four beef farmers considered to have experience of recording comprehensive performance data; an upland suckler herd, a lowland suckler herd, a grass-based grower-finisher, and an intensive finisher. These were identified and initially approached by AHDB. Four beef advisors were also included; three vets with an interest and expertise in the beef sector and a consultant with nutrition experience. University of Nottingham academics and AHDB staff made up the rest of the group (Table 2-1). The four farmers were selected with the aim of incorporating suckler and grower/finisher enterprises, upland and lowland systems, and intensive and extensive systems. Farmers were required to have an interest in data recording, and good historic data. They also had to be willing to provide data (both physical and financial), attend regular meetings, and host two on farm events to facilitate knowledge exchange. Farmers were all male and aged between 30 and 65. Advisors were selected based on suggestions from AHDB and the project team, with the aim of including vets, consultants and nutritionists. Individuals were contacted by the project team to ascertain their interest in involvement in the project, and the final group was a pragmatic reflection of who was able to commit the time to the project. In order to facilitate as broad a spectrum of input as possible, and to allow involvement of people without the time to commit to quarterly meetings, a larger and wider group (the “TAG plus”) was also formed (Table 2-2). TAG meetings were held quarterly from January 2016 to May 2017, with TAG plus members attending the first and final meetings.

| | Position/occupation | Contribution to the TAG |
|---|---|---|
| | **Project leaders** | |
| **Project team** | PhD student, University of Nottingham | Co-ordination of TAG group. Organisation and facilitation of meetings. |
| | Clinical lecturer in dairy health and production, University of Nottingham. Primary project supervisor. | Supervised PhD project and provided expertise around data analysis and simulation modelling. |
| | Professor of cattle health and epidemiology, University of Nottingham. Secondary project supervisor. | Supervised PhD project and provided expertise around data analysis and simulation modelling. |
| | Senior beef and sheep scientist, AHDB | Provided beef industry expertise and project guidance. |
| | Scientific officer (Beef) AHDB | Provided beef industry expertise and project guidance. |
| | Senior analyst – farm economics, AHDB | Provided expertise around financial data recording and analysis. |
| | **TAG** | |
| **Farmers** | Owner of a finishing unit finishing around 5000 cattle/ year in Lincolnshire. | Has a keen interest in performance monitoring and records production data in a bespoke database. Provided performance data for analysis. |
| | Grower and finisher of crossbred cattle in a pasture based system in Herefordshire. | Provided input around growing and finishing beef from the dairy herd. Also uses rotational grazing regimes and is interested in KPIs for forage based systems. Provided performance data for analysis. |
| | Manager of a 150 cow Stabiliser suckler herd in Oxfordshire. Also provides beef consultancy services. | Has an interest in novel building design allowing low labour input, and the effect of fertility on productivity. Provided performance data for analysis. |
| | Owner of a crossbred spring calving suckler herd of 150 in Northumberland. | Provided input from an upland enterprise perspective and performance data for analysis. |
| **Consultants** | Independent beef and sheep consultant. | Interested in maintaining farm sustainability through using home produced feeds to minimise costs and maximise profitability. |
| | Vet and director of a veterinary practice in Northumberland | Has a particular interest in developing physical production targets for measuring animals’ health and benchmarking farms. |
| | Vet practicing in North Yorkshire | Has an interest in benchmarking beef farmers in practice. Provided input around data recording and KPI use in practice. |
| | Vet and regional director of a practice in the South East | Has an interest in infectious disease control and the use of cost-effective screening, eradication and control programmes to maximise productivity. |

*Table 2-1: Members of the technical advisory group (TAG) and their roles within the group*

*Table 2-2: Members of the 'TAG plus' team and their roles within the group*

| TAG plus | |
|---|---|
| **Beef specialist at Scottish Agricultural College (SAC) consulting** | Provide expertise around maximising efficiency in the beef herd. |
| **Beef consultant** | Provide expert input around current use of KPIs in beef enterprises |
| **Beef farmer and AHDB Beef and Lamb chairman** | Provide insight from both a beef farmer and industry aspect |
| **Vet and beef consultant** | Provide insight from both a veterinary and beef consultancy aspect. |

### 2.4.2 TAG meetings

TAG meetings were held quarterly from January 2016 to May 2017. Prior to the first meeting all TAG members were given a copy of the aims and objectives of the project, and at the start of the first meeting a presentation was given outlining these and the contribution that the TAG would make towards them. The objectives of each meeting were drawn up through consultation with AHDB. Meetings were facilitated by project leaders from the University of Nottingham, and a combination of consensus reaching techniques were used as appropriate, including open discussion sessions involving the whole group, sub-group discussion sessions with feedback time, and presentation of data by project leaders (as outlined in the results section). Information was recorded in written minutes taken by project leaders, and where appropriate photographs of whiteboard content. Summaries of all meetings were distributed to the group for further comment after meetings, sometimes requesting that specific tasks be performed, or asking for views on specific topics. Where a consensus was not able to be reached during the meeting, these summaries were used to gather further opinion so that a majority verdict could be agreed by the project team. Summaries of the previous meeting were given at the start of the following meeting for further discussion if required.

The timings, attendees, objectives and outcomes of the TAG meetings are summarised in Table 2-3. The outputs of the TAG meeting discussions have been grouped into several themes: development of a KPI toolkit, discussion around perceived barriers to data recording and use in beef enterprises, discussion around how software can best enable beef farmers to make the most of their data, and discussion around an appropriate definition of enterprise success for use later in the project.

*Table 2-3: Summary of the objectives and outcomes of the TAG meetings*.

| Meeting Date | Attendees | Venue | Objectives and outcomes |
|---|---|---|---|
| **27th January 2016 (10am-4pm)** | TAG and TAG plus | University of Nottingham | **Objective:** Small group discussion with feedback time around KPIs currently used, KPIs that the TAG would like to use but currently do not, and KPIs the TAG feel should be avoided.<br>**Outcome:** A provisional list of KPIs grouped into four categories depending on what aspect of performance they measure. Development of a KPI toolkit allowing farmers and advisors to select relevant KPIs suggested. |
| **27th April 2016 (10am-4pm)** | TAG | University of Nottingham | **Objective:** Small group discussion with feedback time on data required to calculate suggested KPIs, how easy or difficult that data may be to capture, and where it might already exist. Also discussed a definition for overall enterprise success.<br>**Outcome:** Overall enterprise success defined as net margin/cow bred for suckler herds and net margin/head of output for grower/finisher herds. List of data required to calculate KPIs generated and used to collect data from TAG farmers. |
| **20th July 2016 (10am-12 noon)** | TAG | Tele-conference | **Objective:** Discussion around prioritisation of suggested KPIs to provide structure to the toolkit.<br>**Outcome:** TAG members prioritised KPIs and began to develop a KPI hierarchy. This was done partly during the tele-conference and partly independently before the next meeting. |
| **19th October 2016 (10am-4pm)** | TAG | University of Nottingham | **Objective:** Summary of TAG farmer data analysis and open group discussion around ways of displaying data.<br>**Outcome:** TAG found visualising data useful, for example using histograms and box and whisker plots. |
| **23rd January 2017 (10am-4pm)** | TAG | University of Nottingham | **Objective:** Discussion around scoring KPIs and structuring them into a hierarchy to form the KPI toolkit. Definitions of KPIs and ways of presenting them also discussed.<br>**Outcome:** Consensus reached on how KPIs were scored and ranked, and how they should be presented in the toolkit. |
| **19th May 2017 (10am-1pm)** | TAG, some TAG plus and software providers | NEA, Stoneleigh | **Objective:** Presentation of findings to software providers including suggestions on what KPIs the TAG felt were important, and how they could be presented, using examples of TAG farmer data.<br>**Outcome:** Software providers keen to maintain dialogue with farmers and advisors as to how they can enable farmers to make best use of their data. |

### 2.4.3 Development of a KPI toolkit

During discussion with the TAG, one of the first and most recurring points raised was that the diversity of the beef industry makes it impossible to define a ‘blue-print’ of KPIs that will be the most relevant for all beef enterprises at all times. This led to the development of a KPI toolkit (Figure 2-2), containing performance indicators felt to be important by the group, and with definitions of these indicators to aid standardisation of their use (

Figure **2-3**). Performance indicators were suggested by the TAG and grouped into the following categories depending on which part of the system they monitored (although there is inevitably some overlap between metrics): Fertility, Growth and Carcase, Financial, and Health. They were then scored against characteristics of a good KPI and ranked. Characteristics of an optimal KPI were defined again through discussion with the TAG and using a report from the KPI institute (2015). An optimal KPI was defined as:

- Measurable
- Actionable
- Easy to understand
- Timely
- Relevant to efficiency (i.e. incorporating inputs and outputs)
- Comprehensive/specific (as required)
- Relevant to the enterprise's goals

Scoring of KPIs against these criteria was discussed during a TAG meeting and was carried out independently by TAG members between meetings, with the results being collated by project leaders. KPIs were labelled as comprehensive (i.e. monitoring several parts of the system), or specific (i.e. monitoring only one aspect), but this was not used for ranking as it was felt that the importance of whether an indicator was comprehensive or specific would vary depending on the goals of the enterprise. They were also not scored on their relevance to an enterprise's goals, as again this will vary with the specific goals of an individual enterprise. Some characteristics were felt to be more important than others, for example 'measurable' was felt to be more important than 'actionable', and 'easy to understand' more important than 'timely' and 'relevant to efficiency', so scores for these characteristics were weighted accordingly. 'Measurable' was weighted at 2 (so all scores were multiplied by 2), 'actionable' and 'easy to understand' at 1.5 (all scores were multiplied by 1.5), and 'timely' and 'relevant to efficiency' at 1 (scores were unchanged). Scores for each performance indicator were calculated and the metrics were ranked from highest to lowest scoring.

Following ranking of the performance indicators, it was found that the more comprehensive indicators, monitoring more than one aspect of production (e.g. fertility as well as growth), tended to score the highest. This prompted discussion around the idea of a hierarchical toolkit, with comprehensive performance indicators at the top, and more specific performance indicators underneath. This was considered a useful and appropriate structure and so was adopted. Further data analysis suggestions were also included below these as a third level, for example evaluating seasonal variation in performance. This provides a pathway through which producers can monitor overall performance using comprehensive KPIs, but also analyse their data in more detail using the more specific performance indicators. Further analysis suggestions could be used to pin-point areas where productivity could be improved. Figure 2-1 illustrates an example where 200-day weaning weight/kg of cow or heifer bulled is a comprehensive KPI which can be broken down into more specific performance indicators, such as the number of calves weaned, the weight of these calves, and the size of the cows. These performance indicators can be further analysed by looking at when calves are 'lost'; for example, through poor fertility (using scanning percentage), difficult calvings or abortions (using percent of calves born alive), or through high calf mortality rates (using pre-weaning mortality rate). Further analysis can also include looking at the distribution of the data, for example by calculating the range, median or standard deviation, and visualisation of this, for example using histograms or box and whisker plots.

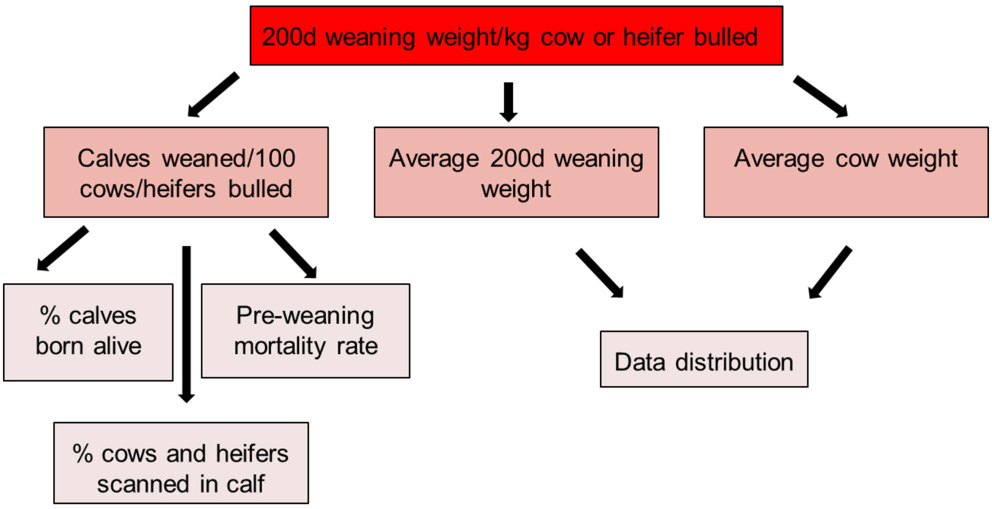


***Figure 2-1: Example of a KPI hierarchy*** *Here, the comprehensive KPI 200d weaning weight/kg cow or heifer bred is broken down into more focused measures of production, such as weaning rates, weaning weights and cow weights. Weaning rates may be further interrogated using calving rates, pregnancy rates and mortality rates, and the distributions of weaning weights or cow weights could also be investigated to gain more information.*

This structure was applied to the KPIs selected by the TAG, and the following KPI toolkit was developed (Figure 2-2), with definitions to aid standardisation of use (

Figure **2-3**).

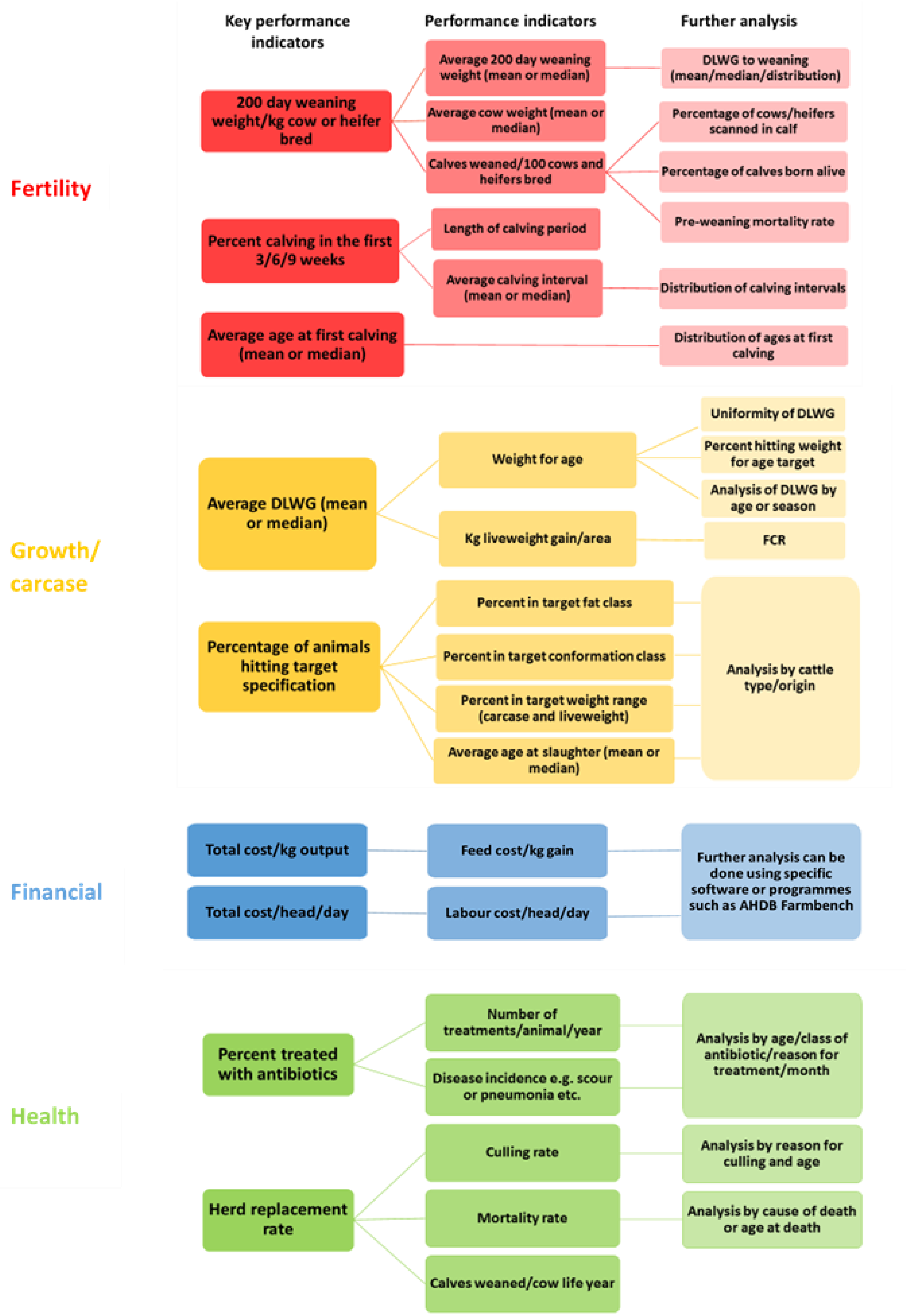


***Figure 2-2: KPI toolkit***. *The toolkit was developed through focus group style discussions, and has been organised into a hierarchical structure, with comprehensive key performance indicators being broken down into performance indicators and further analysis if required*

| Fertility | | |
|---|---|---|
| KPI | 200day weaning weight/kg cow or heifer bred (kgs) | $\frac{\text{Total adjusted 200day kgs of weaned calf}}{\text{Total kgs of cows and heifers bred}}$ |
| | Percent calving in the first 3/6/9w of the calving period * | $\left(\frac{\text{Number of cows and heifers calved in the first 3 weeks}}{\text{Number of cows and heifers bred}}\right) \times 100$ |
| | Average age at first calving (months) | Mean or median herd age at first calving |
| Performance indicator | Calves weaned/100 cows and heifers bred | $\left(\frac{\text{Number of calves weaned}}{\text{Number of cows and heifers bred}}\right) \times 100$ |
| | Average 200day weaning weight (kgs) | Mean or median 200day weaning weight: $\left(\frac{\text{Weaning weight}}{\text{Age in days}}\right) \times 200$ |
| | Average cow weight (kgs) | Mean or median cow weight |
| | Length of calving period* | Number of weeks between start and end of calving period |
| | Average calving interval (days) | Mean or median of the herd calving interval (number of days between two consecutive calvings) |
| Further analysis | Percentage of cows/heifers scanned in calf | $\left(\frac{\text{Number of cows and heifers scanned in} - \text{calf}}{\text{Number of cows and heifers bred}}\right) \times 100$ |
| | Percentage of calves born alive | $\left(\frac{\text{Number of calves born alive}}{\text{Number of cows and heifers bred}}\right) \times 100$ |
| | Pre-weaning mortality rate (%) | $\left(\frac{\text{Number of pre} - \text{weaning deaths}}{\text{Number of calves born alive}}\right) \times 100$ |
| | DLWG to weaning (kgs) | Mean, median or distribution of DLWG to weaning values |
| | Distribution of calving intervals | For example median, range or standard deviation |
| | Distribution of ages at first calving (months) | For example median, range or standard deviation |
| Growth and carcase | | |
| KPI | Average DLWG (kgs/day) | Mean or median DLWG: $\frac{\text{Current weight}-\text{birth weight}}{\text{Age in days}}$ |
| | Percent of animals hitting animal target specification | $\left(\frac{\text{Number of animals hitting target specification}}{\text{Total number of animals finished}}\right) \times 100$ |
| Performance indicator | Weight for age (kgs/day) | $\frac{\text{Weight of animal}}{\text{Age in days}}$ |
| | Weight gain/area (Kgs/Ha) | Total weight gain of group/area grazed by group |
| | Percent in target weight range (carcase and liveweight) | $\left(\frac{\text{Number of animals within target weight range}}{\text{Total number of animals finished}}\right) \times 100$ |
| | Percent in target fat class | $\left(\frac{\text{Number of animals hitting target fat class}}{\text{Total number of animals finished}}\right) \times 100$ |
| | Percent in target conformation class | $\left(\frac{\text{Number of animals hitting target conformation class}}{\text{Total number of animals finished}}\right) \times 100$ |
| | Average age at slaughter (days) | Mean or median age of animals finished |
| Further analysis | Uniformity of DLWG | Proportion of variation in individual animal weight explained by age at weighing |
| | Analysis of DLWG by age or season (kgs/day) | Average DLWG (kg) in each month/age group. DLWG: $\frac{\text{Current weight}-\text{previous weight}}{\text{Days between weighings}}$ |

| | | |
|---|---|---|
| | **Average age at slaughter for heifers/steers/bulls (days)** | Mean or median age at slaughter for heifers/steers/bulls. |
| | **FCR** | $\frac{\text{Total kgs DMI of group}}{\text{Total kgs weight gain of group}}$ |
| **Financial** | | |
| **KPI** | **Total cost/kg output (£/kg)**** | $\frac{\text{Total costs (fixed and variable)}}{\text{Total kgs produced}}$ |
| | **Total cost/head/day (£/head/day) ***** | $\frac{\text{Total costs (fixed and variable)per head}}{\text{Number of days on unit}}$ |
| **Performance indicator** | **Feed cost/kg gain (£/kg)** | $\frac{\text{Total feed cost}}{\text{Finished liveweight} - \text{birth weight or purchase weight}}$ |
| | **Labour cost/head/day (£/head/day)***** | $\frac{\text{Total labour cost (including family labour)per head}}{\text{Number of days on unit}}$ |
| **Further analysis** | **Financial software/AHDB Farmbench** | Further financial analysis available through use of specific software or AHDBs Farmbench service |
| **Health** | | |
| **KPI** | **Percent of cattle treated with antibiotics ****** | $\left(\frac{\text{Number of animals treated with antibiotics}}{\text{Total herd size}}\right) \times 100$ |
| | **Herd replacement rate (%)** | $\left(\frac{\text{Number of cow deaths, culls or sales for breeding}}{\text{Number of cows and heifers put to the bull}}\right) \times 100$ |
| **Performance indicator** | **Number of antibiotic treatments/animal/year ****** | $\frac{\text{Number of antibiotic treatments (courses)in a year}}{\text{Total herd size}}$ |
| | **Calf disease incidence e.g. scour or pneumonia etc.** | $\frac{\text{Number of cases in a year}}{\text{Number of calves born}}$ |
| | **Culling rate (%)** | $\left(\frac{\text{Number of animals culled}}{\text{Number of breeding animals}}\right) \times 100$ |
| | **Cow mortality rate (%)** | $\left(\frac{\text{Number of cow deaths}}{\text{Number of breeding animals}}\right) \times 100$ |
| | **Calves weaned/cow life year** | $\frac{\text{Number of calves reared to weaning by a cow}}{\text{Age of the cow in years}}$ (A mean or median can be calculated for the herd as appropriate) |
| **Further analysis** | **Analysis by age/class of antibiotic/reason for treatment/month.** | Proportion of antibiotic treatment rate, or disease incidence rate, that each age group/class of antibiotic/reason for treatment/month contributes |
| | **Analysis by reason for culling and age** | Proportion of culling rate that each reason for culling/age category contributes |
| | **Analysis by cause of death or age at death** | Proportion of mortality rate that each cause of death/age group contributes |

** Start of calving period calculated from 'bull in' date plus a defined gestation length, or by evaluating the distribution of calving dates where more appropriate.*
*** Suckler herd total kgs is defined as total 200 day weaning weights, store herd total kgs as total liveweight sold, and finisher herd total kgs as total deadweight or liveweight sold.*
**** Head is defined as the number of breeding cows for suckler enterprises and average herd size for store or finisher enterprises.*
***** Suckler herd size is defined as the total number of animals that have been on the holding during the year. Grower/finisher herd size may be defined as the average herd size, or the total number of animals that have been on the holding during the year. Alternatively, number of cattle-days or years may be used as a denominator in herds with fluctuating herd sizes or large numbers of on and off movements.*

***Figure 2-3: KPI toolkit definitions and calculation methods****. These were discussed with the TAG to determine appropriate standardised definitions and calculation methods.*

### 2.4.4 TAG discussion: What are the perceived barriers to data recording and use in beef enterprises?

As previously discussed, for data to be available for routine accurate monitoring of herd performance, it must be practical to collect reliably on a regular basis. This is an area where discussion with the TAG was particularly useful, and several points regarding data availability and perceived barriers to monitoring performance and KPI use were raised:

1. Many KPIs require weight data, however weighing is not something routinely carried out on many beef farms. In addition, the TAG reported that some farmers that do weigh their animals do not record this information, for example they weigh only to identify outliers or select animals to sell, not to monitor trends in weight gain or to analyse uniformity of growth.

2. EID was identified as being of huge benefit in recording data, as was the availability of a good handling system. Cost of such systems was identified as a barrier to uptake.

3. The need for a more integrated supply chain, with greater feedback of data along the chain, was highlighted as a priority for the industry. Reduced (and often unidirectional) data flow was identified as a barrier to effective analysis in beef enterprises, as often only data captured on the current holding is available for analysis.

4. It was acknowledged that the data required to calculate many KPIs may be recorded somewhere, for example in statutory movement records such as BCMS, medicine records, accounts, or kill sheets. It was suggested that one of the main barriers to using this data was its compatibility between systems. Challenges in getting herd management software to integrate with accounting software were reported, and a need for flexible reporting systems, able to produce management and financial reports, was expressed. Herd management software was also described as too complex and not user-friendly enough by some TAG members.

5. It was suggested that farmers tend to be better at measuring physical production parameters than financial parameters, which led to a discussion about how important financial parameters are to farmers, and whether there was a reluctance on the part of both farmers and advisors to discuss financial metrics. The idea that farmers can express more pride in a healthy herd than a profitable one was also discussed.

These aspects were further explored through collection of a wider opinion from a larger set of farmers through a questionnaire (as discussed in Chapter 3).

### 2.4.5 TAG discussion: how can software best enable farmers to make the most of their data?

Throughout TAG discussions, several themes emerged around beef herd data collection and analysis that the project team felt would be useful to share with herd management software providers. In order to pass on these findings, the final TAG meeting incorporated several representatives from herd management software provider companies. It was also felt that any feedback on the challenges faced by software providers in developing these programmes for beef and sheep producers would be of use for the project, and the industry. During this meeting, held on May 19th 2017, the following points were discussed.

1. Outlier values are important to identify as they can have large effects on average values, particularly the mean. The TAG felt that a method of error checking when entering data would be useful, or a way of excluding extreme values before analysis.

2. The ability to provide summary figures other than just the mean was felt to be important by the TAG, as summarising data using a single statistic risks mis-interpretation. For example, a mean figure may be significantly influenced by outlier values, whereas a median one may under-emphasise these values (although in general the median is probably more representative). Both of these risks are higher where the sample size is small, which will often be the case with beef herds.

3. The ability to visualise data in a graph was felt to be important by the TAG. Graphs tend to be much more engaging than tables of numbers, and different types of graphs for displaying data distributions, such as histograms and box and whisker plots, were discussed. The importance of representing dispersion of continuous parameters was appreciated, as was the ability to do this over time (as in Figure 2-4). Displaying seasonal variation in performance, or variation year on year, was felt to be useful by the TAG as a method of pinpointing problem times. Figure 2-4 illustrates a method of displaying DLWG dispersion throughout the year using data from a pasture-based grower-finisher enterprise. This farm had previously experienced a reduction in DLWG in spring (around turnout) and had initiated a transition period and buffer feeding protocol at this time to counteract it. The graph illustrates that although the fall in median DLWG had stabilised, there was still a large variation in DLWG around this time, and so still some animals potentially not performing optimally.

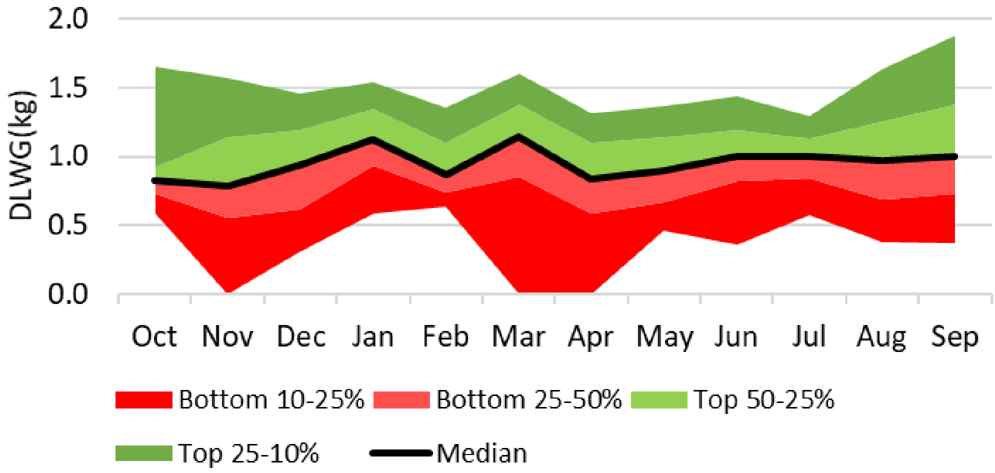


***Figure 2-4: Dispersion and trend in median of DLWG over 12 months****This graph is of data from a pasture-based grower-finisher enterprise, and illustrates how average DLWG varies throughout the year, as well as how the extremes of DLWG vary. This may be of use for identifying causes of extremely good (or extremely poor) production.*

4. Defining a herd size or a 'population at risk' when calculating rates (e.g. treatment rates/mortality rates) can be challenging in enterprises where cattle are frequently being bought and sold and may stay on the unit for variable periods of time. In this instance the use of cattle-years as a denominator (rather than an average herd size) may be more appropriate.

5. Targets should be adjustable so that they can be tailored to an individual enterprise's current performance to ensure realistic performance goals.

6. How the data is displayed and broken down should also be adaptable, for example treatment rate could be analysed by month, year, condition treated, type of antibiotic used, age of animal etc. Which of these methods of analysis is of most interest is likely to vary between enterprises, as well as within an enterprise over time.

7. Farmers are often aiming for uniformity of product, and ways of representing this were discussed. Figure 2-5 illustrates uniformity of weight gain, with the $R^2$ value representing the proportion of variation in animal weight explained by age (1 being the maximum), the y intercept being an estimated average birth weight (35kg) and the gradient representing the average daily weight gain (0.87kg/day). In this example over 90% of the variation in weight is explained by age, indicating very uniform weight gain across all recorded weights on this enterprise in 2015. Representing individual animal data in this way is also a good way of identifying outliers (Hermans et al., 2018).

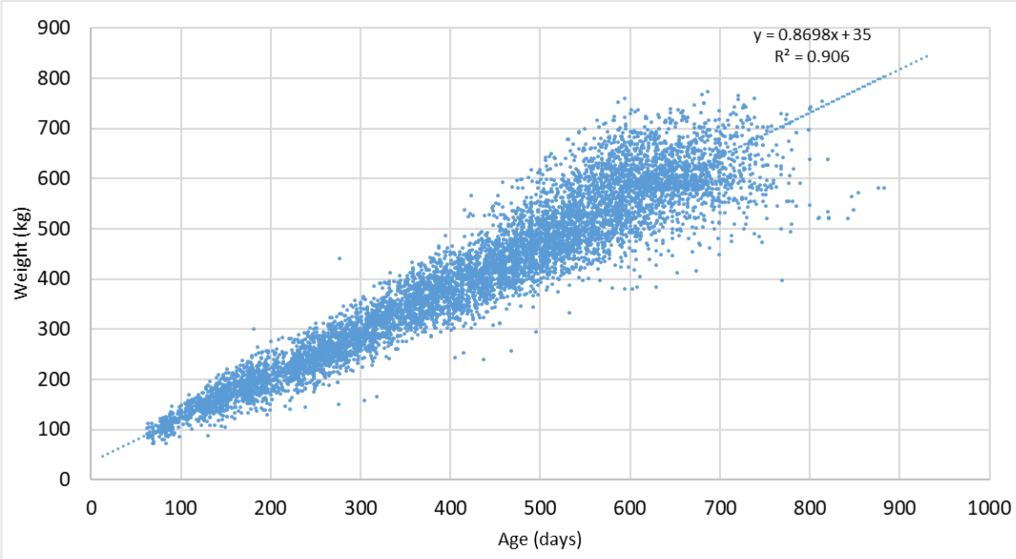


***Figure 2-5: Scatter plot of weight and age values over one year****.This graph Illustrates growth uniformity in a grower/finisher enterprise using data collected in 2015. Where a farmer is aiming for a uniform product, graphs such as these may be of use. The coefficient of x shows the average growth rate (0.87kg/day) with the Y intercept (35kg) being the estimated birth weight. The $R^2$ value indicates how much variation in weight is explained by age (and so how much is due to other, un-recoded factors). This can be used as a measure of uniformity; in a completely uniform herd, with an $R^2$ value of 1, all of the variation in weight would be explainable by age.*

8. Consensus opinion was that being able to identify individual cows, as well as monitor trends across groups, was of use as illustrated in Figure 2-6. Cow efficiency (calf weaning weight as a proportion of dam weight) is often used to make management decisions regarding individual cows, and so displaying this at an individual cow level was felt to be appropriate. Here the cattle are also identified by their age to further assist analysis. In this example, the farmer was aiming to increase his cow efficiency by culling his largest cows and was switching from continental breed types to smaller Aberdeen Angus and Herefords. The only animal on this graph achieving a commonly quoted target of weaning a calf of 50% her own body weight is the lightest one. These are the types of situations where current performance should be taken into account when defining targets; increasing cow efficiency in this way is a long-term goal so targets need to be realistic and expectations should be managed. It must also be borne in mind that this is an upland SDA (severely disadvantaged area) farm, and although extensive pasture improvement has been carried out, lowland suckler farms, or those creep feeding calves, may achieve higher cow efficiencies (but with greater inputs).

9. Standardised data entry aids analysis. For example, providing tick box options for reason for treatments or cause of death, rather than free text input, provides discrete categories for analysis.

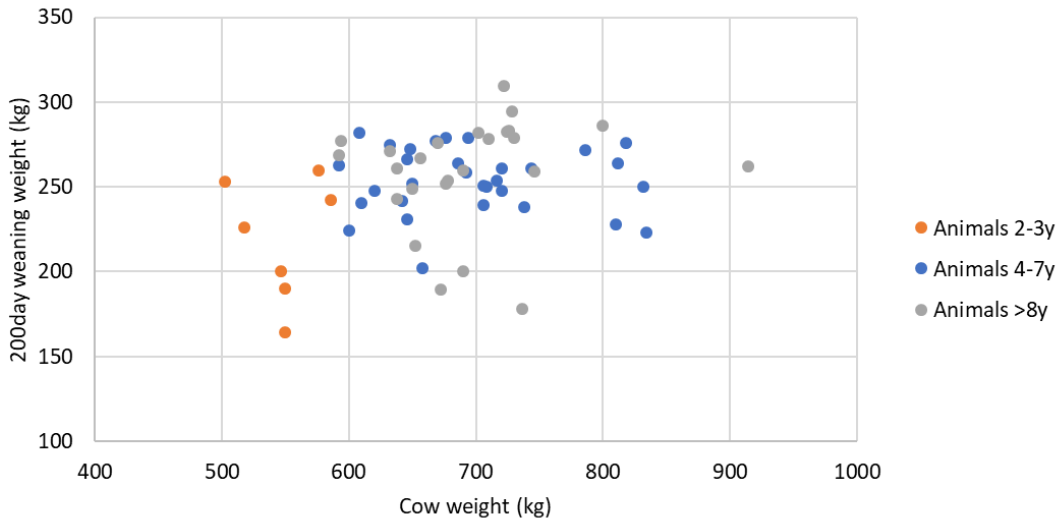


***Figure 2-6: Scatter plot of individual cow efficiency*** *(200 day weaning weight as a proportion of cow weight) and age (colour coded) for one calving season on an upland suckler enterprise. If a target of 50% was used here, just one animal (the lightest) would have achieved the target.*

10. A consistent file format across different software types could help allow data to travel with an animal from birth to slaughter, and back along the supply chain from processors back to producers. It was felt that data sharing in this way would be of benefit for the industry.

11. Farmers are often required to record data in multiple places, increasing risk of human error and time commitment from farmers. Although it was recognised that herd management software is increasingly incorporating pre-existing data, it was felt that data transfer in both directions, i.e. into and out of software, would be beneficial. Compatibility between different software packages, for example those recording physical data and those recording financial data, so that both can be analysed together, was also felt to be beneficial.

12. Some specific pieces of data were required to calculate certain KPIs that it was felt may not be routinely recorded by software packages. For example, a 'predicted start of calving date' (calculated from the start of breeding date) is required for calculating the percentage calving in the first 3, 6 or 9 weeks of the calving period.

### 2.4.6 TAG discussion: what is an appropriate definition of enterprise success?

In order to be able to analyse correlations between KPIs and overall enterprise success, a suitable definition of enterprise success was required. Through discussion with the TAG, it was accepted that there was not one definition that would define enterprise success for every type of beef herd. Whilst physical factors (i.e. factors relating purely to cow performance rather than economic performance, for example growth, health and fertility) may show success in some areas, they may come at increased cost and so lower overall profitability. It was therefore decided that the definition should include financial parameters. Fixed and overhead costs were identified as the biggest drivers of profitability, and so cost of production was discussed as a potential marker of enterprise success. It was acknowledged however that inputs can also be volatile and should be accounted for. Net margin, i.e. the difference between costs and revenue, incorporates both inputs and outputs and is a commonly used financial metric in other sectors. It was decided that it should ideally be calculated on a full economic basis, i.e. incorporating both fixed and variable costs and imputed costs such as family labour and rent etc. However, the potential challenges in calculating enterprise specific costs on a multi-enterprise farm were acknowledged, and the possibility of evaluating KPIs in relation to fixed and variable costs separately was also discussed.

## 2.5 Discussion

A combination of consensus forming methods were used in a hybrid approach to facilitate discussion around use of performance indicators in beef herds. These included small group TAG meetings (similar to those of the NGT), as well as open sessions allowing more unstructured discussion. Conference style meetings were also used to present project findings to a wider audience and allow open discussion.

The NGT is commonly used in medical research, and uses structured, facilitated meetings to collect information from a group of experts (Jones and Hunter, 1995). A review of the literature may be carried out to provide background information and to inform initial discussion, as was the case in this study. During meetings, individuals are encouraged to record their opinions independently, and then feedback to the group for discussion. Resulting judgments or decisions are then recorded by the group individually, and summarised by the facilitator (World Health Organisation, 2014). Aspects of the NGT were incorporated into the TAG meetings held as part of this study, such as presentations around existing relevant literature, and individual ranking of performance indicators. In order to allow more free expression of views and opinions however, sessions for open discussion were also included in the meetings. To ensure all members of the group were able to contribute as much as possible, opportunity for further comment by e-mail was provided after each meeting. Meetings were facilitated by the project team, with the aim of encouraging participation and preventing dominance of any individual members, although trained facilitators could also have been used.

When co-ordinating groups for such meetings, it is useful to have a definition of what constitutes an ‘expert’, and to try and avoid bias in the selection of participants so as to provide a balanced opinion. In this study, participants were selected in collaboration with AHDB, and although a specific definition of expert was not stipulated, the aim was to incorporate as many aspects of the beef industry as possible, so as to reduce opinion bias. Farmers, recognised as being interested in data collection and analysis, were identified by AHDB. Enterprise types included lowland and upland farms, intensive and extensive systems, and suckler and finisher herds. Advisers were also identified by the project team, and a combination of vets and consultants were included. AHDB scientists and University of Nottingham academics completed the group. The aim was for the group to contain representation from as many areas of the beef sector as possible. However, the demographic was not diverse, with the farmers and advisors being almost exclusively male and of a similar age. The requirement for an interest in data analysis and knowledge exchange will also have led to some selection bias, and the farmers not fully representing the beef sector as a whole.

Larger meetings, held at the beginning and the end of the opinion gathering part of the project, incorporated a wider variety of participants from across the beef industry. These included some beef specialists and farmers who were unable to commit to quarterly meetings, as well as some additional representation, such as beef herd management software providers. These meetings were more similar to a conference style meeting, with a larger number of participants and more open discussion. Similar techniques have been used in a veterinary context before, for example to validate indicators of sheep welfare (Phythian et al., 2011), where an expert panel of 30 was co-ordinated, with experts defined as ‘having a minimum of 10 years sole experience of sheep farming in the UK sheep industry, and/or professional achievements in industries and organisations allied to sheep farming, veterinary services and welfare research.’ A one-day meeting was held for the panel to discuss welfare indicators for sheep, structured according to the NIH guidelines. A worksheet was distributed to participants prior to the meeting, in which each expert was asked to list welfare issues for different types of sheep (ewes, rams etc.). These were categorised according to the five freedoms framework (Farm Animal Welfare Council, 2009), and a summary was distributed to all participants prior to the meeting.

In the current study, an agenda was distributed to meeting participants prior to each TAG meeting so that members could consider areas of discussion prior to the meeting, however no structured task was set. Minutes were circulated after each meeting, with opportunity for further comment. After some meetings, comment around a particular aspect was requested, or specific tasks were set, such as ranking of a list of performance indicators suggested during group discussion. In a similar way to the use of the five freedoms as a framework to base welfare indicators around, in this study performance indicators were grouped according to the area of performance they monitored; fertility, growth, health or finance. These groupings were also used during development of the simulation model, with sub-models being created for each group.

In a similar way to the expert panel meeting described by Phythian et al. (2011), TAG meetings started with a presentation to members around what the meeting was aiming to achieve, and any relevant current knowledge in the areas to be discussed.

Progress since the previous meeting was presented, along with results of data analysis from TAG member farms. TAG members were also often divided up into smaller groups for discussion, with feedback sessions to the whole TAG.

Discussion with the TAG through six quarterly meetings was invaluable in guiding the project and ensuring that the outcomes were useful and practical at the farmer and advisor level. Some of the points raised did not relate directly to beef KPIs, but to the beef industry in general, such as the importance of an integrated supply chain. However, the project team felt that these points were useful to discuss in order to put the use of data within the English beef industry in context. The compatibility of herd management software, both between and within programmes (i.e. the ability to generate reports incorporating physical and financial parameters) was also highlighted as an industry problem and is something that was taken forward to software development company representatives at the final meeting.

Many of the KPIs suggested during the TAG meetings involve weight data, and both cow and calf weights are a common component of measures of cow efficiency (Roughsedge et al., 2003b). Weighing is not routinely carried out on many beef farms. Increasing availability of weigh scales through loan schemes via local vets or agricultural merchants was suggested by the TAG as a way of increasing weight data recording. Weighing animals at markets would also increase the amount of weight data available, as well as providing a greater degree of transparency at purchase and sale. This practice is common in some areas but not countrywide. EID was highlighted by the TAG as being helpful in allowing regular weight monitoring, as well as being hugely beneficial for data recording in general. EID has been compulsory in breeding sheep in the EU since 2010 (European Commission, 2016), and is mandatory in cattle in Denmark (Danish Veterinary and Food Administration, 2015), with many other governments considering a similar policy. Barriers to adoption of EID systems proposed by the TAG include expense (although it was noted that this is decreasing), and a lack of awareness of the benefits of the technology. EID is also crucial in automated data collection, another aspect of production that the TAG felt could increase data recording and performance monitoring on beef farms.

The use of already recorded mandatory data to monitor performance, such as movement and medicine records, was highlighted as a way of introducing farmers to performance monitoring and engaging them in data recording. Data can be downloaded from BCMS and calving dates can be used to calculate indicators such as % calving in the first three weeks of the calving period, assuming the start of the breeding period is known (Borsberry, 2007). Medicine records could also be used, for example to calculate antibiotic usage, and kill sheet and invoice data could be a source of costings data, sales figures, and cattle weights and grades.

Predicting performance was highlighted by the TAG as a way of decreasing the inherent lag time that there is between an event occurring and the data being recorded and analysed. Using pregnancy diagnosis results to calculate the percent calving in the first 3, 6 or 9 weeks of the calving period was highlighted as a way of monitoring current fertility, rather than fertility 9 months previously. A similar concept has been suggested for the poultry industry, with the use of 'lead' and 'lag' KPIs (Manning et al., 2008). 'Lead' KPIs focus on current performance and allow 'intra-crop' adjustments to be made. 'Lag' KPIs focus on more historic data meaning that changes can only be implemented for the next batch, i.e. are 'inter-crop' indicators. Using regular weight data to provide accurate daily liveweight gains (DLWG) is an example of an inter-crop indicator that can be used to make management changes to a current batch, for example to adjust feeding protocols.

An appropriate definition of enterprise success was required to evaluate how well correlated KPIs are with overall performance as a way to test their usefulness. It was appreciated that it was impossible to have a single best definition to cover all types of enterprise, but that an indicator incorporating financial parameters would be most appropriate. Net margin calculated on a full economic basis, and reported per cow bred, was chosen. This is an indicator of sustainability which is an important aspect when businesses are operating in a volatile market. However, it will be affected by 'external' factors such as market prices. It was highlighted by the TAG that farmers tend to be better at recording physical rather than financial parameters, suggesting that this may be what motivates them. Similarly, a study looking into farmers' motivations towards lameness control found that 'pride in a healthy herd' was a bigger motivator than economic factors (Leach et al., 2010).

The use of a performance indicator hierarchy, providing a small number of comprehensive KPIs that monitor overall enterprise productivity, and a toolkit of more specific performance indicators, allowing bespoke combinations to be tailored to individual farms and problems, was the main outcome of the TAG meetings. This was then further built upon by working to define how these KPIs influence overall enterprise success.

## 2.6 Conclusions

Several main themes emerged from the TAG meetings. These included the prioritisation of performance indicators into a hierarchy, incorporation of financial parameters into performance indicators, the importance of fertility parameters in suckler herds and of weight data in both suckler and grower/finisher herds, how compatibility of data throughout the supply chain would be of benefit, the benefits of technologies such as EID and automated data collection, and the use of data that is currently recorded elsewhere e.g. medicine records or movement data. Many of these areas were further explored through distribution of a questionnaire to a larger set of farmers as discussed in Chapter 3.

# Chapter 3: Appraisal of farmer attitudes to recording and using data

## 3.1 Introduction

It is important to consider farmer attitudes and motivations towards data capture and analysis when investigating how data can be used to help beef farmers maximise the productivity of their enterprises. Although this was explored through discussion with the TAG (as discussed in Chapter 2), it was considered that opinions from a wider group of farmers, who may better represent the beef industry as a whole, would be of use. It was hoped that collecting views from more farmers, with different enterprise types, would help to ensure that the outputs of the project were relevant to as many beef farmers as possible across the sector. The questionnaire also sought to gain a deeper understanding of what data is routinely recorded on farm, how this information is captured and where it is stored, as well as finding out more about the perceived challenges hindering beef farmers recording and using data. The aim was to use this information to inform herd management software providers on how their products can best meet the needs of beef farmers, and to help ensure that data capture and analysis guidance and advice provided to farmers is realistic and relevant to the beef industry in the UK.

Questionnaires are a frequently used tool to assess farmers' attitudes, opinions and motivators in a variety of situations from technology uptake to lameness control (Leach et al., 2010, Adrian et al., 2005, O'Kane et al., 2017). They can also be used to find out about current practices and performance (O'Shaughnessy et al., 2013, Wittum et al., 1990). This questionnaire aimed to incorporate both of these aspects, investigating farmers opinions towards data capture and analysis, as well as what data is captured and where it is stored.

In contrast to the group discussions described in the last chapter, questionnaires allow collection of opinion without the need to be in same geographical location, and so are useful for collecting views from different areas. This may be of particular use in the beef sector, where we may expect different beef systems to predominate in different areas.  They also tend to allow collection of a larger number of opinions and views than interview or group discussion would enable, and are typically used where the objective is to profile a population (Rowley, 2014). In addition to this, questionnaires allow anonymous input which may encourage honesty and openness in responses. However, this lack of direct interaction with the researcher may also lead to inaccurate responses being submitted, or questions being misunderstood. Other downsides to questionnaires include the opportunity for respondents to miss questions out (either intentionally or accidentally), and the lack of opportunity for discussion (unless a Delphi technique is used).

Open and closed questions may be used to collect information on facts, attitudes, beliefs, behaviours or experiences, with open questions lending themselves to more qualitative methods of analysis, and closed questions to more quantitative methods. Open questions are often used for collecting information on views and opinions and are useful in hypothesis generating or when there is little pre-existing knowledge on a subject. Closed questions can be used to collect information on what is done or characteristics of a system (i.e. facts). In reality, a combination of these two methods is often used in order to both understand what is done and why it is done that way. For the purposes of this project, this will allow validation of the TAG discussions, i.e. are the views and practices of the group representative of the wider beef farming population, and will put further data analysis in context helping to ensure that project outputs are relevant to beef farmers and advisors.

## 3.2 Aims

The aim of this chapter was to gain a wider farmer opinion on the benefits and challenges of data capture and analysis, and to investigate what data is collected by beef farmers currently, how it is used and where it is stored. Themes that emerged during the TAG meetings, such as the role of EID in data capture, were also further explored.

## 3.3 Methods

### 3.3.1 Questionnaire design and distribution

A pilot questionnaire was designed with the above aims in mind and was distributed during two farmer knowledge exchange (KE) events organised as part of the project. Following this, five semi-structured interviews with beef farmers were conducted by phone to further inform question design. The amended questionnaire was then posted on Survey Monkey (www.surveymonkey.com) for three months between December 2016 and February 2017, and a link distributed via a contact list of beef farmers held by AHDB. Hard copies of the questionnaire were also distributed at farmer KE events and beef discussion groups.

The questionnaire included questions around the farm location and enterprise type, as well as information about additional enterprises. Questions on the use of herd management software and EID were included, as were aspects of these technologies that were liked or disliked, and motivations for using or not using software and EID. In addition, what data was recorded on farm and where it was stored was ascertained, as well as frequency of recording and what the data was used for. Questions around additional data that farmers would like to record (and why they currently do not do this), and how much they value their data were also included. A combination of quantitative and qualitative methods were used including both closed multiple choice questions and more open questions with free text responses, as well as dichotomous and rating scale questions (Appendix 1).

### 3.3.2 Data collection and cleaning

Data was collected and analysed anonymously. 143 responses were collected over the three months the questionnaire was open, 9 of which were hard copies completed at KE events. These were downloaded from Survey Monkey into Microsoft Excel (Microsoft Corp.). Three responses were deleted during data cleaning as they were largely incomplete. Where appropriate, free text question responses were grouped into suitable categories for analysis. For example, an extra herd type category 'Mix' was added as several free text responses describing enterprise type stated that a mix of enterprise types were combined (often a suckler herd alongside buying in extra growers/finishers). Herd type categories were further combined due to the small numbers in some categories, creating 3 groups: Suckler, Grower/finisher and Other. Following data cleaning, the questions were divided into four sections for analysis:

1. Herd details
2. Herd management software and electronic identification (EID) use
3. Data recording
4. Data use

### 3.3.3 Data analysis

Descriptive analysis techniques were used to outline trends in herd size, location, type (including additional enterprises within the farm) and labour requirements. Graphical visualisation was used to investigate and display data collected around herd management software use (including why respondents used software and what they liked or disliked about it), EID use (including what respondents found most useful about EID and why it was not used on some enterprises). Data types captured and locations for recording and storing data were analysed descriptively using a table and conditional formatting. Information on the frequency and application of data use, the ease of data capture and analysis, and the perceived value of data for different enterprises was also evaluated and displayed graphically.

Chi-squared tests were used to evaluate the statistical significance of associations between herd type and use of software or EID. They were also used to investigate associations between additional enterprises (e.g. sheep) on the farm, and the use of software or EID. Mann-Whitney U tests were used to evaluate associations between herd size and use of software or EID. They were also used to investigate associations between number of head per full time equivalent staff member and the use of software or EID. Statistical analysis was carried out using Minitab software (Minitab Inc., 2010).

## 3.4 Results

### 3.4.1 Herd details

Following data cleaning, 140 responses were available from 39 counties (North, South, East and West Yorkshire were grouped together), mainly in England, but also including Wales, Scotland and Northern Ireland. The highest number of respondents were from Yorkshire, closely followed by Durham, Cumbria and Devon. The regional distribution of respondents is shown in Figure 3-1. The large majority of the respondents classed their herd type as ‘suckler’, as shown in Figure 3-2.

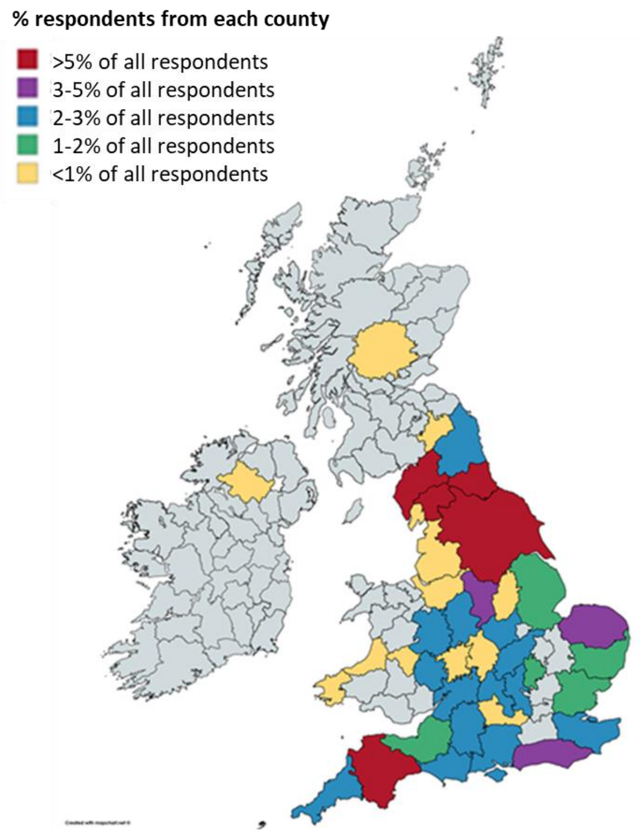


***Figure 3-1: Regional distribution of survey respondents*** *The colours on the map represent the percentage of all respondents from each county, with the highest number of respondents from Yorkshire, Durham, Cumbria and Devon.*

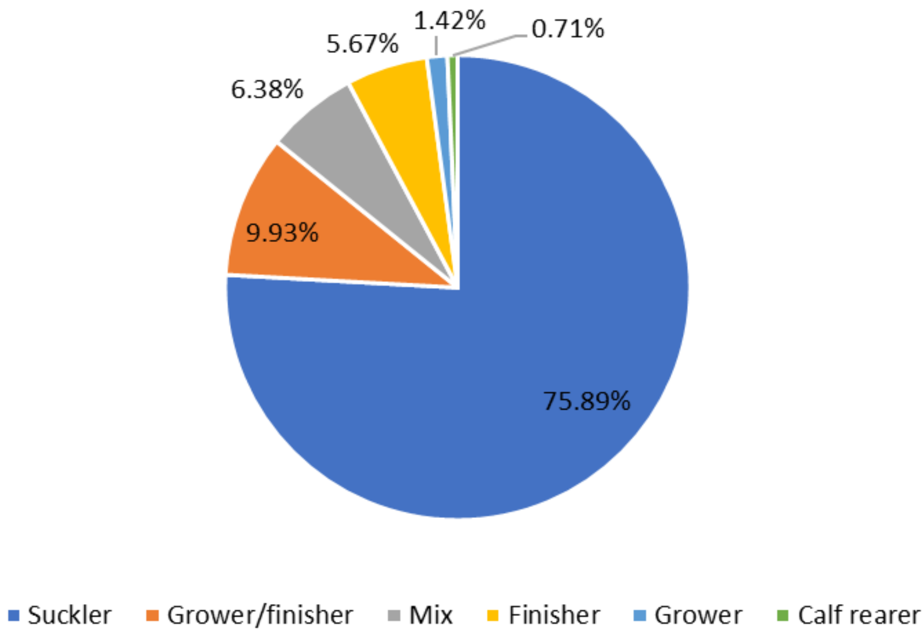


***Figure 3-2: Types of enterprise of survey respondents*** *The majority of respondents reported suckler type enterprises, with grower/finisher type systems the next most common. There was a similar number of mixed and finisher type enterprises, with fewer grower only or calf rearer systems.*

The median herd size of the suckler herds was 75 breeding cows (mean 101), the largest herd having 1300 and the smallest having seven. Of 140 responses, 125 (89%) had an additional enterprise or enterprises, with sheep and arable being the most common. The average number of staff (full time equivalents) varied between the enterprise types, with mixed enterprises (i.e. those having a suckler herd with additional growers/finishers) having the highest number of staff, and growers/calf rearers having the lowest. When herd size was taken into account however, suckler enterprises had the lowest number of head/staff member, closely followed by grower/finisher enterprises. However, there were relatively small numbers of respondents in every herd type category other than 'suckler'. To allow for this, some categories were combined and three broader categories were created for further analysis: 'Suckler' (n=106), 'Grower/finisher' (n=14) and 'Other' (n=20) (Table 3-1).

***Table 3-1: Combined enterprise type characteristics**. This includes mean herd size, mean number of full-time equivalent staff and mean number of head/staff member.*

| Enterprise type | Number of Respondents | Average herd size | Average number of staff | Average head/staff member |
|---|---|---|---|---|
| **Suckler** | 106 | 101 | 1.3 | 71 |
| **Grower/finisher** | 14 | 130 | 1.2 | 107 |
| **Other** | 20 | 422 | 1.7 | 216 |

### 3.4.2 Herd management software and EID use

Almost half of respondents used some form of herd management software (48%). This varied between different herd types, as illustrated in Table 3-2.

***Table 3-2: Herd management software use**. Proportion of respondents reporting use of herd management software in three enterprise type categories*

| Enterprise type | Number of respondents | % Yes | % No |
|---|---|---|---|
| **Suckler** | 104 (2 unanswered) | 50 | 50 |
| **Grower/finisher** | 14 | 21 | 79 |
| **Other** | 18 (2 unanswered) | 56 | 44 |

Half of suckler herds surveyed used herd management software, and use tended to be higher in suckler and 'other' herds than in grower/finisher herds. This was not statistically significant (p=0.09), although this could be due to the small number of herds in categories other than 'suckler'.

The size of herds using software was significantly larger (median 100, mean 216) than that of herds not using software (median 50, mean 88; p<0.01). Number of head of stock per staff member (full time equivalent) was also higher for enterprises using herd management software (median 80, mean 123) than for those not using software (median 48, mean 73; p<0.01). Herd size being too small was also a popular reason stated by respondents for not using herd management software, as illustrated in Figure 3-3.

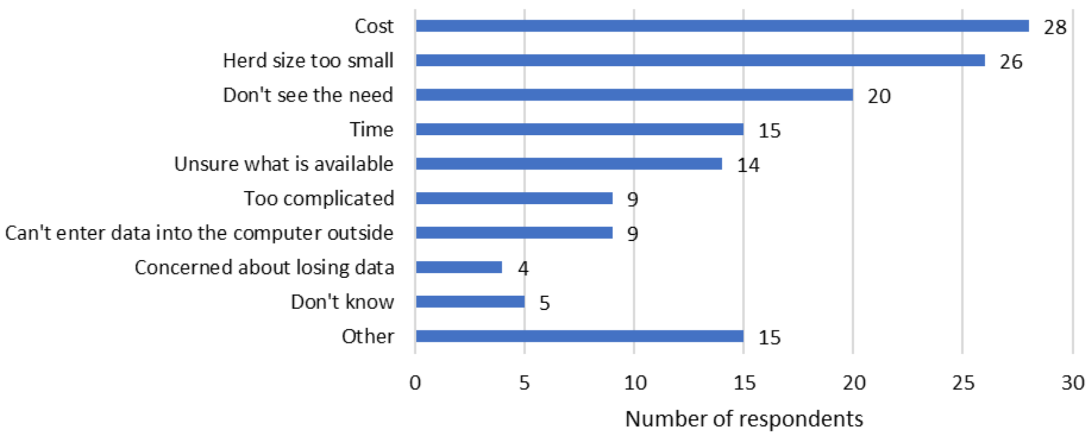


***Figure 3-3: Reasons for not using herd management software****: In the bar chart illustrating different reasons given by respondents for not using herd management software, cost and small herd size were the two most popular responses.*

A total of 71 respondents reported that they do not use any herd management software (4 respondents did not answer this question and 65 reported using software). The most popular reason given for not using herd management software was cost (28 responses/39% of those that reported not using software), but having a small herd and not seeing the need were also popular responses (26 responses/37% and 20 responses/28%respectively). 15 respondents gave other reasons for not using software. These included lack of IT skills or knowledge, use of their own spreadsheet system, concerns about transferring data if software becomes obsolete, and having to record data manually elsewhere in addition to recording it in software. Three respondents also expressed plans to use software in the future.

18 software types were recorded by 65 respondents using herd management software, and interestingly 14% of those using software stated that they used their own home-made and bespoke spreadsheets or databases (this was also a reason given for not using herd management software, so the true value in the population sampled may be higher). When questioned about what they liked about their herd management software, ease of data entry was the most popular response (46 responses/71% of those that use software). The way the data is displayed and the reports generated were the next most popular responses (49% and 45% respectively of those that use software), followed by the ability to record data for multiple enterprises (23%), KPI calculation (22%) and benchmarking (18%). Four respondents identified compatibility between theirs and others software packages as a positive feature (6%). 13 producers gave other reasons for liking their software, these included the ability to link with the British Cattle Movement Service (BCMS) and the Cattle Tracing System (CTS), the availability of a cloud based facility allowing easy access for multiple people and in different places, and the flexibility/ability to customise and modify software to an individual farms requirements.

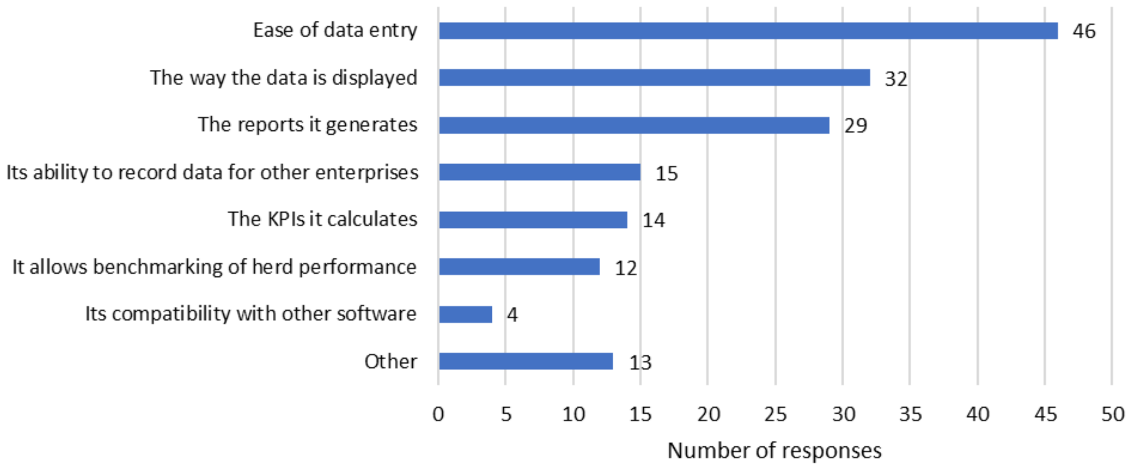


***Figure 3-4: Aspects of herd management software that respondents liked.*** *The bar chart illustrates that ease of data entry and the way the data is displayed were the two most popular responses. The ability of software to generate reports was also popular amongst respondents.*

Of the 65 respondents that used herd management software, 41 commented on what they would change about the software they currently use. Several themes emerged amongst these comments:

- Eight said they would not change anything about the software they currently use (although some of the 24 'non-responses' to this question could also indicate this).
- Six said they would change the reports that their software generated, for example to include cow efficiency reports, to include cattle no longer on the holding, and to report sire and EBV (estimated breeding value) information.
- Four commented that they would like their software to allow them to record data remotely i.e. 'in the field' via an app, and to be cloud based to allow multiple people access in multiple places.
- Four commented that they would like their software to be more compatible with other systems, for example financial programmes, farm systems such as diet feeders, and Signet Breeding Services (a genetic evaluation service which is part of AHDB Beef and Lamb).
- Three would like their software to record more, and examples given included veterinary and medicine data, grassland management information, and 200 day or 400 day weights.
- Three thought their software was too complicated and would like it to be easier to use and to get the information out that they require.
- Two would like their software to allow benchmarking.
- Two would like their software to be more beef focussed, and not a slightly altered dairy program.

15% of respondents (22 herds) used EID in their beef herd (33% of herds that used management software). 113 herds reported not using EID and 5 did not answer this question. The median herd size of those using EID is 105 (mean = 315), whereas the median herd size of those not using EID is 75 (mean 106). Again, as is the case with herd management software uptake, the larger herds are significantly more likely to use this technology ($p<0.01$). Similarly, the number of head/staff is significantly increased in herds using EID ($p<0.01$). However, the small number of herds using EID has to be taken into account when interpreting this, as do the few very large herds using EID as the boxplot below highlights.

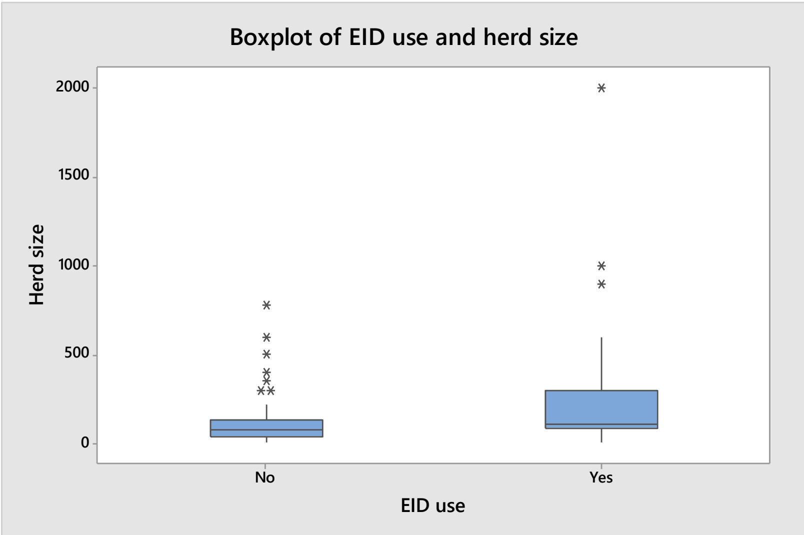


***Figure 3-5: Distribution of herd sizes using and not using EID**. Herds using EID were significantly larger than those not, however the wide distribution of herd size for herds using EID should also be considered.*

The use of EID varied between enterprise types, as illustrated in Table 3-3. Again, uptake was greater in suckler and 'other' herds than grower/finisher herds ($p<0.01$). The use in 'other' herds was also significantly higher than use in the suckler herd category ($p<0.01$).

***Table 3-3: Use of EID in different enterprise types.** 'Sucker' and 'Other' herds reported the highest use of EID.*

| Enterprise type | Number of respondents | % Yes | % No |
|---|---|---|---|
| **Suckler** | 104 (2 unanswered) | 14 | 86 |
| **Grower/finisher** | 13 (1 unanswered) | 8 | 92 |
| **Other** | 18 (2 unanswered) | 33 | 67 |

The aspect of EID found most useful by the respondents was enabling easy and quick recording of data, however providing better traceability of animals along the supply chain was also commented on. The main reason respondents gave for not using EID was not seeing the need for it (57 respondents/50% of those not using EID), although cost of the equipment (tag reader and software etc.) was also a common reason (37 respondents/33% of those not using EID). 25 respondents (22%) expressed a desire to use EID in the future. 19 respondents (17%) quoted the cost of EID tags as a reason for not adopting it, and 15 respondents (13%) do not use it as it is not compulsory (Figure 3-6). Reasons for not using EID given under 'other' included that it was not economically justifiable, that there was a lack of compatibility with the current software used, and that manual data entry would still be required.

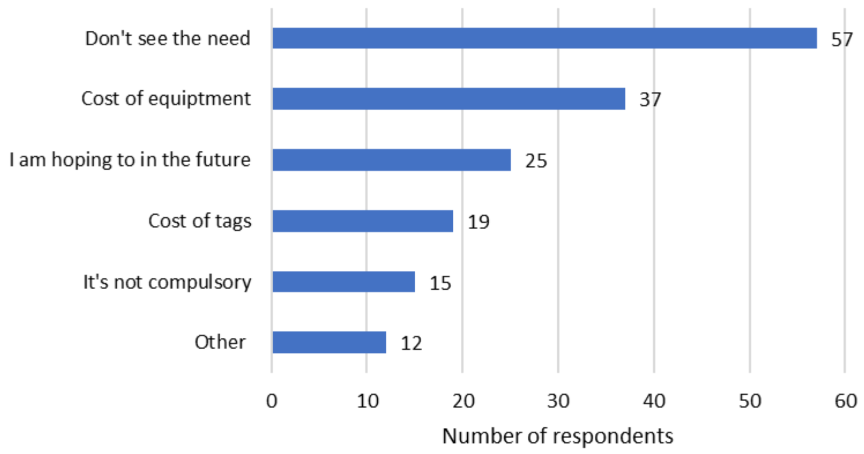


***Figure 3-6: Reasons given for not using EID.*** *The bar chart illustrates that 'not seeing the need' and 'cost' were the two most popular reasons given for not using EID. 25 respondents also reported that they were hoping to use this technology in the future, suggesting these figures may increase.*

### 3.4.3 Data recording

Table 3-4 indicates the data types collected by respondents, and where these were recorded. In general, paper-based systems appeared to be most popular, although for recording weights and movements herd management software was more popular.

Data most infrequently recorded was feed intake, closely followed by abattoir feedback, lameness, weights and financial data. All respondents record medicine use, and all but one record movements (although this is a statutory requirement so the response may be due to a misunderstanding of the question). Where respondents indicated that they recorded data elsewhere, it was largely in home-made bespoke spreadsheets (10 respondents).

71 respondents expressed an aspiration to record more data; of these 42% (30) identified weight data as the area in which more recording was desirable. The next most popular answer was feed intake, to allow calculation of FCR (feed conversion ratio), which was suggested by 15% (11) of those that would like to record more. Three respondents would like to record more financial data, and two suggested cow efficiency, grass growth and health status. Two respondents also commented that they felt they did not make the best use of the data that they already record and would like to focus on this rather than recording more data. Of the respondents that would like to record more data, time was quoted as the main barrier to doing this (40 responses, 36%). 31(28%) quoted lack of technology and 19 (17%) quoted cost. 22 gave other reasons for not recording more data, these included lack of knowledge and

understanding of technology, lack of access to a weigh scale, and difficulty weighing cattle when out at pasture.

***Table 3-4: Data types collected by questionnaire respondents, and storage locations**. The numbers indicate the number of respondents recording that data type in each recording system (if data was recorded in multiple places respondents were asked to tick multiple boxes). The colour coding reflects the numbers, with darker shades indicating more popular data types and recording systems. Overall, paper-based systems were the most popular.*

| | Herd management software | Paper-based system | Online statutory recording | Do not record |
|---|---|---|---|---|
| **Weights** | 54 | 52 | 4 | 36 |
| **Feed intake** | 16 | 36 | 0 | 65 |
| **Calving events** | 58 | 69 | 49 | 11 |
| **Bull in/out/AI dates** | 37 | 80 | 2 | 13 |
| **PD results** | 40 | 66 | 1 | 23 |
| **Calving ease** | 40 | 64 | 4 | 28 |
| **Medicine use** | 47 | 90 | 7 | 0 |
| **Reason for medicine use** | 42 | 84 | 7 | 3 |
| **Lameness** | 32 | 51 | 3 | 40 |
| **Individual animal infectious disease status** | 30 | 61 | 2 | 31 |
| **Abattoir feedback** | 34 | 55 | 5 | 42 |
| **Movements** | 60 | 48 | 80 | 1 |
| **Financial** | 29 | 56 | 1 | 34 |

### 3.4.4 Data use

47 respondents used their data at least once a month. This category of frequency of data use also has the highest average herd size (median = 94), as shown in Figure 3-7. This graph suggests that larger herds tend to use data more frequently. Frequency of data use also varied with herd type, as illustrated in Figure 3-8. Due to small numbers of respondents with herd types other than suckler however, it is difficult to identify clear trends.

Respondents were asked how they use the data that they record, and the responses are illustrated in Figure 3-9. The most popular use was for individual animal management (86 responses/61% of all respondents), closely followed by making breeding decisions (83 responses/59%) and monitoring herd performance (76 responses/54%). Financial management was the fourth most popular data use category with 60 respondents reporting that they use their data for this (43%). Comments made in the 'other' category included monitoring ration plans, for gaining accredited heard health status/farm assurance, and for promotion of the herd. One respondent was very honest when describing why they did not use their data: "Having no longer got a software system, I am bad at collating the information manually, every now and again I might work out cost of finishing bulls etc. Normally with the price of beef it becomes a depressing exercise, therefore I am not enthused about too regularly working out that I am the proud owner of expensive lawnmowers”.

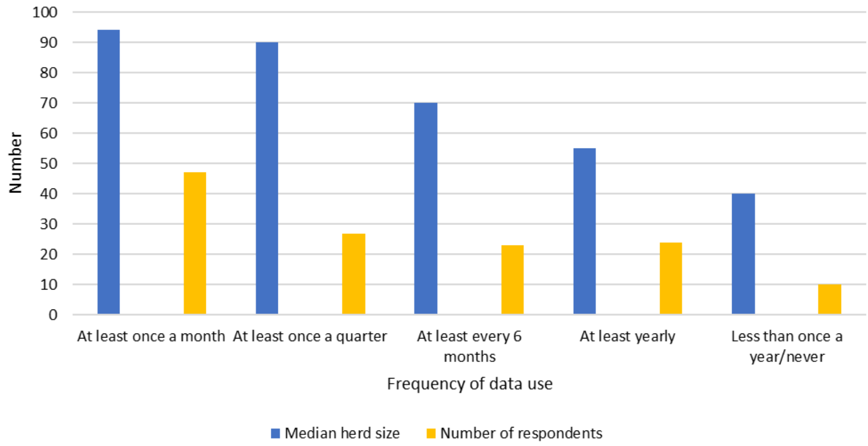


***Figure 3-7: Frequency of data use and herd size.****The bar chart shows the frequency of data use reported by respondents, the number of respondents recording in each frequency bracket (yellow bars), and the median herd size in each recording frequency bracket (blue bars). This illustrates that larger herds tend to use their data more.*

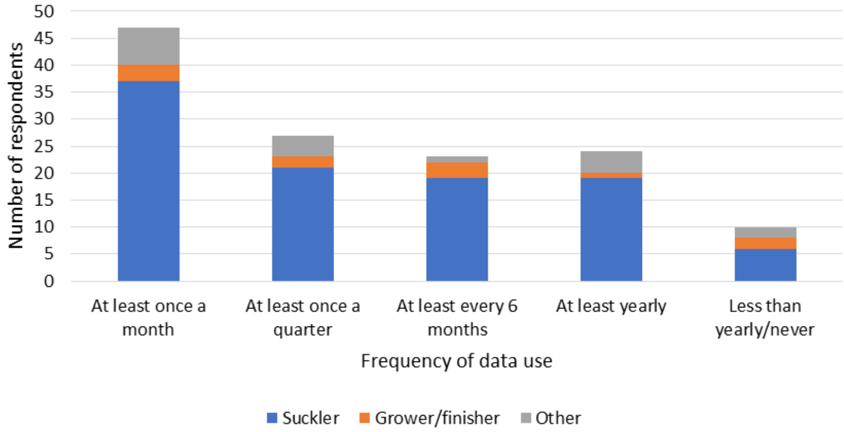


***Figure 3-8: Frequency of data use and herd type****.The stacked bar chart illustrates herd type within frequency of data recording bracket. Over half of respondents report to use their data either at least once a month or at least once a quarter.*

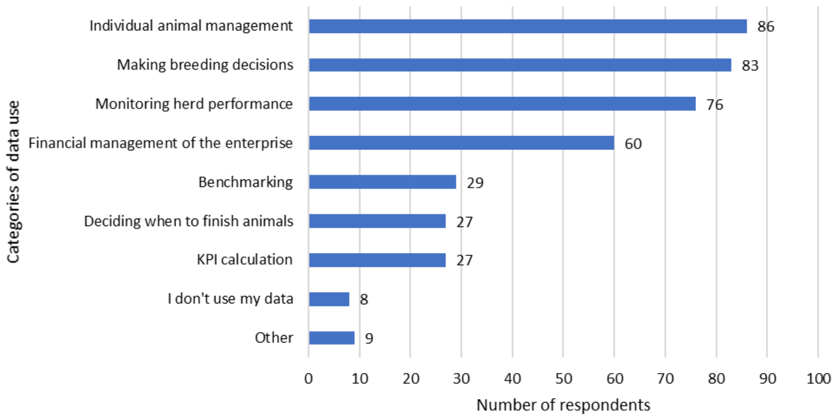

*__Figure 3-9: Areas where respondents use their data__.The bar chart shows the various ways respondents reported using their data. Individual animal management was the most popular response, closely followed by informing breeding decisions.*

When asked about ease of data analysis, it appeared that respondents tended to find data collection easier than analysis (although the difference is very small), as illustrated in Figure 3-10. This highlights an area where more guidance could be provided for farmers to assist with these perceived difficulties.

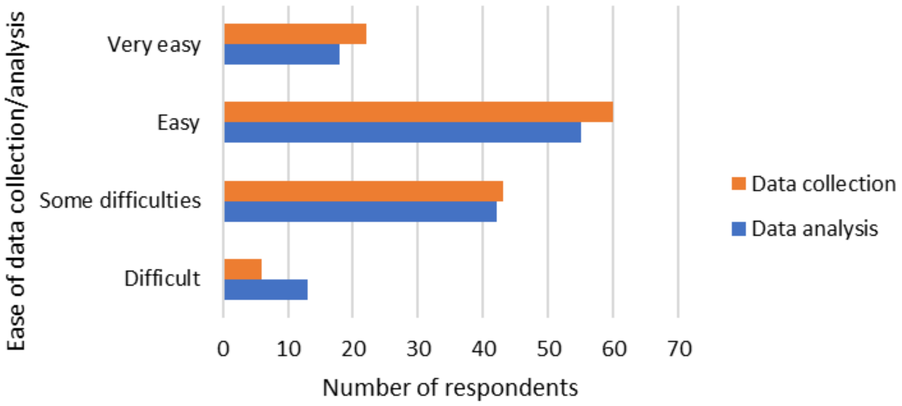


*__Figure 3-10: Respondents opinion on ease of data collection and analysis__. Data collection is represented by the orange bar and data analysis by the blue bar. Respondents were asked to place each into one of four categories from very easy to difficult. Although the difference is small, it appears that data analysis is perceived to be more challenging than data collection.*

Respondents were asked to score how valuable they perceived their data to be for their enterprise (with 1 being unimportant and 100 being very important). The median score across all respondents was 80 (mean=76). Scores ranged from 0 – 100, but the skewed distribution, illustrated in the histogram below (Figure 3-11), suggests that in general the farmers surveyed value their data relatively highly.

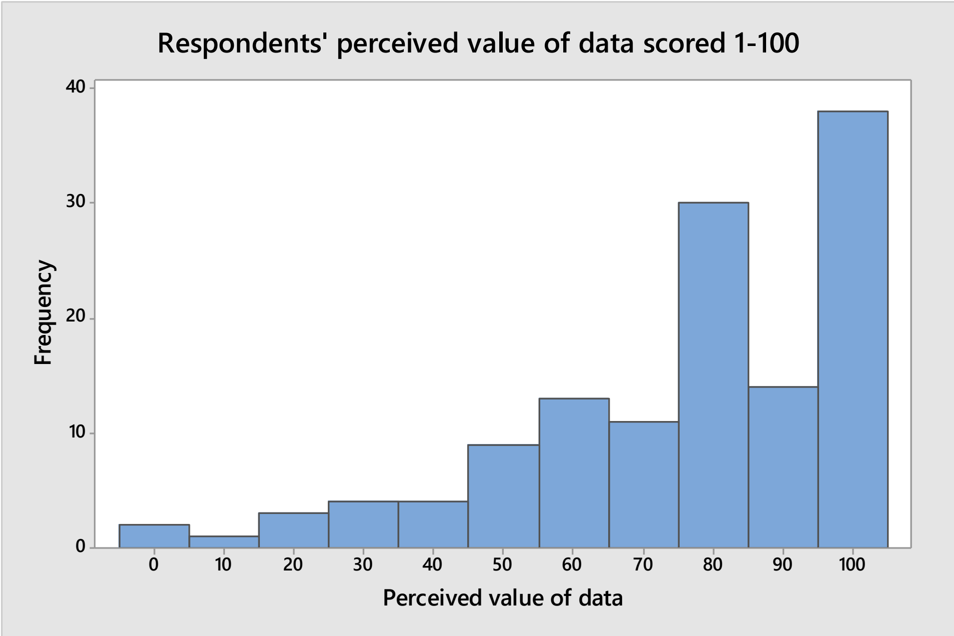


*__Figure 3-11: Histogram of respondents' perceived value of data__, with 1 being unimportant and 100 very important*

Figure 3-12 shows these scores against herd size and for different herd types. Managers of large herds often perceive collection and analysis of data as being of value, but there is more varied opinion amongst smaller herds. There is a large variation in the perceived value of data amongst suckler enterprises, which represent the majority of the respondents, however respondents with finisher and mixed enterprises often value data more highly.

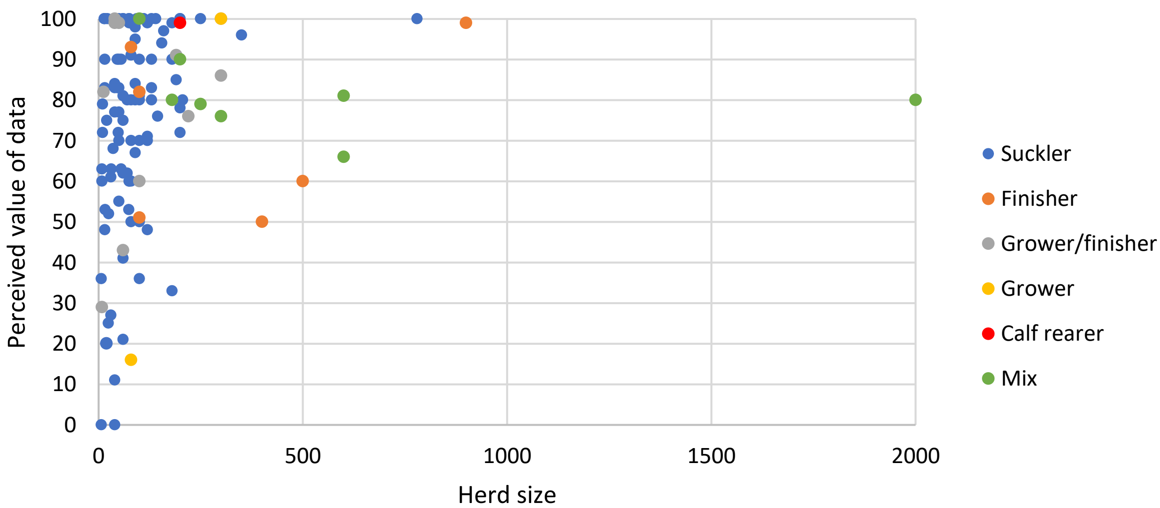


*__Figure 3-12: Perceived value of data, herd size, and enterprise type__.The scatter plot illustrates how respondents' perceived value of data varied with enterprise type and herd size.*

## 3.5 Discussion

The aim of this questionnaire was to expand on opinions collected through TAG discussion; by incorporating a wider spectrum of beef farmer opinion around data capture and use for informing herd management decisions it was hoped that views voiced through TAG discussion could be validated, and that the opinions of the wider beef farmer population could be best represented.

Respondents farmed in 39 counties, mainly in England, but also in Wales, Scotland and Northern Ireland. Suckler enterprises made up 76% of respondents, and herd size ranged from 7 to 1300 with a median of 75 and a mean of 101. This is higher than the national average of 26 (AHDB Beef and Lamb, 2019b), which may reflect the types of herds on the mailing list used for distribution of the questionnaire, and those interested in participating in a project on data use and analysis.

The large proportion of respondents with suckler enterprises created some limitations when analysing results, as the dominance of the suckler herd category reduced the chances of demonstrating significant associations. The diversity of the beef industry, and the wide variety of herd types of the respondents, meant that broader categorisation of herd type was required, and so some detail of the data was lost as a result. To address this, other herd types such as grower or finisher enterprises could be targeted directly to increase the numbers in these categories. However, it was beyond the scope of this part of the project to collect more survey responses from specific herd types.

Herd size was measured as number of breeding cows for suckler herds, and average herd size over a year for growers/finishers. Average herd size may be difficult to estimate for some enterprises, for example intensive finishers where herd size varies greatly throughout the year, depending on beef prices etc. A way around this may have been to ask farmers to quote herd size in number of cow-years, in order to take into account how long cattle spend on the unit. However, it was felt that this would be more challenging to calculate and may put farmers off completing the questionnaire. The great variation in herd sizes and enterprise types recorded highlights the heterogeneity of the beef industry. This was echoed during a study of beef and sheep farmer opinions on technology uptake in Scotland, where it was noted that the diversity of the enterprises studied highlighted many different and enterprise specific barriers to technology uptake (Kyle et al., 2017).

The main route of distribution for the questionnaires was via an AHDB mailing list, although some were also distributed at farm KE events and discussion group meetings. This may have introduced a degree of selection bias, as the results may reflect the types of enterprise for which contact details are held by AHDB, and the types of enterprise interested in being involved with a project on data capture and analysis. For example, farmers who are on AHDB's distribution list are likely to engage with the levy board and so could be seen as more proactive and forward thinking than farmers who do not. As the questionnaire was mainly distributed as an e-mail, completing it also required internet access and IT skills (and may not have been done by the farmer).

Likewise, farmers willing to spend time completing a questionnaire on data capture and use are likely to have an interest in this area. These farmers may therefore be more likely to performance record and use innovative technologies, thus biasing our responses towards a more forward thinking 'data savvy' type farmer. In addition, the average herd size of the respondents' enterprises was larger than the national average. As the results of this questionnaire indicate that larger herds are more likely to use software and EID, the level of uptake of these technologies amongst the respondents may be higher than across the beef farmer population as a whole. However, the aim of this questionnaire was to incorporate a wider spectrum of farmer opinion than available in the TAG, and it is felt that this was achieved.

In order to allow for these selection biases, further distribution lists could have been sought, for example breed societies or the National Beef Association (although this still requires farmers internet access, IT skills and a willingness to complete the questionnaire). Hard copies of the questionnaire could have been distributed in an attempt to reach those beef farmers not on electronic distribution lists, for example via veterinary surgeons, or at markets or county shows. Surveying a truly 'random' sample of the population is a common problem in questionnaire distribution for several reasons: it is often difficult to accurately define the target population, and it is almost imposible to avoid bias towards individuals more likely to respond to a survey (e.g. because it is in an area of interest, or time available). Therefore, in reality most surveys use non-probability convenience samples, as used in this study (Rowley, 2014).

48% of respondents used some form of herd management software. This appeared to vary by enterprise type, with 'suckler' and 'other' herds using software more often than 'grower/finisher' herds, although this was not statistically significant (possibly due to the dominance of the suckler category). Larger herds were however significantly more likely to use herd management software ($p<0.01$). In addition, cost and herd size being too small were the most popular reasons given by respondents for not using herd management software. This is in contradiction to other studies, where enterprise size was found to have no significant association with technology uptake (Lima et al., 2018). This study was of commercial sheep farmers, and it is suggested that the discrepancy could be due to larger than national average flock sizes being included in the study. As previously mentioned, there was a huge variation in herd size in the beef enterprises surveyed in the current study, from seven breeding cows to 1300, which may make effects of herd size on EID adoption more readily detectable.

14% of respondents using software used home-made bespoke programs. The most popular aspects of herd management software that respondents liked were ease of data entry, the way the data was displayed and the reports generated. However, when asked what they would change about their software, adding information to the reports generated was a common theme. Other popular responses included the ability of software to be compatible with other programs, the ability to enter data remotely, and for the system to be cloud based. A study exploring beef and sheep farmers opinions on EID and software use in Scotland also commented on the lack of compatibility between different software packages as a perceived barrier to technology uptake (Kyle et al., 2017).

16% of respondents use EID in their beef enterprise, and again this appears to be more common in larger herds ($p<0.01$). The aspect of EID found most useful by the respondents was enabling quick and easy recording of data, however providing better traceability of animals along the supply chain was also commented on. This is in agreement with a survey of beef and sheep farmers in Scotland, where farmers agreed that EID increased efficiency and accuracy of data recording (Kyle et al., 2017). The main reason respondents gave for not using EID was not seeing the need for it, although cost of the equipment (tag reader and software etc.) was also a common reason given. This is in agreement with studies carried out in Wales (Hybu Cig Cymru, 2015) and Scotland (Morgan-Davies and Lambe, 2015), where farmers reported financial constraints as a major barrier to EID uptake in sheep flocks. Simplification of software and/or provision of training were suggested by both reports as methods of increasing uptake, with the Scottish report also suggesting demonstration of value added by EID. Studies investigating motivators for technology uptake on farms echo this, with demonstration of 'practicality' and 'usefulness' of technology positively affecting uptake whilst 'external pressure', i.e. pressure from legislation, negatively affects uptake (Lima et al., 2018). This study also suggests that cost-effectiveness, rather than purely cost, may be a significant deciding factor.

The increased use of both software and EID in larger herds, with a higher number of cattle per member of staff, could be interpreted as technology uptake allowing for larger herd sizes without increasing staffing levels. However, it may also reflect economies of scale in larger herds. Favourable cost-benefit ratios of technology uptake in larger herds, due to larger administrative overheads, has also been suggested as a reason why use may be higher in these herds (Kyle et al., 2017).

Many of the respondents had multi-enterprise farms, with sheep and/or arable enterprises in addition to beef being the most common combinations. The use of EID and software was not significantly different between those farms that had beef and sheep and those that just had beef (or beef with other enterprises). As EID tags are compulsory in sheep, it was hypothesised that uptake in the cattle enterprise of farms which also had sheep enterprises may be higher. However, the proportion of sheep farmers using EID for management purposes, rather than just the statutory movement purposes, has been reported to be only 21% (Lima et al., 2018), and the results of this survey would suggest that a sheep enterprise does not appear to increase uptake of

EID or herd management software in a beef enterprise on the same farm (although the survey sample size was small and not designed to address this specific question).

When questioned about where data is recorded, paper-based systems appear to be the most popular for most data types. Half of respondents would like to record more data, and of these weight data was the most common factor respondents would like to record. Time was the most popular reason for not recording more data, closely followed by lack of technology. Conversely, of the respondents who currently use EID in their herds, the aspect found most useful was enabling quick and easy recording of data, thus saving time. This suggests that overcoming the lack of technology barrier may also help to overcome the lack of time barrier.

Forty-seven respondents use their data at least once a month, and again larger herds appear to use data more often. This may be due to the potential rewards of collecting data from large herds being greater than for small herds, i.e. there is more data to collect and larger numbers mean changes identified over a small period of time are less likely to be due to chance. The most popular ways that respondents used their data was for individual animal management, making breeding decisions and monitoring herd performance. It has been suggested that farmers may see the purpose of EID as solely for traceability (Kyle et al., 2017), rather than for disease control or herd management. This may lead to a degree of resistance to uptake if the potential benefits to the farmer are not communicated effectively.

When questioned about ease of data collection and analysis, it appears that respondents tend to find data collection easier than analysis (although the difference is very small). This is perhaps a surprising finding, as it was felt that data capture would be the challenging part for the farmer, with analysis carried out either through herd management software or in conjunction with advisers. A possible explanation for this is that it reflects the uptake of technologies such as EID assisting in data capture. Alternatively, it may suggest a shortage of support for beef farmers in analysing data they have collected. This highlights an area where there is potential for vets and advisers to engage with farmers around data analysis, ensuring that they are able to make the most of data that they collect.

Respondents generally see the value in collecting and using data to help manage their enterprises, with a median value score collected of 80 (1 being not important and 100 being very important). However, it should be noted that those farmers on the AHDB distribution list, and those choosing to complete the questionnaire, are likely to be those with an interest in data recording and analysis.

Another commonly used consensus forming method is the Delphi method (World Health Organisation, 2014), consisting of multiple rounds of questionnaires which are filled in by individuals anonymously. Between each round, a summary of all responses for the previous questionnaire is circulated, with the aim of all participants reaching a consensus. This technique is useful to increase the number of participants in a discussion, and potentially to increase the geographical area included, without requiring travel of all members. The anonymity it provides may prevent conflict between members and allow more freedom for views to be expressed, and allows equal participation by all, but it is a time-consuming technique, and response rates may decrease with each round. This technique has been used in a veterinary context when establishing welfare indicators for dairy cattle, pigs and hens (Whay et al., 2003b). Using this method allowed 154 experts to be approached, although only 35 questionnaires were returned, a response rate of 22%.

As described in Chapter 2, in the current study small group focus group meetings were utilised to allow face to face discussion. In slightly larger conference style meetings, existing literature was presented and there was scope for more open discussion. Meetings were structured with set aims and objectives, although setting of more specific tasks prior to meetings may have been beneficial. A questionnaire was distributed in addition to the meetings to expand on the opinions around data capture and storage collected during discussion. As this was carried out in conjunction with meetings, it was felt that a Delphi method was not required, and to try and optimise response rates a basic questionnaire was used. This allowed a wide geographical spread of respondents (from 39 counties), which would have been challenging to attain through face to face meetings. Limitations to the questionnaire have been discussed previously, for example the potential for selection bias as the questionnaire was distributed through and AHDB mailing list, and the dominance of suckler herds in the herd type represented. However, it provided an insight into what data farmers are recording and how, and further investigated some of the challenges around data capture and analysis on farm.

A combination of methods were used for gathering opinions and forming consensus in this study, and it has been suggested that using a 'hybrid approach' such as this may help to avoid potential problems with using these methods in isolation (Hutchings et al., 2006). However, it has also been commented that the existence of a consensus does not necessarily make it right (Jones and Hunter, 1995). Methods to further test the consensus outcomes, such as using welfare indicators derived through consensus forming methods to assess welfare on farms (Whay et al., 2003a), may be used to evaluate the appropriateness of the indicators selected, and the practicalities of recording the data required. Potential challenges, such as intermittent or inconsistent recording (Whay et al., 2003a), may be identified, and benchmarking or target setting may be carried out. Data from farmer members of the TAG was obtained and used for this purpose, as discussed in Chapter 2.

## 3.6 Conclusions

Farmers in this sample tended to value their data highly, and many would like to record more or make better use of what they currently collect. Almost half of respondents use herd management software, but over 50% of these commented on aspects of their software that could be improved to better meet their needs. Data analysis appeared to be viewed as slightly more challenging than data collection by respondents, indicating that this could be an area where increased guidance for farmers may be particularly effective in overcoming challenges to data use. This is an area where there would appear to be potential for more veterinary and advisor involvement on beef enterprises. Other than cost and time, lack of technology and knowledge were commonly quoted barriers to data collection and use. These again are areas where the industry may be able to provide more assistance to farmers in using their data to make informed management decisions.

# Chapter 4: A single-herd study investigating associations between measures of herd performance

## 4.1 Introduction

Opinions around data collection and analysis on farm were discussed with beef farmers and industry representatives during focus group (TAG) meetings as discussed in Chapter 2. This was expanded on through distribution of a questionnaire as described in Chapter 3. In addition to discussion around data capture and use, farmer members of the TAG were also requested to provide production data for analysis. This included calculation of KPIs highlighted as important by the TAG (and included in the KPI toolkit), investigation of trends over time (for example between seasons or pre and post management changes) and linking of physical performance indicators to financial output where possible. It also allowed evaluation of the practicalities of extracting data from various software packages for further analysis and created case studies for use in knowledge exchange articles and on farm events.

Analysis and interpretation of farm data often poses some challenges; the data often reflects complex systems where many variables interact to influence an outcome. It is also often collected over a long time period and may be from different enterprise types, further increasing the potential for confounding. This is particularly true in the beef sector where small herd sizes, a long production cycle and a typically extensive system all limit data availability, making evaluation of performance indicators and their potential influence on production efficiency challenging.

One farm in the TAG was able to provide a large dataset, containing production and financial data for 20,037 cattle between 2010 and 2016. This allowed investigation into factors associated with performance outcomes on this unit. Regression analysis can be used to explore the relationship between an outcome (or dependent) variable and one or more explanatory (independent or predictor) variables. This allows evaluation of the degree to which each explanatory variable individually is associated with the outcome one, and so can be used to analyse the effect several different performance indicators have on a single overall performance metric within that dataset. This may then highlight areas of performance that it may be beneficial for a farmer to focus on. The literature contains several examples of how multiple regression has been used to analyse beef herd data, for example to investigate the influence of cow traits (such as lactation yield and BCS) on calf growth (both average daily gain and 210 day weaning weight) (Arthur et al., 1997), or the influence of neonatal morbidity on weaning weight (Wittum et al., 1994b). Risk factors for calf mortality (Bleul, 2011), dystocia (Waldner, 2014a) and the effects of twinning (Gregory et al., 1990) have also been investigated using these techniques. However, use at a whole farm level, i.e. incorporating physical and financial measures and including multiple aspects of production (e.g. fertility, health and growth) appears to be more limited.

## 4.2 Aims

The aim of this chapter was to demonstrate analysis that can be done with large farm data sets where they are available, and how this can be used to inform herd management. Although regression analysis is unlikely to be used by vets in practice, it can be incorporated into software and allows deeper interrogation of data drawing associations between aspects of performance.

## 4.3 Methods

### 4.3.1 Data collection

In spring 2016, data was collected from a beef finishing system in the East Midlands, producing 20,037 animals between 2010 and the first quarter of 2016. Cattle were kept on outdoor loose straw yards and fed a total mixed ration with concentrate formulation on a least cost basis. Cattle of various breeds and ages were purchased from markets throughout the year and taken through to finishing. Data was recorded in a bespoke Microsoft Access (Microsoft Corp.) database either automatically via EID tags and software system, or entered manually by farm staff. The following data was available:

- Animal details (including animal ID, date of birth, breed, dam and sire if available).
- Treatment events (including date and animal ID, drug used, volume and reason for use).
- Weighing events (including date, animal ID and weight).
- Movement events (including animal ID and date).
- Culls (with reason for cull where available).
- Deaths on farm (with cause of death where available).
- Youngstock/store sales (with weights).
- Sales to slaughter (with carcase grade, live weight and deadweight where available).
- Financial/feed information (including gross and net cost of production each time this had been calculated over the past three years with an indication of what time period each figure covered, sale prices of finished animals and young stock/stores and feed/head/day cost.

Data was exported into Microsoft Excel (Microsoft Corp.) for analysis, and outliers were removed based on evaluation of distributions and where values were felt to be biologically implausible. Each animal was a line of data, with on and off weights recorded allowing an overall DLWG during time on farm to be calculated. The raw dataset contained 20,037 lines of data. Histograms were assessed visually to identify univariate outliers. 1508 lines were removed as they were missing crucial data (such as weight data), 2046 lines were removed as they were felt to be erroneous. For example, where two weights were taken less than 14 days apart DLWG values often appeared very high or very low due to natural variation in weight (for example the effect of rumen fill) and a low denominator. Multivariate outliers were identified during model fit assessment. 235 lines were removed when assessing model fit; 49 as the standardised residuals were not normally distributed, and 186 as they were outliers for influence and leverage. Parameters were estimated with and without outliers and did not differ significantly. The final dataset contained 16,248 lines of data.

### 4.3.2 Model building

A multivariable continuous outcome regression model was built to explore factors associated with on-farm DLWG (Model 1), and a separate multivariable logistic regression model was built to investigate the predictors of whether or not an animal received an antibiotic treatment (Model 2). DLWG was chosen as an outcome as consensus of the TAG was that it was a crucial KPI for finishing enterprises. Antibiotic treatment was chosen due to farmer interest, and to use as a proxy for disease incidence. Model building was carried out in MLwiN 2.35 (Rasbash et al., 2015). Explanatory variables were added to the model sequentially and coefficients and standard errors calculated. Models were built by forward stepwise selection, with continuous variables being retained in the model when the estimated absolute coefficient was greater than twice the standard error (equivalent to $p<0.05$). For categorical variables, all categories were retained in the model if one or more showed a significant association with the outcome variable. All rejected variables were re-offered to the final model and retained if they met the criteria described above. Where multiple categories within a variable showed similar estimated coefficients, they were combined in order to maintain as sparse a model as possible. For example, when evaluating the effect of purchase month on DLWG in Model 1, spring months (Feb, March and April) had very similar estimated coefficients, as did autumn months (September, October and November). These two groups of three months were therefore compared to the rest of the year, providing the model with three categories rather than 12. Likewise, where there were very few data points in a category this was combined with another category. For example, there were very few animals in some of the breed categories, so these were combined to create an 'other' category. The models took the form:

Model 1: $$DLWG_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} \dots\dots \beta_n X_{ni} + e_i$$

$DLWG_i$ is the DLWG value for the $i^{th}$ individual. $\beta_0$ is the model intercept, i.e. the DLWG value when all other variables in the model are at their average value (as all continuous variables are centred around their mean). $e_i$ represents the residual, i.e. the difference between the $i^{th}$ individual's DLWG value and that predicted by the predictor variable(s), i.e. the *X* value(s) in the model. $X_{1i}$ represents the first predictor variable value for the $i^{th}$ individual, and $\beta_1$ its coefficient (i.e. the change in DLWG for a 1 unit change in the predictor variable, whilst holding all other variables (i.e. $X_2$ up to $X_n$ constant).

Model 2: $$logit(Antibiotic\ treatment\ Y/N)_i = log\left(\frac{\pi_i}{1-\pi_i}\right)$$
$$= \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} \ldots \ldots \beta_n X_{ni} + e_i$$

$logit(Antibiotic\ treatment\ Y/N)_i$ is the log of the odds that animal *i* will receive an antibiotic treatment. $\pi_i$ is the probability of the $i^{th}$ individual receiving an antibiotic treatment, and the coefficients in this model are the ratio of the change in log odds of the event happening per unit change in the predictor variable. The potential predictor variables offered to the models, and the outcome variables, are described in Table 4-1.

***Table 4-1: Potential explanatory and outcome variables used for building regression models***

| Variable | Variable type |
|---|---|
| **On-farm DLWG (kg)** | Continuous, centred around population mean (outcome variable in Model 1) |
| **Antibiotic treatment** | Model 1 – Categorical: 0,1 or >1 antibiotic treatments<br>Model 2 - Binary: 0 or at least 1 antibiotic treatments (outcome variable in Model 2) |
| **Purchase price (£/kg)** | Continuous, centred around population mean |
| **Purchase month** | Categorical: months as individual categories |
| **Source (i.e. market or seller purchased from)** | Categorical:<br>1 – 7 = most frequent 7 sources, i.e. the top 7 places animals are purchased from.<br>0 = all other sources. |
| **Age at purchase (months)** | Continuous, centred around population mean |
| **Breed** | Categorical: Hereford, Angus, Continental, Dairy and Other |
| **Weight/age at purchase (kg/month)** | Continuous, centred around population mean |

## 4.4 Results

This was a single farm dataset containing data for 16248 cattle between 2010 and 2016. A mean of 2710 head of cattle were produced per year (median 1795 and range 41 to 5154). Cattle spent on average (mean) 163 days on farm (median 152 days). Mean weight at purchase was 419kg (median 418kg) and mean weight at sale was 614 kg (median 611kg), with a mean DLWG of 1.3kg (median 1.3kg). A total of 383 antibiotic treatments were given, with 110 animals having a single treatment and 273 having more than one.

### 4.4.1 Model 1: Investigating predictors of DLWG using multiple regression

Six predictor variables were found to have significant associations with DLWG in this dataset as displayed in Table 4-2.

*Table 4-2: **Model 1 – Predictors for mean DLWG from purchase to slaughter on a large finishing unit.** Outputs of the multiple regression model investigating associations between predictor variables and DLWG are displayed in the table, including coefficients, standard errors and p-values. For categorical variables the reference category (against which other categories are compared) is shown. The coefficients indicate the associated change in outcome variable (DLWG) with each unit change of predictor variable.*

| Model term | Coefficient | Standard error | P-value |
|---|---|---|---|
| **Outcome: on-farm daily liveweight gain (kg)** | | | |
| **Intercept** | 1.39 | 0.009 | |
| **Purchase price (£/kg, centered around mean)** (n=16248) | 0.059 | 0.009 | <0.01 |
| **Purchase month: Jan/May/Jun/Jul/Aug/Dec/** (n=6601) | Reference | | |
| **Purchase month: Feb/Mar/Apr** (n=4349) | 0.031 | 0.006 | <0.01 |
| **Purchase month: Sept/Oct/Nov** (n=5298) | -0.055 | 0.006 | <0.01 |
| **Antibiotic treatment: none** (n=16052) | Reference | | |
| **Antibiotic treatment: one** (n=110) | -0.144 | 0.030 | <0.01 |
| **Antibiotic treatment: more than one** (n=86) | -0.212 | 0.034 | <0.01 |
| **Source: Other** (n=7920) | Reference | | |
| **Source 1** (n=1710) | 0.060 | 0.009 | <0.01 |
| **Source 2** (n=2069) | 0.052 | 0.008 | <0.01 |
| **Source 3** (n=538) | -0.020 | 0.014 | >0.05 |
| **Source 4** (n=1709) | 0.086 | 0.009 | <0.01 |
| **Source 5** (n=1450) | 0.039 | 0.009 | <0.01 |
| **Source 6** (n=399) | 0.057 | 0.016 | <0.01 |
| **Source 7** (n=453) | -0.011 | 0.015 | >0.05 |
| **Age at purchase (months, centered around mean)** (n=16248) | 0.006 | 0.001 | <0.01 |
| **Breed: Hereford** (n=1686) | Reference | | |
| **Breed: Angus** (n=1668) | -0.042 | 0.011 | <0.01 |
| **Breed: Continental** (n=5633) | -0.109 | 0.009 | <0.01 |
| **Breed: Dairy** (n=6707) | -0.123 | 0.009 | <0.01 |
| **Breed: Other** (n=554) | -0.118 | 0.015 | <0.01 |

The intercept in the table represents the predicted DLWG for an animal at mean value for all the continuous explanatory variables, and for the reference category for the categorical ones. So, a Hereford animal with a mean purchase price and age at purchase, bought from an “other” source not in spring/autumn has a predicted DLWG of 1.4kg/day. Associations between the outcome variable and the explanatory variables are listed below:

1) **Purchase price/kg:** The coefficient of 0.059 indicated that each £/kg increase in purchase price was associated with an increase in DLWG of 0.059kg/day.

This was a significant association with a p-value <0.01. For example, a 400kg animal costing £800 (£2.00/kg) would be expected to grow 0.03kg/day faster than a 400kg animal costing £600 (£1.50/kg).

2) **Purchase month:** The reference category was 'other' (May/Jun/Jul/Aug/Dec/Jan), so the model showed that animals purchased in the spring (Feb/March/April) were associated with a DLWG increase of 0.031kg compared to those purchased in either May-August or December-January. Animals purchased in the autumn however (September/October/November) were associated with a DLWG reduction of 0.055kg compared to animals purchased in either May-August or December-January. Both of these predictors had a significant association with DLWG with p-values both <0.01.
3) **Number of antibiotic treatments:** The reference category was 0 treatments, so the model showed an association between an animal receiving one antibiotic treatment and a DLWG reduction of 0.144kg, and for those receiving more than one antibiotic treatment an associated DLWG reduction of 0.212kg. Again, both predictors had a significant association with DLWG with p-values both <0.01.
4) **Source:** The reference category was 'other', allowing demonstration of how the estimated DLWG values change for each of the most frequent seven source farms, compared to the rest. Sources 1, 2, 4, 5 and 6 were associated with DLWG increases of 0.039kg to 0.086kg compared to 'other' sources (p<0.01). Animals from sources 3 and 7 were not associated with a significantly different DLWG compared to those from sources in the 'other' category. (p>0.05).
5) **Age at purchase:** The coefficient of 0.006 indicated an associated increase in DLWG of 0.006kg for every month increase in the age of animal at purchase (p<0.01). Although this was significant statistically, as the DLWG increase was so small for every month increase in animal age, whether it is significant practically is doubtful.
6) **Breed:** The reference category here was 'Hereford', so an animal in the 'other' breed category was associated with a DLWG 0.118kg lower compared to an animal in the 'Hereford' category. In the same way, an animal in the 'Continental' category was associated with a DLWG 0.109kg lower than an animal in the 'Hereford' category, an animal in the 'Dairy' category by a DLWG 0.123kg lower, and an animal in the 'Angus' category, by 0.042kg lower (p<0.01).

This model showed several variables that were significantly associated with DLWG. Although most of the effect sizes were relatively small, the effect of more than one antibiotic treatments on DLWG was considerable. The $r^2$ value of the model (the proportion of variation in outcome explained by the combination of predictor variables) was 4.6%.

### *4.4.1.1 Assessing model fit*

Model fit was assessed by calculating and visualising the DLWG residuals, standardised residuals, leverage and influence values. A histogram of the standardised residuals was evaluated to check for approximation to a normal distribution (Figure 4-1a, it would be expected that 95% of residuals would lie between -2 and +2). Leverage (Figure 4-1b) and influence (Figure 4-1c) values were also evaluated. This identified some outliers which were removed: 49 as the standardised residuals were not normally distributed, and 186 as they were outliers for influence and leverage. The model parameters were re-estimated and did not differ significantly (significant associations remained unchanged with minor changes in the coefficients). Standardised DLWG residuals were plotted against predicted values to assess homoscedasticity (Figure 4-1d), and predicted values were plotted against observed values to determine the total variance in outcome variable explained by the model.

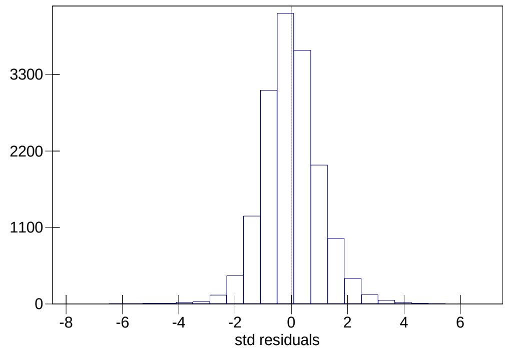


Figure 4-1a: Histogram of standardised DLWG residuals

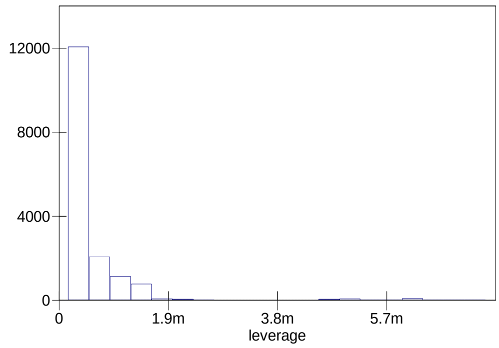


Figure 4-1b: Histogram of leverage values

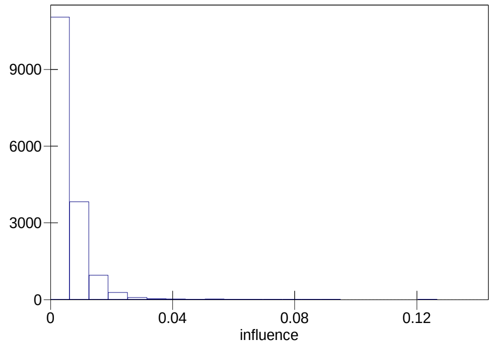


Figure 4-1c: Histogram of influence values

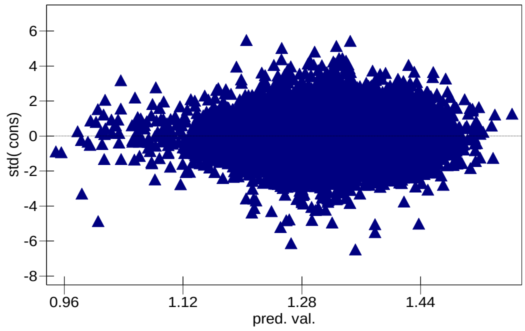


Figure 4-1d: Standardised DLWG residuals plotted against predicted values

***Figure 4-1: Model 1 - Assessing model fit*** *Model fit was assessed by evaluating the distribution of the standardised residuals to check for approximation to a normal distribution (Figure 4-2a, it would be expected that 95% of residuals would lie between -2 and +2). Leverage (Figure 4-2b) and influence (Figure 4-2c) values were also evaluated. Standardised DLWG residuals were plotted against predicted values to assess homoscedasticity (Figure 4-2d).*

### 4.4.2 Model 2: Investigating predictors of antibiotic treatment using multiple regression

In order to investigate variables associated with an animal receiving an antibiotic treatment, a logistic regression model was used. Predictor variables were added to the model as previously described. Several of the predictor variables showed no significant associations with the outcome variable, possibly because only a small number of cattle receive antibiotic treatments (2.3% of all animals). All variables with no significant association were removed from the model. The coefficients generated in this model were exponentiated to generate odds ratios which are easier to interpret. Two predictor variables were found to have significant associations with whether or not an animal received an antibiotic treatment or not, as displayed in Table 4-3.

***Table 4-3: Model 2 – Predictors for antibiotic treatments.*** *Outputs of the logistic regression model investigating associations between predictor variables and antibiotic treatments are displayed in the table, including coefficients, odds ratios and p-values. The coefficients are exponentiated to give the odds ratios which make the associations more readily interpretable.*

| Model term | Coefficient | Odds ratio | P-value |
|---|---|---|---|
| **Outcome: Antibiotic treatment** | | | |
| **Intercept** | N/A | | |
| **Weight/age at purchase (kg/month, centred around mean)** (n=16484) | -0.049 | 0.952 | <0.01 |
| **Age at purchase (months, centred around mean)** (n=16484) | -0.082 | 0.921 | <0.01 |

1) **Weight/age at purchase:** The odds of an animal receiving an antibiotic treatment reduced by around 5% (OR = 0.952) with each unit increase in the ratio between weight at purchase (kg) and age at purchase (months). For example, a 12-month old animal weighing 300kg has a weight for age value of 25kg/month (300/12), whereas a 9-month old animal weighing 300kg has a weight for age value of 33kg/month (300/9). This is an increase of 8kg/month, which in this model was associated with a 40% (8 x 5) reduction in the odds of being treated with antibiotics.
2) **Age at purchase:** The odds of an animal receiving an antibiotic treatment also reduced with increasing age at purchase. The OR of 0.921 reflects a reduction in odds of being treated of around 8% with each month increase in age at purchase. This association allowed for the effect of weight for age (i.e. this was the effect of age alone).

#### *4.4.2.1 Assessing model fit*

The fit of a logistic regression model can be assessed by the Hosmer-Lemeshow test, which is a chi-square statistic calculated from observed and estimated values (Peng et al., 2002). Observed and predicted antibiotic treatment outcomes (i.e. treatment or no treatment) were compared. Predicted treatment outcomes were ranked and divided into 13 equally sized categories (13 was chosen as the first number greater than 10 which would divide the total number of predictions equally). The number of predicted treatments in each category was then compared to the number of actual treatments, as displayed in Table 4-4. A chi-square test was then done to compare the two groups, which were found to be not significantly different (p=0.14).

***Table 4-4: Model 2 – Assessing model fit****. Table of observed and expected treatment numbers from logistic regression model. A chi-square test is carried out on these to check they are not significantly different (Hosmer-Lemeshow test)*

| *Category* | *Number in category* | *Sum of predicted treatments* | *Sum of actual treatments* |
|---|---|---|---|
| **1** | 1268 | 17 | 19 |
| **2** | 1268 | 21 | 26 |
| **3** | 1268 | 22 | 25 |
| **4** | 1268 | 25 | 31 |
| **5** | 1268 | 26 | 14 |
| **6** | 1268 | 28 | 17 |
| **7** | 1268 | 29 | 31 |
| **8** | 1268 | 30 | 23 |
| **9** | 1268 | 32 | 28 |
| **10** | 1268 | 34 | 38 |
| **11** | 1268 | 36 | 42 |
| **12** | 1268 | 39 | 42 |
| **13** | 1268 | 46 | 49 |
| **Total** | 16484 | 385 | 385 |

## 4.5 Discussion

Analysis of herd performance data provided by farmers in the TAG allowed evaluation of the practicalities of obtaining and interpreting this data, as well as investigation of methods of analysis that lend themselves to the complex nature of farm systems. A large dataset available for one herd allowed multiple regression analysis to be used to investigate the associations between performance metrics and illustrated how data analysis can be used to inform herd management decision making.

There were some limitations with this dataset, for example there was a lot of missing or seemingly erroneous data. Data cleaning resulted in removal of 3789 lines of data, 1508 due to missing data, 2046 due to implausible or erroneous data and 235 lines when assessing model fit. Some of these may have been input error, for example entering an overall animal sale price rather than a per kg sale price. In addition, animals weighed twice with a short interval (less than 14 days) often had very large or very small DLWG values due to the natural variation in cattle weight and a small denominator over which to spread relatively large changes. Antibiotic treatments were used as a proxy for disease incidence, but anti-inflammatory alone treatments were not considered and so some disease events may have been missed. It is not known whether it was always the same member of staff inputting the data, or whether there were standard protocols for determining whether or not to treat animals for example, so this is another potential source for error. These are challenges typical of using real life data, and the balance between removing sufficient outliers to eliminate some of the 'noise', whilst not removing so many that erroneous associations are identified, can be a difficult one to strike.

Model 1 identified several significant variables associated with DLWG on this farm. More expensive animals per kg were associated with a significant (albeit small) increase in weight gain, whilst accounting for the month of purchase, where the animal was purchased from, the breed of animal and the age at purchase. Factors such as the vaccination or health status of the animal, or the quality of its genetics, may be involved in explaining the increased growth rates observed in more expensive animals. The model also showed that animals purchased in the spring tended to have a higher DLWG than those purchased at other times of year, and those purchased in the autumn tended to have a lower DLWG. Again, this was accounting for all other variables in the model, and so increased pneumonia rates in animals purchased in the autumn would seem to be unlikely as the number of antibiotic treatments given was accounted for. Factors that may explain the variation in DLWG between animals purchased at different times of year could include variation in ration ingredients and weather changes (cattle are housed outside in straw yards in this system). Cattle will also stay on farm for very variable time periods, with those purchased in the autumn more likely to spend a winter on the farm than those purchased in the spring.

The requirement for an antibiotic treatment (or treatments) was significantly associated with a reduction in DLWG. This could be used to inform decision making around the use of vaccination protocols with the aim of reducing antibiotic use, and the associated potential growth increase. For example, the associated decrease in DLWG of 0.144kg/day with one antibiotic treatment would equate to a reduction in liveweight gain of 21.89kg for an animal staying on the farm for 152 days (the median value in this dataset). This would equate to a sale price reduction of £78.80 using the dataset's median liveweight sale price of £3.60/kg (this only accounts for loss of revenue due to reduced weight gain though, and does not account for reduced feed intake, or costs associated with drugs or time).The number of animals receiving a single antibiotic treatment was 110, which multiplied by £78.80 was £8668. The number of animals receiving more than one treatment was 86, and the cost associated with this was £116/animal (0.212 x 152 x 3.60), or £9977 in total. This resulted in a total sale price reduction of £18,644, which could then be weighed up against the cost of vaccinating the herd (16248 animals). Antibiotic treatments for specific conditions could be included in the model, for example pneumonia, to further investigate the potential production benefits of specific interventions. As antibiotic use on this farm was low however, identifying significant associations when carrying out analysis on specific conditions was difficult, as such small numbers were treated for each condition. This example illustrates how analysis of herd data can be of benefit to farmers when deciding whether to implement a vaccination control protocol or other disease control measures. In a similar way, evaluation of source of purchase, age at purchase and breed variables may be used to help farmers make decisions around purchase policies, and to identify classes of animals that perform well within their system.

The overall variance in DLWG explained by the model was low at 4.6%, indicating that although this herd records a lot of data, there are many other variables influencing DLWG. If recorded, data such as genetic information, vaccination or disease status, average temperatures during time on farm and feeding protocols could be used to further investigate predictors of this variable. The relatively small effect sizes of the significant predictor variables will also contribute to the low $r^2$ value. For the variables with a larger effect size (e.g. the number of antibiotic treatments), low numbers of animals receiving an antibiotic treatment meant that although the effect on an individual's DLWG was high, the overall effect on DLWG was small. This is a challenge inherent in investigating events that happen infrequently.

An Australian study investigated similar predictors of beef performance that could be assessed on entry to the feedlot (Cusack et al., 2007). These included breed, sex, entry weight, and the presence or absence of permanent incisors (as a proxy for age). The relationship between these predictors and growth rate, BRD incidence and mortality was assessed. As in this study, breed and age were significantly associated with growth rate, as was treatment for BRD. Environmental temperature was also recorded in the Australian study, and minimum temperature was found to be correlated with BRD incidence. Climate data might be something that could be added to herd performance data with the aim of explaining more variation in outcomes such as DLWG and treatment rates. Although the ability of the farmer to control climate is limited, it may indicate where management changes could be made at certain times of year to improve performance, or certain times of year where production could be concentrated to make the most of a favourable climate. An Italian study, collecting beef production data via a survey, also investigated predictors of DLWG in cattle (Sturaro et al., 2005). Significant predictors of variation identified included farm type, genotype (breed), a measure of morbidity and mortality, and season of sale. In this study, the model explained 83.3% of variation in growth rate. The low unexplained error in the Italian model may be due to the large size of the dataset, batching the animals for analysis (which will help to control for outliers and reduce overall variation in DLWG) and possibly using data from a relatively uniform system.

Model 2 was developed to further investigate variables associated with the likelihood of an animal receiving an antibiotic treatment, and illustrated that animals that were light for their age at purchase, and that were young at purchase, were more likely to require an antibiotic treatment. In the case of animals light for their age at purchase, this could be associated with previous illness inhibiting growth rates and also requiring further treatment. Young animals may be more susceptible to stressors around transport than older animals, and so more likely to require antibiotics as a result. They may also just be less suitable for this type of finishing system. Analysis such as this may be used by a farmer to inform management and purchasing decisions with the aim of reducing antibiotic use.

The models presented display data from an individual beef enterprise, which can often provide superior uniformity of data (for example standardised recording categories) especially for large finisher herds with a short production cycle where data can be generated relatively quickly. This can provide good statistical power and useful insights into finishing systems in this country; an area which is under-represented in the literature. However, comparisons should be made with caution and the results should not be directly applied to other beef farms, particularly in a sector as diverse as the beef sector. For results to be more readily applicable to other beef enterprises, datasets from many farms can be combined for analysis. There are several examples of this in the literature, where larger datasets are used, including many farms over several years. For example, data from nine herds over two years was used to investigate the influence of neonatal health on weaning weight of beef calves (Wittum et al., 1994b), and reductions in weaning weight of 16.5kg and 10.7kg were associated with respiratory disease and diarrhoea respectively. On an even larger scale, 43,627 herds across three years were included in a Swiss study investigating risk factors of perinatal and postnatal mortality in cattle (Bleul, 2011). This provided not only national mortality rates for each of the years, but also identification of risk factors for mortality applicable to Swiss farms. Analysis of data from multiple herds, including multiple breeds and system types, provides the best option for allowing generalisation of results across a beef sector. Such data may be available through statutory recording systems, such as BCMS (Gates, 2013, Hyde et al., 2020), or medicine records and veterinary practice sales data (Hyde et al., 2017). However, the content, and so the metrics able to be calculated, can be limited. For more detailed data, and particularly for financial data, voluntary recording systems are likely to be required. This can then be used to inform decision making on individual farms, where large datasets are often not readily available, and may encourage greater recording of data on beef farms as the potential benefits are demonstrated.

Availability of large datasets also presents the opportunity for predictive analysis, allowing predictions to be made about future performance based on previous data. The lag time between an event happening, the data being recorded and analysed, and then being used to inform management decisions may be long (such as calving interval data), or short (such as DLWG data), but there will inevitably be a lag time. Use of current data to predict future trends allows more proactive decision making, and predictive analytics such as this have been used in the context of mastitis control and predicting livestock bodyweights (Morota et al., 2018, Gomes et al., 2016, Green et al., 2016).

Machine learning is a tool (or set of tools) commonly used for these types of predictive analytics, and is able to 'learn' from previous data to alter future calculations accordingly (Hudson et al., 2018). Machine learning may be 'supervised' (when the outcome is known), or 'unsupervised' (where the outcome is unknown). In (supervised) machine learning, cross validation can be used to test the predictive ability of the model. This involves splitting the dataset and using part for training and part for testing (Morota et al., 2018). The training dataset is used to produce the model, with the training error being the error in the predictions of that model. The testing dataset can then be used to test the accuracy of the predictions of the model, with the testing error being the error in the predictions of the model using the testing data (this will inevitably be larger than the training error). The difference in these values give an approximation of the generalisation error, or the ability of the model to make predictions using future, un-seen data (if generalisation error is low, the generalisation ability of the model is considered high). K-fold cross validation is often carried out, which repeats this process 'k' number of times using different subsets of the data and averages the results. An alternative to this is external cross validation, where a separate dataset is used to test the predictions in the model. Using these validation methods for Model 1 for example, would allow prediction of around 5% of the variation in DLWG for similar animals on this farm. This is clearly very low, and not appropriate for a predictive model. Regression analysis is useful in this scenario however, as it allows investigation into which predictors of our outcome variables (DLWG and antibiotic treatments) are important, and their relative effects. It is useful for describing data and identifying potentially causal relationships (which can then be tested, for example, in randomised trials). For example, Model 2 illustrated that an animals age at purchase had a greater association than its weight (relative to its age) with the probability of it receiving an antibiotic treatment. The farmer might therefore decide to purchase older animals with the aim of reducing the requirement for antibiotic use. This type of analysis is difficult to do with machine learning, where the aim is generally to make predictions about un-seen data.

## 4.6 Conclusions

Analysis of data from complex systems, such as farm systems, lends itself to multiple regression, where individual and independent associations between each predictor variable and an outcome variable can be defined. This allows deeper interrogation of farm data than is currently often achievable. Identification of predictors of performance measures, such as DLWG or antibiotic treatment numbers, can help farmers maximise production by allowing more informed decision making. So far only one 'level' of data has been used when exploring the relationships, i.e. individual animals within a farm. These methods can however be extended to explore multiple levels of data. For example, multiple farms across several years may be incorporated, providing a better understanding of the complex relationships between the many variables affecting an 'outcome' on farm.

# Chapter 5: Analysis of correlations between performance indicators and overall enterprise success

## 5.1 Introduction

In the previous chapter, multiple regression was used to analyse data from a single farm and to investigate the relationships between various performance indicators. This is of use at the individual farm level and can be applied, where the data is available, to enable farmers to make more informed herd management decisions. Multiple regression is also useful for analysing industry level datasets containing information from many herds over several years, such as the AHDB Stocktake database (now replaced by Farmbench: www.ahdb.org.uk/farmbench). This service allowed producers to record and monitor both their financial and physical performance, and to benchmark themselves against similar farms. In addition to providing individual farm information, the data was used to produce a reference document for the beef industry as a whole (AHDB Beef and Lamb, 2016b). The data has also been used to draw international comparisons with countries that are competing with the UK in the global beef market. International comparisons were provided by the international comparison network Agri benchmark (www.agribenchmark.org). 'Typical' virtual farms from up to 30 member countries were used along with an internationally standardised method of analysis to benchmark the farms.

Analysis of such datasets, incorporating many farms over a number of years, may be used to investigate associations between herd performance and overall enterprise success that are more easily applied to beef enterprises across the sector. For example, in a study using multiple regression to investigate the effect of various neonatal health factors on weaning weight, data was collected from 2609 calves from nine herds over two years (Wittum et al., 1994b). Likewise, 29970 births from 203 herds were included in a study which used logistic regression to evaluate risk factors associated with neonatal mortality and dystocia (Waldner, 2014a). Risk factors for calf mortality (Bleul, 2011), dystocia (Waldner, 2014a) and the effects of twinning (Gregory et al., 1990) have also been investigated using these techniques. National data may also be used, for example CTS data (Gates, 2013), which was used in a multivariable model to evaluate reproductive performance of beef and dairy herds across the UK. In all of these studies using data from multiple herds, the likelihood that animals within a herd are more likely to perform in a similar way than animals from different herds, which would cause clustering of data, was considered. A herd level effect was generally included as part of the regression model; either herd was added to the model as a random intercept (Waldner, 2014a), or forced into the model as a fixed effect (Wittum et al., 1994b). Fixed effects models simply include 'herd' in the model as a categorical predictor, so the 'effect' for each herd is clear in the model and it is easy to compare between them. This quickly becomes cumbersome however if there are more than a small number of herds. A random intercept model is of a slightly different structure, so when herd is accounted for in this way the model becomes a multilevel model, with individual animals nested within herds. Here each herd has its own intercept (termed a random intercept as it is allowed to vary), and the herd intercepts are assumed to come from a normal distribution. This allows us to see how much variation there is at each level (if this is of interest), for example how much variation in the outcome variable is just due to the herd (whilst controlling for all the explanatory variables in the model). Further levels may be added, for example where there are multiple measures from each animal, such as interservice intervals (ISI) in dairy cows (Remnant et al., 2015). In this example, a multilevel regression model was used to evaluate the associations between potential predictors of ISI, and ISI using a three level structure: interservice intervals, cows and herds.

Various definitions of enterprise success exist in the literature, for example income over feed costs (IOFC) can be used as an indicator of profitability where fixed costs are not available (Atzori et al., 2013). Data from a dairy herd stochastic simulation model was used to identify principal components in determining IOFC, and multiple regression of these principal components against IOFC was done to estimate coefficients. Gross margin has also been used (Kristensen et al., 2008). In this latter study, data from a Monte Carlo simulation was analysed by analysis of variance (ANOVA) to determine associations between performance indicators for the dairy herd and gross margin.

## 5.2 Aims

The aims of this chapter were to investigate the associations between performance indicators and an overall measure of enterprise success using a multi-farm dataset. This was done for both suckler herds and grower/finisher herds and the significant associations for each herd type were compared. Use of a multi-farm dataset would allow greater insight into relationships between performance indicators and enterprise success, with the results being more generalisable across herds.

## 5.3 Methods

### 5.3.1 Data collection and cleaning

Data for analysis was provided from AHDB's Stocktake database. This data was collected by AHDB staff to ensure standardised input, but the farmer was able to view the data and generate reports. Economic margins for individual enterprises within mixed farms could be analysed, as opposed to whole farm margins, which is of great benefit in multiple enterprise farms. Margins after cash costs only, and on a full economic basis, could also be analysed which allowed factors such as depreciation to be taken into account. The database contained data from 56 suckler enterprises and 36 grower/finisher enterprises across the three years 2013, 2014 and 2015. These datasets contained financial information, and through discussion with the TAG, definitions of enterprise success were determined to be: net margin/cow bred in suckler herds, and net margin/head of output in grower or finisher herds. Where available, performance indicators in the KPI toolkit were extracted from the data. Where performance indicators were not available in the dataset, but could be calculated from the data available, this was done. Performance indicators were then divided into fertility, growth, health and financial categories, in order to replicate the structure of the KPI toolkit described previously.

Distributions of the intended outcome variables, i.e. definitions of enterprise success (net margin/cow bred and net margin/head of output) were evaluated using histograms, and outlier values were removed. These outliers consisted of one farm in the suckler dataset that had a significantly lower net margin in all of the three years, and two farms in the grower/finisher dataset that had very low numbers of animals or head of output over the three years. Individual variables were also evaluated within each unit of data (farm), and some continuous variables were categorised. This was particularly useful for continuous variables where many zero values were recorded, and it was felt that this represented a different management strategy. For example, many herds in the dataset recorded a 0% scanning percentage. It was considered that this was likely to be because this procedure was not carried out, or the results were not available at the time of data collection, rather than reflecting the fertility of the herd. Therefore, the variable was made categorical with herds either recording 0% scanning rates (89 records), 1-90% (27 records), or over 90% (45 records). These categories were based on distribution, so that each category had a reasonably even split of the data.

A number of the financial variables were aggregates or totals of other variables (for example, totals of fixed and variable costs), and were therefore highly or completely correlated with each other. Including these aggregate variables in the same model as their components would be inappropriate, so only variables at the lowest level (such that no variable was calculated directly from any other variable in the model) were included, with those showing significant associations retained in the model. The more comprehensive financial variables were investigated using a separate model. All the potential predictor variables for the suckler and the grower/finisher regression models in their relevant categories are displayed in Table 5-1 and Table 5-2 respectively.

### 5.3.2 Descriptive analysis

Performance indicators highlighted as important in earlier stages of the project were correlated with the appropriate measure of overall enterprise success in a bivariate way initially: scatter plots (for continuous variables) and bar charts (for categorical variables) were used to investigate the relationship between overall enterprise success (net margin/cow bred and net margin/head of output) and each performance indicator in turn. Where appropriate, some data was excluded from analysis, for example only block calving herds were included when correlating percent calving in the first 3 weeks with net margin/cow bred. Simple linear regression was used to assess the statistical significance of each relationship.

***Table 5-1: Predictor variables used in suckler model building.*** *Variables have been grouped by the area of performance that they monitor. Variable type is given, and where variables are categorical, the categories are included. All continuous variables are centred around the population mean.*

| Area of performance | Variable | Variable type |
|---|---|---|
| **Fertility** | % calving in the first 3 weeks | Continuous |
| | Age at first calving | Categorical: 2, 2.5 or 3 years. |
| | Calving period | Continuous |
| | Calves weaned/100 cows bred | Continuous |
| | % scanned in calf | Categorical: 0%, 1-90% and >90% |
| | % calves born alive | Continuous |
| | Cow:Bull ratio | Categorical: 0%, 1-50% and >50% |
| **Growth** | Average weight at weaning | Continuous |
| | DLWG to weaning | Continuous |
| | Creep feed fed (kg/calf weaned) | Continuous |
| | Cow size | Categorical: Small, medium or large |
| **Health** | Pre-weaning mortality rate | Continuous |
| | Cow mortality rate | Continuous |
| | Replacement rate | Continuous |
| **Financial** | Total cost/kg output (liveweight) | Continuous |
| | Gross output (including herd replacement cost) | Continuous |
| | Fixed costs/cow bred or head of output | Continuous |
| | Fixed costs as a % of total costs | Continuous |
| | Variable costs/cow bred or head of output | Continuous |
| | Variable costs as a % of total costs | Continuous |
| | Feed and forage costs/cow bred or head of output | Continuous |
| **Specific financial** | Labour cost/cow bred or head of output | Continuous |
| | Gross output (excluding replacement costs in the suckler herd) per cow bred or head of output | Continuous |
| | Veterinary and medicine costs per cow bred or head of output | Continuous |
| | Bedding costs per cow bred or head of output | Continuous |
| | Contracting and machine hire costs per cow bred or head of output | Continuous |
| | Machinery repairs and spares cost per cow bred or head of output | Continuous |
| | Fuel costs per cow bred or head of output | Continuous |
| | Property maintenance and water costs per cow bred or head of output | Continuous |
| | Depreciation (machinery and property) per cow bred or head of output | Continuous |
| | Imputed net field rent per cow bred or head of output | Continuous |
| | Imputed cost of finance per cow bred or head of output | Continuous |
| | Suckler herd replacement cost/cow bred | Continuous |

***Table 5-2: Predictor variables used in grower/finisher model building.*** *Variables have been grouped by the area of performance that they monitor. Variable type is given, and where variables are categorical, the categories are included. All continuous variables are centred around the population mean*

| Area of performance | Variables | Variable type |
|---|---|---|
| **Growth** | DLWG | Continuous |
| | Average weight gain | Continuous |
| | Average age at slaughter | Continuous |
| **Health** | Mortality rate | Continuous |
| **Financial** | Total cost/kg output (liveweight) | Continuous |
| | Gross output (including herd replacement cost) | Continuous |
| | Fixed costs/cow bred or head of output | Continuous |
| | Fixed costs as a % of total costs | Continuous |
| | Variable costs/cow bred or head of output | Continuous |
| | Variable costs as a % of total costs | Continuous |
| **Specific financial** | Feed and forage costs/cow bred or head of output | Continuous |
| | Labour cost/cow bred or head of output | Continuous |
| | Gross output (excluding replacement costs in the suckler herd) per cow bred or head of output | Continuous |
| | Veterinary and medicine costs per cow bred or head of output | Continuous |
| | Bedding costs per cow bred or head of output | Continuous |
| | Contracting and machine hire costs per cow bred or head of output | Continuous |
| | Machinery repairs and spares cost per cow bred or head of output | Continuous |
| | Fuel costs per cow bred or head of output | Continuous |
| | Property maintenance and water costs per cow bred or head of output | Continuous |
| | Depreciation (machinery and property) per cow bred or head of output | Continuous |
| | Imputed net field rent per cow bred or head of output | Continuous |
| | Imputed cost of finance per cow bred or head of output | Continuous |
| | Total cost of beef cattle purchases and transfers/head of output | Continuous |
| | Total machinery and power costs (excluding depreciation)/head of output | Continuous |

### 5.3.3 Model building

To explore relationships between multiple performance indicators and overall enterprise success simultaneously, multiple regression analysis was used as described previously. This allows investigation of the relationship between a dependent (or outcome) variable and one or more independent (or predictor) variables, allowing evaluation of the degree to which each independent variable is associated with the dependent one. Here it was used to analyse the effect several different performance indicators have on an overall indicator of enterprise success (i.e. net margin/cow bred) simultaneously. In order to account for the potential clustering of farms (i.e. performance of the same farm is more likely to be similar across the years than that of different farms), a two-level nested structure was used, with herd years nested within herds (i.e. herd was included as a random effect in the model). Year was included in the model as a fixed effect to allow for the influence of year on herd performance (for example economic climate and weather etc.). As previously, model building was carried out in MLwiN 2.35 (Rasbash et al., 2015). Models were built by forward selection, with variables being retained in the model when a significant association was identified (p<0.05), and all rejected variables being re-offered to the model at the end.

The models took the form:

$$Net\ margin\ per\ cow\ bred\ or\ head\ of\ output_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} \ldots + \beta_n X_{nij} + e_{ij} + u_j$$

Where $Net\ margin\ per\ cow\ bred\ or\ head\ of\ output_{ij}$ is the net margin value for the $ij^{th}$ herd-year (*ij* = herd *j* in year *i)*, $\beta_0$ is the model intercept, $X_{1ij}$ represents the first predictor variable value for the $ij^{th}$ herd-year, and $\beta_1$ its coefficient. $e_{ij}$ represents the residual and *uj* is the herd level random effect for herd *j*.

Separate models were created for financial and physical predictor variables. This was to minimise multiple predictors in a model representing the same aspect of performance, and to allow evaluation of the relationships between physical variables and net margin/cow bred without the dominance of the financial predictor variables when explaining the variance in the financial outcome variable. Where two potential predictor variables biologically or financially measured the same aspect of production, or were directly calculated from one another, the variable that resulted in the model with the highest $r^2$ value, i.e. the variable that resulted in the model explaining the most variation in the outcome variable, was retained.

Model fit was assessed through evaluation of distribution of standardised residuals, leverage and influence, and through plotting standardised residuals against predicted values, and the overall variance in observed net margin/cow bred explained by the model was determined.

## 5.4 Results

### 5.4.1 Descriptive analysis of suckler herd dataset

This dataset contained data from 56 suckler herds between 2013 and 2015. The mean suckler herd size was 95 (median 74) with 10 year round calving herds and 46 block calving herds. Correlations between potential predictor variables and net margin/cow bred were evaluated using scatter plots. P-values and $r^2$ values were calculated to assess significance and proportion of variation in net margin/cow bred explained by each variable (continuous variables only), the results of which are summarised in Table 5-3.

Calves weaned/100 cows bred was strongly significantly associated with net margin/cow bred and explains the most variation in net margin/cow bred of the fertility factors. Percent calving in the first 3 weeks and calving period explain the least variation in net margin/cow bred, but this could be due to the smaller sample size for block calving specific indicators as previously discussed. All performance indicators in the growth category were significantly associated with net margin/cow bred, with the average weight at weaning showing the greatest association (although the $r^2$ value for all of the growth variables were small). In the health category, pre-weaning mortality rate and cow mortality rate were significantly associated with net margin/cow bred, whereas replacement rate was not.

In the financial variables categories, many performance indicators were significantly associated with net margin/cow bred. Total costs/kg output explained the most variation in net margin/cow bred at over 80%, and fixed costs/cow bred alone explained over 60%. Variable costs/cow bred was not significantly related to net margin/cow bred and explained less variation (although expressing variable costs as a % of total costs increased $r^2$ value).

### 5.4.2 Multiple regression of physical performance indicators and net margin/cow bred in the suckler dataset

Results from a multiple regression model with net margin/cow bred as the outcome are shown in Table 5-4. Model fit was assessed and appeared satisfactory (Appendix 2). The model identified five physical performance indicators significantly associated with net margin/cow bred, which together explained 29% of the total variation in net margin.

The significant difference in net margin/cow bred between 2013 and 2014 ($p<0.05$) and 2013 and 2015 ($p<0.01$), highlighted the importance of allowing for year of production when investigating relationships between physical performance indicators and financial outputs in this dataset. Investigation of fertility performance indicators identified a significant association between herds with a target age at first calving of 2.5 years and a decrease in net margin/cow bred of £89.54, compared with herds aiming to calve heifers at 2 years ($p<0.01$). Herds with a scanning percentage of 1-90% were also significantly associated with a net margin/cow bred decrease of £105.59 compared to enterprises with a scanning percentage of >90% ($p<0.05$). Investigation of growth performance indicators illustrated an increase in net margin/cow bred of £0.83 ($p<0.05$) with each kg increase in weaning weight. The difference between the best and the worst performing herds in this category was 204.67kg, equating to a difference in net margin/cow bred of £170 (this relates to actual weaning weight as opposed to a value adjusted for age at weaning, so does not account for age at weaning). Both pre-weaning and cow mortality rates were also significantly associated with net margin. Each calf death/100 cows or heifers bred was associated with a net margin/cow bred reduction of £13.09 ($P<0.05$). This equated to a difference in net margin/cow bred of £170 between the best (0% pre-weaning mortality rate) and the worst (13% pre-weaning mortality rate) performing herds. Each percentage increase in cow mortality rate was associated with a £12.43 reduction in net margin/cow bred, equating to a difference in net margin/cow bred between the best (0% cow mortality rate) and the worst (14% cow mortality rate) of £174.

*Table 5-3: **Descriptive analysis of Stocktake data for suckler herds**. The $r^2$ values indicate the proportion of variation in net margin/cow bred explained by each of the variables (with 1 being the maximum value), and the p-value indicates the statistical significance of this correlation.*

| ***Area of performance*** | ***Mean and median value in dataset*** | | ***Performance Indicator*** | ***p-value*** | ***$r^2$*** |
|---|---|---|---|---|---|
| | ***Mean*** | ***Median*** | | | |
| **Fertility** | 30% | 27% | % calving in the first 3 weeks (year-round calving herds excluded and farms split into spring, autumn and multi-block calvers) | >0.05 | 0.00479 |
| | 15 weeks | 13 weeks | Calving period (year-round calving herds excluded) | >0.05 | 9.84 x 10-5 |
| | 85 | 86 | Calves weaned/100 cows bred | <0.001 | 0.070 |
| | 87% | 88% | % calves born alive | <0.01 | 0.059 |
| | 34 | 33 | Cow:bull ratio | >0.05 | 0.000 |
| **Growth** | 293kg | 290kg | Average weight at weaning | <0.01 | 0.044 |
| | 1.1kg | 1.1kg | DLWG to weaning | <0.05 | 0.025 |
| | 57kg | 0kg | Creep feed fed (kg/calf weaned) | <0.05 | 0.027 |
| **Health** | 2.6% | 2.0% | Pre-weaning mortality rate | <0.01 | 0.0543 |
| | 2.3% | 2.0% | Cow mortality rate | <0.01 | 0.0442 |
| | 16.9% | 16.8% | Replacement rate | >0.05 | 0.00107 |
| **Financial** | £3.09 | £2.78 | Total cost/kg output (liveweight) | <0.001 | 0.814 |
| | £270,000 | £134,000 | Total gross output (including herd replacement cost) | <0.01 | 0.0407 |
| | £503 | £479 | Fixed costs/cow bred | <0.001 | 0.611 |
| | 67% | 68% | Fixed costs as a % of total costs | <0.05 | 0.0363 |
| | £180 | £167 | Variable costs/cow bred | >0.05 | 0.00877 |
| | 24% | 23% | Variable costs as a % of total costs | <0.001 | 0.0695 |
| **Specific financial** | £98.70 | £81.10 | Feed and forage cost/cow bred | >0.05 | 0.00557 |
| | £137 | £129 | Labour cost/cow bred | <0.001 | 0.347 |
| | £51,600 | £40,100 | Suckler herd gross output/cow bred (excluding replacement costs) | <0.001 | 0.0956 |
| | £32.70 | £31.50 | Veterinary and medicine costs for the suckler herd/cow bred | >0.05 | 0.0221 |
| | £30.90 | £29.30 | Bedding costs for the suckler herd/cow bred | <0.01 | 0.0429 |
| | £40.10 | £34.60 | Contracting and machine hire costs for the suckler herd/cow bred | >0.05 | 0.0164 |
| | £26.10 | £24.10 | Machinery repairs and spares costs for the suckler herd/cow bred | <0.001 | 0.0668 |
| | £28.60 | £24.70 | Fuel costs allocated to the suckler herd/cow bred | <0.001 | 0.137 |
| | £21.30 | £16.80 | Property maintenance and water costs for the suckler herd/cow bred | <0.05 | 0.0388 |
| | £74.50 | £61.10 | Depreciation (machinery and property) for the suckler herd/cow bred | <0.001 | 0.199 |
| | £67.40 | £64.90 | Suckler herd replacement cost/cow bred | <0.001 | 0.0769 |
| | £116 | £101 | Imputed suckler herd net field rent/cow bred | <0.001 | 0.330 |
| | £34.90 | £36.90 | Imputed cost of finance allocated to the suckler herd/cow bred | <0.001 | 0.0956 |

*__Table 5-4: Results of multiple regression of physical performance indicators for suckler herds.__ Coefficients, standard errors and p-values are displayed, and for categorical variables the reference category is shown. The coefficients indicate the associated change in outcome variable (net margin/cow bred) with each unit change of predictor variable. The standard errors are used to determine the p-value, with a value less than half the coefficient indicating a p-value of <0.05, and a value < one third the coefficient indicating a p-value < 0.01.*

| Model term | Coefficient | Standard error | p-value |
|---|---|---|---|
| **Outcome: Net margin/cow bred** | | | |
| **Intercept** | -216.330 | 31.470 | |
| **Year: 2013** (n=53) | Reference | | |
| **Year: 2014** (n=54) | 68.290 | 31.948 | <0.05 |
| **Year: 2015** (n=56) | 106.539 | 31.770 | <0.01 |
| **Age at first calving: 2 years** (n=70) | Reference | | |
| **Age at first calving: 2.5 years** (n=75) | -89.540 | 29.734 | <0.01 |
| **Age at first calving: 3 years** (n=18) | -68.627 | 45.150 | >0.05 |
| **Scanning percentage: >90%** (n=45) | Reference | | |
| **Scanning percentage: 1-90%** (n=27) | -105.594 | 40.144 | <0.05 |
| **Scanning percentage: 0%** (n=89) | 31.595 | 32.160 | >0.05 |
| **Average weight at weaning (kg/head) (centred around mean)** (n=163) | 0.825 | 0.319 | <0.05 |
| **Pre-weaning deaths/100 cows or heifers put to bull (centred around mean)** (n=163) | -13.094 | 5.100 | <0.05 |
| **Cow mortality rate (%) (centred around mean)** (n=163) | -12.432 | 5.582 | <0.05 |

### 5.4.3 Multiple regression of financial performance indicators and net margin/cow bred in the suckler dataset

Financial variables were analysed separately from physical variables as previously discussed. A regression model including the comprehensive financial variables was built, and demonstrated that total cost/kg output explained most variation in net margin/cow bred. When this was broken down into fixed and variable costs in the regression model, fixed costs explained the most variation in net margin/cow bred, reflecting the descriptive analysis results. Specific financial variables were then incorporated into a regression model using the protocol previously described, with net margin/cow bred again the outcome variable, and year forced into the model as a fixed effect variable. Model fit was assessed as described and appeared satisfactory (Appendix 2). The outputs from this model are displayed in Table 5-5.

Fuel cost/cow bred was associated with largest effect size, i.e. the largest variation in net margin/cow bred at £2.07 (p<0.01) decrease in net margin/cow bred for each £1 increase in fuel cost/cow bred. Bedding, veterinary and medicine, and contracting and machine hire costs demonstrated very similar effect sizes, showing an associated £1.51, £1.53 and £1.49 decrease in net margin/cow bred respectively for each £1/cow bred increase in costs (p<0.01). Total labour cost, replacement cost, depreciation, imputed field rent, machinery repairs and spares and gross output all showed small effect sizes of between £1.21 and £0.69 decrease in net margin/cow bred for each £1 increase in costs/cow bred. The model explained 92.4% of the total variation in net margin/cow bred.

*Table 5-5: **Results of multiple regression of financial indicators for suckler herds** Coefficients, standard errors and p-values are shown. The coefficients indicate the associated change in outcome variable (net margin/cow bred) with each unit change of predictor variable. The standard errors are used to determine the p-value, with a value less than half the coefficient indicating a p-value of <0.05, and a value < one third the coefficient indicating a p-value < 0.01.*

| Model term | Coefficient | Standard error | p-value |
|---|---|---|---|
| **Outcome: Net margin/cow bred** | | | |
| **Intercept** | -211.579 | 7.633 | |
| **Year: 2013** (n=47) | Reference | | |
| **Year: 2014** (n=49) | 13.954 | 10.602 | >0.05 |
| **Year: 2015** (n=50) | 32.724 | 10.932 | <0.01 |
| **Fuel cost allocated to the suckler herd/cow bred (centred around mean)** (n=146) | -2.068 | 0.342 | <0.01 |
| **Bedding costs for the suckler herd/cow bred (centred around mean)** (n=146) | -1.514 | 0.229 | <0.01 |
| **Veterinary and medicine costs for the suckler herd/cow bred (centred around mean)** (n=146) | -1.526 | 0.244 | <0.01 |
| **Contracting and machine hire for the suckler herd/cow bred (centred around mean)** (n=146) | -1.492 | 0.157 | <0.01 |
| **Total labour cost/cow bred (allocated to the suckler herd, including paid and unpaid labour) (centred around mean)** (n=146) | -1.208 | 0.086 | <0.01 |
| **Suckler herd replacement costs/cow bred (centred around mean)** (n=146) | -0.913 | 0.073 | <0.01 |
| **Depreciation (machinery and property allocated to the suckler herd)/cow bred (centred around mean)** (n=146) | -0.854 | 0.100 | <0.01 |
| **Imputed suckler herd net field rent/cow bred (centred around mean)** (n=146) | -0.826 | 0.074 | <0.01 |
| **Machinery repairs and spares for the suckler herd/cow bred (centred around mean)** (n=146) | -0.813 | 0.256 | <0.01 |
| **Suckler herd gross output (excluding replacement costs)/cow bred (centred around mean)** (n=146) | 0.695 | 0.043 | <0.01 |

### 5.4.4 Descriptive analysis of the grower and finisher herd dataset

This dataset contained data from 36 grower/finisher herds between 2013 and 2015. The mean head of output produced per year was 71 (median 54). Scatter plots were used to investigate relationships between net margin/head of output and other variables as previously. P-values and $r^2$ values were then calculated to assess the statistical significance of the relationship, and the amount of variation in net margin explained by each performance indicator. The results are summarised in Table 5-6.

In this dataset none of the physical performance indicators (growth or health) were significantly correlated with net margin/head of output. Of the financial indicators, both labour and feed costs/head of output were significantly correlated with net margin/head of output, with labour costs accounting for 13% of the variation in net margin and feed costs just under 6%. Variable and fixed costs showed a significant relationship with net margin/head of output when expressed per head of output (but not when expressed as a % of total costs). Fixed costs/head of output account for just under 13% of the variation in net margin/head of output, and variable costs just over 10%. Total costs/kg output (liveweight) was also significantly correlated with net margin/head of output, accounting for 34.5% of variation seen in net margin/head of output.

***Table 5-6: Descriptive analysis of the Stocktake dataset for grower/finisher herds****. The $r^2$ values indicate the proportion of variation in net margin/head of output explained by each of the variables (with 1 being the maximum value), and the p-value indicates the statistical significance of this correlation*

| ***Area of performance*** | ***Mean and median value in dataset*** | | ***Performance indicator*** | ***p-value*** | ***$r^2$*** |
|---|---|---|---|---|---|
| | ***Mean*** | ***Median*** | | | |
| **Growth** | 0.88kg | 0.78kg | DLWG | p>0.05 | 0.0112 |
| | 281kg | 280kg | Average weight gain | p>0.05 | 0.00120 |
| | 2854kg | 1330kg | Kg produced/forage ha | p>0.05 | 0.000256 |
| | 484days | 566days | Average age at slaughter | p>0.05 | 0.0146 |
| **Health** | 1.2% | 0% | Mortality rate | p>0.05 | 0.00326 |
| **Financial** | £2.38 | £2.32 | Total cost/kg output (liveweight) | p<0.001 | 0.345 |
| | £84,900 | £61,200 | Total gross output | p>0.05 | 0.0200 |
| | £422 | £366 | Fixed costs/head of output | p<0.001 | 0.127 |
| | 30.79% | 28.53% | Fixed costs as a % of total costs | p>0.05 | 0.0158 |
| | £305 | £274 | Variable costs/head of output | p<0.001 | 0.101 |
| | 22.9% | 20.7% | Variable costs as a % of total costs | p>0.05 | 0.00641 |
| **Specific financial** | £209 | £181 | Feed and forage cost/head of output | p<0.05 | 0.0585 |
| | £108 | £92.80 | Labour cost/head of output | p<0.001 | 0.132 |
| | £1185 | £1175 | Gross output/head of output | p<0.05 | 0.0619 |
| | £13.40 | £11.30 | Veterinary and medicine costs for the beef enterprise/head of output | p<0.001 | 0.155 |
| | £45.30 | £35.00 | Bedding costs for the beef enterprise/head of output | p<0.001 | 0.125 |
| | £23.50 | £12.40 | Contracting and machine hire costs for the beef enterprise/head of output | p>0.05 | 0.00961 |
| | £18.50 | £15.70 | Machinery repairs and spares costs for the beef enterprise/head of output | p>0.05 | 0.00744 |
| | £21.30 | £17.60 | Fuel costs allocated to the suckler herd/cow bred | p>0.05 | 0.0126 |
| | £25.10 | £22.70 | Property maintenance and water costs for the beef enterprise/head of output | p>0.05 | 0.0282 |
| | £81.00 | £56.80 | Depreciation (machinery and property) for the beef enterprise/head of output | p<0.01 | 0.0860 |
| | £32.70 | £28.20 | Imputed cost of finance allocated to the beef enterprise/head of output | p<0.05 | 0.0465 |
| | £65.70 | £58.60 | Total machinery and power costs (excluding depreciation) for the beef enterprise/head of output | p>0.05 | 0.0201 |
| | £64.40 | £49.30 | Imputed beef enterprise net field rent/head of output | p<0.05 | 0.0443 |

### 5.4.5 Multiple regression of the Stocktake grower/finisher dataset

Results from a multiple regression model with net margin/head of output as the outcome are displayed in Table 5-7. No physical performance indicators showed a significant association with net margin/head of output in this dataset, and so specific financial performance indicators were used as predictors.

***Table 5-7: Results of multiple regression of financial indicators for grower/finisher herds*** Coefficients, standard errors and p-values are shown. The coefficients indicate the associated change in outcome variable (net margin/head of output) with each unit change of predictor variable. The standard errors are used to determine the p-value, with a value less than half the coefficient indicating a p-value of <0.05, and a value < one third the coefficient indicating a p-value < 0.01

| Model term | Coefficient | Standard error | P-value |
|---|---|---|---|
| **Outcome variable: Net margin/head of output** | | | |
| **Intercept** | -137.999 | 5.989 | |
| **Year: 2013** (n=27) | Reference | | |
| **Year: 2014** (n=36) | -8.528 | 7.886 | P>0.05 |
| **Year: 2015** (n=33) | 4.551 | 8.351 | P>0.05 |
| **Bedding costs for the beef enterprise/head of output (centred around mean)** (n=96) | -1.437 | 0.063 | P<0.01 |
| **Machinery repairs and spares for the beef enterprise/head of output (centred around mean)** (n=96) | -1.224 | 0.260 | P<0.01 |
| **Depreciation (machinery and property) for the beef enterprise/head of output (centred around mean)** (n=96) | -1.199 | 0.068 | P<0.01 |
| **Imputed beef enterprise net field rent/head of output (centred around mean)** (n=96) | -1.062 | 0.099 | P<0.01 |
| **Total labour cost/head of output (paid and unpaid, allocated to the beef enterprise) (centred around mean)** (n=96) | -1.061 | 0.053 | P<0.01 |
| **Imputed costs of finance allocated to the beef enterprise/head of output (centred around mean)** (n=96) | -1.045 | 0.284 | P<0.01 |
| **Feed and forage cost for the beef enterprise/head of output (centred around mean)** (n=96) | -0.996 | 0.026 | P<0.01 |
| **Total cost of beef cattle purchases and transfers/head of output (centred around mean)** (n=96) | -0.965 | 0.019 | P<0.01 |
| **Beef enterprise gross output/head of output (centred around mean)** (n=96) | 0.945 | 0.017 | P<0.01 |
| **Contracting and machine hire for the beef enterprise/head of output (centred around mean)** (n=96) | -0.901 | 0.169 | P<0.01 |
| **Property maintenance and water costs for the beef enterprise/head of output (centred around mean)** (n=96) | -0.724 | 0.203 | P<0.01 |

Bedding costs/head of output demonstrated the largest effect size and was associated with a decrease in net margin/head of output of £1.44 for each £1 increase. Machinery repairs and spares and depreciation on machinery showed the next largest effect sizes, with associated £1.22 and £1.20 reduction in net margin/head of output respectively for each £1 increase in cost/head of output. Each £1 increase in costs/head of output associated with field rent, labour and finance was associated with a decrease in net margin/head of output of around £1.05. Costs of feed and forage, beef cattle purchases and transfers, contracting and machine hire, and property maintenance and water costs, were all significantly associated with net margin/head of output with effect sizes between -£1.00 and -£0.72/head of output. Each £1 increase in gross output of the beef enterprise was associated with a £0.95 increase in net margin/head of output.

Again, the fact that so many financial variables are significantly associated with net margin/head of output (a financial outcome) is to be expected, as they are all essentially components of the outcome. Only veterinary and medicine costs/head of output, fuel costs/head of output, and total machinery and power costs /head of output were not significantly associated with net margin/head of output. The model allows these associations to be quantified, and overall explains 98.6% of the variation in net margin/head of output. This reflects the dominance of financial explanatory variables in explaining net margin/head of output in the grower/finisher dataset as opposed to the suckler dataset, where the financial explanatory variables model only explained 92.4% of the overall variation in net margin/cow bred.

## 5.5 Discussion

In contrast to the regression models in the previous chapter, which used data from an individual farm and did not differentiate between years, data in this analysis was collected from multiple farms across three years. This created a hierarchical structure to the data, with repeated measurements for individual farms. In the previous chapter each animal was a line of data that only appeared once in the dataset. In this chapter, each farm is a line of data, and it appears 3 times (once for each of the three years), necessitating the use of a multi-level model to avoid clustering.

Combining data from multiple herds may make results more generalisable across farms. It will also make datasets larger, which may be particularly useful when investigating predictors for events which may not happen frequently, such as antibiotic treatments, mortality or morbidity events. However, using datasets from multiple farms may present additional challenges, as differences in breeds, herd management systems and other factors may provide potential for increased error. It also requires compatibility of data from different herds, which may be challenging if different measures have been recorded in different ways and stored in different formats.

Here, data from multiple herds was analysed, and factors associated with overall enterprise success (defined as net margin/cow bred for suckler herds or net margin/head of output for grower/finisher herds), were evaluated. Data from suckler herds was analysed separately to data from grower or finisher herds, due to the difference in relevant performance indicators between the two herd types. Physical performance indicators were also analysed separately to financial performance indicators, as when present in a model simultaneously the financial performance indicators explained most variation in the financial outcome variable. This is to be expected; as higher levels of correlation would be expected between two variables measuring the same aspect of performance, i.e. between two financial variables, than between a financial outcome variable and physical predictor variables. Significant associations for both physical and financial performance indicators were identified in the suckler dataset, whereas only financial indicators showed significant associations in the grower/finisher dataset. This may indicate the greater relative importance of financial inputs into the business, or the reduced amount of physical data that tends to be recorded in these systems. It may also go some way to explain the typically more limited input of veterinary surgeons on these types of enterprises. Further investigation of the associations between physical performance indicators and financial success of grower/finisher enterprises may be possible using simulated data. This, potentially coupled with use of statutory recorded data (Hewitt et al., 2018), and the advent of compulsory preventative veterinary involvement on farm assured beef farms (Red Tractor Assurance, 2019), may result in increased evidence around use of performance indicators in grower/finisher herds, and result in more involvement of vets on beef farms. Additionally, increased training of vets around beef specific aspects of cattle production (as well as potentially financial aspects of farm management), may increase the confidence of vets when getting involved in these conversations with beef farmers.

### 5.5.1 Associations between physical performance indicators and net margin

In the suckler herd dataset, several physical performance indicators showed statistically significant associations with net margin/cow bred. These included age at first calving, scanning percentage, average weight at weaning, pre-weaning deaths/100 cows or heifers put to the bull and cow mortality rate. In the grower/finisher dataset however, significant associations were identified only between financial performance indicators and net margin/head of output. This reflects the greater significance of financial performance indicators in grower/finisher herds in this dataset, whereas in suckler herds physical performance indicators had a greater influence on net margin.

#### *5.5.1.1 Age at first calving*

In the current study, herds with a target age at first calving of two and a half years were associated with a net margin/cow bred decrease of £89.54 compared to herds aiming to calve heifers at two years ($p<0.01$). Herds aiming to calve heifers at three years were not associated with a significantly different net margin/cow bred than those with a target age at first calving of two years ($p>0.05$). This may be due to the small numbers of herds in each category (only 18 herds recorded a target of three years for age at first calving), or a reflection of this category representing farm protocol, rather than actual age at first calving. It could also suggest that herds calving at two and a half rather than either two or three years, may be more likely to follow other management strategies, such as calving all year round or having multiple calving blocks, which may also have an influence on net margin/cow bred. This is in agreement with other studies that have reported an increase in profitability when calving heifers at two years (Doren et al., 1985, Hickson et al., 2010, Roughsedge et al., 2005). One of these studies assigned an economic value to age at first calving of -£170 (Roughsedge et al., 2005), assuming that heifers are bred to calve at two years of age but fail to conceive and calve at three years of age. This is significantly higher than the value from the current regression model, however it is the average of two values representing two different management strategies; the first culling heifers unable to calve at two, the second assuming they are retained to calve at three. The values determined for these two scenarios were £80 and £260 respectively, the lower of which (which may represent a more likely management strategy in the herds analysed), is similar to the difference reported here in net margin/cow bred for farms aiming to calve at two and two and a half. It is clearly important that heifers are sufficiently well grown to enable calving at two years of age, and it has been demonstrated that high levels of assisted calving can negatively influence profitability if this is not the case (Hickson et al., 2010).

#### *5.5.1.2 Scanning percentage*

Before incorporation into the model, scanning percentage was categorised as some herds in the dataset did not scan cows in their herds for pregnancy diagnosis, leading to many zero values being recorded. Categories were 0%, 1-90% scanning rate and 90-100% scanning rate. The regression model identified a significant association between herds having a scanning percentage of between 1-90%, and a net margin/cow bred decrease of £105.59 compared to herds with a scanning percentage of >90% ($P<0.05$). No significant differences in outcome were identified between herds recording a zero value scanning percentage and those achieving over 90%, which probably reflects the fact that herds recording zero values do not pregnancy diagnose, rather than having very poor fertility. It also suggests that herds that do not scan have fertility more similar to those recording scanning rates between 1 and 90% than those recording scanning rates of over 90%. Changes in profitability have been associated with conception rates in previous studies, for example a study using partial budgeting, along with assumed levels of reproductive performance, found that the economic value increase (£/%) in conception rate varied between 0.1 and 0.7 at first oestrus, and 0.25 to 1.28 at subsequent oestrus, depending on other herd reproductive parameters such as calving interval and post-partum anoestrus interval (Amer et al., 1996). These appear lower than the values described in the current study, however there are several differences that should be considered when drawing comparisons. Categorical data was used in the current study, with pregnancy rates grouped (as described above) and economic values quoted as net margin (£)/cow bred. A continuous conception rate was used by Amer at al. (1996) with economic values quoted as net cost (£) per 1% change in conception rate (based on the cost of retaining a barren cow). Therefore, we might expect a 1% change in performance to be associated with a lower economic value than moving from one performance category to another. The data used to calculate the economic values is also separated by almost 20 years, and costs are likely to have increased significantly since 1996. In addition, the simulation model makes several assumptions, such as barren cows being retained rather than sold and replaced. This may not be the case on all farms; un-recorded management strategies such as this may also affect predicted economic implications of changes in fertility between simulated and real data.

Interestingly, fewer of the fertility performance indicators than expected appeared to be significantly correlated with net margin/cow bred. This could be due to the relatively small sample size, particularly in categories where year-round calving herds were excluded, such as calving period and percent calving in the first 3 weeks (11 herds were recorded as being year round calving at some point between 2013 and 2015). It could also be related to inaccuracies in how the data is recorded, and the high degree of variability in fertility performance.

#### *5.5.1.3 Average weight at weaning*

The current regression model indicated a significant association between each kg increase in herd average weaning weight and a £0.83 increase in net margin/cow bred ($p<0.05$). As this is an average weaning weight taken across each herd, it does not account for variation in age at weaning between herds, i.e. herds weaning calves later are likely to have higher average weaning weights. It also does not account for whether or not the calves were creep fed, as this again is likely to increase weaning weights (kg of creep fed/head of calf weaned was offered to the regression model but no significant association was identified). There is a wide range of average weaning weights reported in this dataset (191kg to 396kg), and these do appear to be correlated with age at weaning (correlation coefficient = 0.38). However, the association identified by the current model is in agreement with previously reported suggestions, such as the estimate of a 10kg increase in weaning weight increasing profit by £6.50 per calf (Roughsedge et al. 2005).

#### *5.5.1.4 Pre-weaning deaths per 100 cows or heifers bred*

An association between a 1% increase in the pre-weaning mortality rate and a £13.09 reduction in net margin/cow bred was identified by the current regression model ($p<0.05$). The dataset showed a wide range of pre-weaning mortality rates (0-13%), with a median of 2%. This is in line with figures reported in the literature (Gates, 2013, Tarres et al., 2005, Wittum et al., 1994a), although again a wide range of figures are often reported (Patterson et al., 1987). This is likely to be due to the many factors that can affect calf mortality rate within a beef production system, for example disease incidence (Ganaba et al., 1995) age of dam (Gates, 2013), and whether or not the calf is a twin (Elghafghuf et al., 2014). This information is not available for further analysis in the current dataset, but such relationships are investigated in the following chapters using a simulated dataset. In both dairy and beef herds, the cost of a calf death have been reported to be between £140 and £310 (Kossaibati and Esslemont, 1997, Wittum et al., 1993). This is total cost figure however, rather than a net margin/cow bred per percentage increase figure, making direct comparisons difficult to draw. The median herd size in this dataset is 74, so a 1% increase in pre-weaning deaths is equivalent to 0.74 calves dying. Taking the associated reduction in net margin/cow bred from the regression model and extrapolating it to produce a per calf death value results in a net margin/cow bred reduction of £9.60 per calf death (13.09 multiplied by 0.74). Likewise, converting the total cost value taken from the literature (£225) into a cost/cow bred value (by dividing it by 74), results in a total cost/cow bred value of £3. This is only a third of the equivalent value extrapolated from the current study. This may be due to the age of the studies cited (i.e. the change in economic climate between the cited studies and the current analysis), and the different metrics used (i.e. net margin/cow bred and total cost/cow bred).

#### *5.5.1.5 Cow mortality rate*

A similar association was identified between cow mortality rate and net margin/cow bred: for each percentage increase in cow mortality rate, an associated £12.43 reduction in net margin/cow bred was observed. A range from 0% to 14% cow mortality rate was recorded in the dataset with a median of 2%, again very similar to the values recorded for calf mortality rate, and again similar to values reported in the literature (Motus and Emanuelson, 2017, Oishi et al., 2013, Waldner et al., 2009, Orpin and Esslemont, 2010). Cow mortality rate and pre-weaning mortality rate do not appear to be correlated however (correlation coefficient = 0.086), i.e. herds with low cow mortality rates do not appear to necessarily have low pre-weaning mortality rates, suggesting that the associations identified by the model are separate. The cost of cow mortality in dairy herds has been reported to be significantly higher than that of calf mortality, at between £2000 and £3000 per death (Kossaibati and Esslemont, 1997, Orpin and Esslemont, 2010), in comparison to the similarities in net margin/cow bred associations with cow and calf mortality identified in the current study. This is likely to be due in part to the different outputs of the production systems, i.e. litres of milk from the dairy herd and kg of weaned calf from the suckler herd. A mortality case in the dairy herd therefore results in a loss of milk and purchase or retention of a replacement heifer, whereas a case of mortality in the suckler herd results in just purchase or retention of a replacement heifer.

The ability to link these physical performance indicators with a financial outcome, and so allocate a financial implication to them, is important in allowing farmers to make more informed management decisions. The low availability of suitably large datasets for this kind of analysis, including both physical and financial data, has limited these sorts of investigations in the beef sector.

### 5.5.2 Comparison of the suckler and grower/finisher financial models

Of the financial performance indicators, several showed significant associations in both the suckler and the grower/finisher datasets, for example total labour costs and depreciation. Some only showed significant associations in one of the datasets, for example veterinary and medicine costs and fuel costs were significantly associated with net margin/cow bred in the suckler dataset only, whereas the imputed cost of finance and feed and forage costs were only significantly associated with net margin/head of output in the grower/finisher dataset. These comparisons are summarised in Table 5-8.

*Table 5-8: Summary of financial performance indicator associations with net margin/unit increase for suckler and grower/finisher herds in the Stocktake dataset.*

| *Performance indicator* | *Suckler* | *Grower/finisher* |
|---|---|---|
| | *Associated increase in net margin for each unit increase in performance indicator (£)* | |
| **Fuel cost** | -2.068 (p<0.01) | |
| **Bedding cost** | -1.514 (p<0.01) | -1.437 (p<0.01) |
| **Veterinary and medicine cost** | -1.526 (p<0.01) | |
| **Contracting and machine hire** | -1.492 (p<0.01) | -0.901 (p<0.01) |
| **Total labour cost** | -1.208 (p<0.01) | -1.061 (p<0.01) |
| **Replacement cost** | -0.913 (p<0.01) | |
| **Depreciation (machinery and property)** | -0.854 (p<0.01) | -1.199 (p<0.01) |
| **Imputed net field rent** | -0.826 (p<0.01) | -1.062 (p<0.01) |
| **Machinery repairs and spares** | -0.813 (p<0.01) | -1.224 (p<0.01) |
| **Gross output** | 0.695 (p<0.01) | 0.945 (p<0.01) |
| **Imputed cost of finance** | | -1.045 (p<0.01) |
| **Feed and forage cost** | | -0.996 (p<0.01) |
| **Total cost of beef cattle purchases and transfers** | | -0.965 (p<0.01) |
| **Property maintenance and water costs** | | -0.724 (p<0.01) |

The higher influence of veterinary and medicine costs on net margin on the suckler herd compared to the grower/finisher herd is to be expected, as the breeding and calving stages of the beef production cycle are likely to require higher inputs in these areas than growing and finishing stages. The higher influence of fuel costs on net margin in the suckler herd over the grower/finisher herd however is less easy to explain, but may be due to the typically more extensive suckler systems requiring more fuel input than more intensive grower/finisher systems, for example for feeding or transporting animals. Mean fuel cost/head of output in the grower/finisher dataset was £21.30 (median was £17.60), whereas in the suckler dataset, mean fuel cost/cow bred was £28.60 (median was £24.70).

Replacement costs are only of relevance in the suckler herd, and so are not included in the grower/finisher dataset, in the same way as cost of cattle purchases and transfers are not of relevance to the suckler herd (where the output is a weaned calf as in this dataset), and so are not included.

Imputed cost of finance, feed and forage cost, and property maintenance and water cost were found to be significantly associated with net margin/head of output in the grower/finisher dataset, but not with net margin/cow bred in the suckler dataset. Property maintenance and water costs may be more influential in a more intensive style system typical of grower/finisher enterprises, and feed/forage costs are likely to represent a higher proportion of overall costs in a growing or finishing system (particularly if this involves housing animals) than in suckler herd which may spend more time grazing.

Effect sizes also vary between the regression models of the two datasets, for example bedding costs, contracting and machine hire, and labour costs are associated with a greater decrease in net margin/cow bred in the suckler herd than with net margin/head of output in the grower/finisher herd. Depreciation on machinery and property, imputed field rent and machinery repairs and spares however, were associated with a greater decrease in net margin/head of output in the grower/finisher dataset than with net margin/cow bred in the suckler dataset. Labour costs may be expected to be higher, and so represent a greater proportion of inputs and a larger influence on net margin/cow bred in the suckler herd, due to the labour required around calving. For those herds calving inside, this may also explain some of the increased costs around bedding. The greater importance of contracting and machine hire in the suckler herds, and the contrasting importance of depreciation on machinery, and machinery repairs and spares in the grower/finisher herds, could be interpreted as the suckler herds in this dataset contracting out/owning less of their own machinery for their arable work, with the grower/finisher enterprises tending to own their own machinery. This may also help to explain the slightly greater importance of bedding costs in the suckler herds, i.e. they may be less likely to make it themselves and more likely to buy it in. The greater effect size seen in grower/finisher herds in gross output may be due to the greater value of output, i.e. output from the suckler herd is weaned calves, and output from the grower/finisher herds are stores or finished cattle. As in the grower/finisher dataset, this is calculated per head of output. This is also not affected by fertility and mortality etc., whereas calculating per cow bred in the suckler dataset means that fertility rates and mortality rates have the potential to reduce the numerator relative to the denominator.

The denominator used in the outcome variable between the two datasets is obviously different (net margin/cow bred and net margin/head of output). The values of these between the two datasets are similar however, with average number of cows bred in the suckler enterprises being 95 (median = 74) and average head of output in grower finisher enterprises being 71 (median 54). This is also similar to the mean size of the grower/finisher enterprises across the year, which is 69 (median 47), suggesting that head of output fairly accurately reflects average herd size. The number of cows bred however may reflect actual herd size to a lesser degree, as it will not account for cull cows or calves. This would make the denominator used in the suckler data analysis an underestimation of the actual herd size, and so the net margin/cow bred may therefore appear relatively higher than net margin/head of output. This may result in relatively larger effect sizes in the suckler analysis than in the grower analysis when comparing the two regression models.

Analysis of physical and financial data from a large number of beef herds across England has allowed associations between physical performance and financial output to be evaluated. This is an important addition to the literature, with previous studies tending to be based around simulated data and partial budgeting techniques. Both 'real' and simulated data can provide insight; 'real' data is useful to learn about a system, but datasets can be small and have a lot of 'noise' (variation that cannot be explained by recorded measures). Simulated data is beneficial when data is difficult or costly to record and can provide large datasets with less 'noise', but some knowledge or information about the system being modelled is required. The use of 'real' data in this study meant that the sample size was small and selection was biased towards herds that were more proactive in data recording and performance monitoring. Data was also recorded by farmers (although collected by AHDB staff), and so there was potential for human error and variation in recording techniques. Challenges around data capture in beef herds often limits the use of 'real' data, but where information is required about a system, analysis of relatively large datasets such as these is beneficial. Advancing technology around automated data collection techniques may increase availability of such data in the future.

## 5.6 Conclusions

Multiple regression allows the effects of several predictor variables (performance indicators in this case) on an outcome variable (net margin per unit in this case) to be evaluated simultaneously. Several significant associations were identified in the suckler herd dataset, both in the physical performance indicator model and the financial performance indicator model. Although no significant associations between physical performance indicators and net margin/head output in the grower/finisher dataset were identified, the model did illustrate significant associations of net margin/head of output with several financial performance indicators. The lack of clarity in the physical performance indicator model is probably due to there being too few data points and there being too much 'noise' (i.e. too many other factors introducing variation). Simulation modelling is particularly useful in these situations, and this method was investigated to further clarify these relationships as discussed in Chapters 6 and 7.

# Chapter 6: Review of literature to inform inputs for development of a suckler herd stochastic simulation model

## 6.1 Introduction

Analysis of 'real farm' data can allow relationships between performance metrics and enterprise success (net margin/cow bred) to be evaluated, as discussed in Chapter 5. There are however limitations to using data collected 'in the field': The practicalities around data capture on farm, the long production cycle of many beef systems, the typically extensive nature of these systems and small herd size, all mean that collecting large enough data sets to allow statistically significant conclusions to be drawn about the relationships between performance metrics and overall enterprise success can be challenging. The diversity of the beef industry, and the many and varied data capture programmes and software available, also mean that collecting a standardised data set incorporating multiple farms may be difficult. In order to evaluate the relationship between physical performance metrics and financial indicators of enterprise success, assimilation of physical and financial data from individual herds is also required, and this presents additional challenges around compatibility of data sets. The data analysed in Chapter 5, sourced from the AHDB Stocktake program, included data from 56 suckler herds and 36 grower/finisher herds over three years. This provided an insight into the relationships between various performance indicators and net margin, and illustrated how farm data could be used to inform farm management decision making.

Modelling 'real' data in this way allowed evaluation of relationships between outcome and explanatory variables, and suggestions to be made about reasons for these associations. Unrecorded (or unrecordable) variables may mask or cause a lack of clarity in these analyses. In these instances, simulation modelling can be used to control for this by keeping such variables constant. Simulation modelling is based on prior knowledge of the system, whereas data modelling is based on observed data, and does not necessitate any prior knowledge. Regression modelling does however require a dataset, whereas a simulation model can be built without such data (although external data can be used for validation of a simulation model). Therefore, simulation models are often used when availability of data is low, for example if collection is costly, time-consuming, dangerous or un-ethical. Conversely, information about the system may not be available, and simulation modelling often requires assumptions to be made. A combination of simulation modelling and data modelling may be used in order to benefit from the advantages of both types of data (Kim et al., 2017)

### 6.1.1 Simulation modelling concepts

Simulation modelling allows a data set to be created and analysed which mimics or simulates a real-world system. This allows the relationships between inputs and outputs of the system to be evaluated and allows prediction of outputs based on the inputs provided. Individual factors can be manipulated and the effects of this investigated, whilst still allowing for the other variables influencing the system. Information from a variety of sources can also be assimilated into the model, and used to inform decision making for a set of individual conditions (Stygar and Makulska, 2010).

Simulation models can be described as deterministic or stochastic. A simple calculation would be described as deterministic, where for a given set of inputs the output would always be the same. In a stochastic model, input values are drawn randomly from a pre-determined distribution of values (a probability distribution) and outputs vary accordingly. This introduces uncertainty into the model, and so is particularly useful when simulating complex systems with inherent uncertainty, such as farm systems. When the simulation is carried out a large number of times, for example simulating multiple cows in a herd or multiple herds, output distributions are created displaying higher levels of variation than those from deterministic models (Villalba et al., 2006, Shafer et al., 2007). The relationships between these output distributions and the input distributions can then be analysed. Incorporation of this probabilistic element to mathematical modelling, using values drawn randomly from probability distributions and many iterations (i.e. running the simulation many times), is commonly referred to as Monte Carlo simulation (Metropolis and Ulam, 1949). Simulation models may also be referred to as either dynamic or static, with dynamic models including time as a variable (Jalvingh, 1992).

### 6.1.2 Input distributions

Stochastic simulation model design involves defining input distributions from which values can be drawn randomly. This can be an area of contention as defining these distributions is liable to be, at least in part, subjective in nature, and can potentially have significant effects on the model outputs and so the conclusions drawn. Where limited evidence is available to inform these distributions, expert or peer opinion may be used (Heller et al., 2011). Where evidence is available, it may have been generated in different ways between studies leading to conflicting results, or the requirement for extrapolation of results from the evidenced scenario to that simulated in the model. For example, various definitions of calf mortality rate were used in the literature consulted, from calves dying up to 45 days (Wittum et al., 1994a), to those dying up to four months of age (Nix et al., 1998), or 180 days (Gates, 2013). Input distributions are commonly uniform, where any value between a minimum and maximum is equally likely to be drawn. This is useful for exploring all possible scenarios that could exist in a simulation model, but may not be appropriate if the variable under investigation does not have a uniform distribution in real life situations. Alternatively, distributions may be betaPERT or triangular, where values closer to a defined central point are most likely to be drawn (Audigé and Beckett, 1999). This is useful for exploring the most common situations in more detail, but relies on knowledge of what the more likely outcomes are. BetaPERT distributions have a more rounded shape than triangular distributions which is often useful when reflecting real world situations. Other potential distributions include binomial, where there are only two possible outcomes, and discrete, where there are several distinct outcomes. These distributions are illustrated in Figure 6-1. Any distribution could potentially be used as an input distribution, but distributions such as those described above, which are set within a range (bounded), are useful when modelling probabilities (as the value has to be within 0 and 1), or where the value cannot be negative, for example calf weight. Examples of unbounded distributions include normal and logistic distributions, and some distributions may be partially bounded (for example with a known minimum but no maximum value) such as exponential distributions.

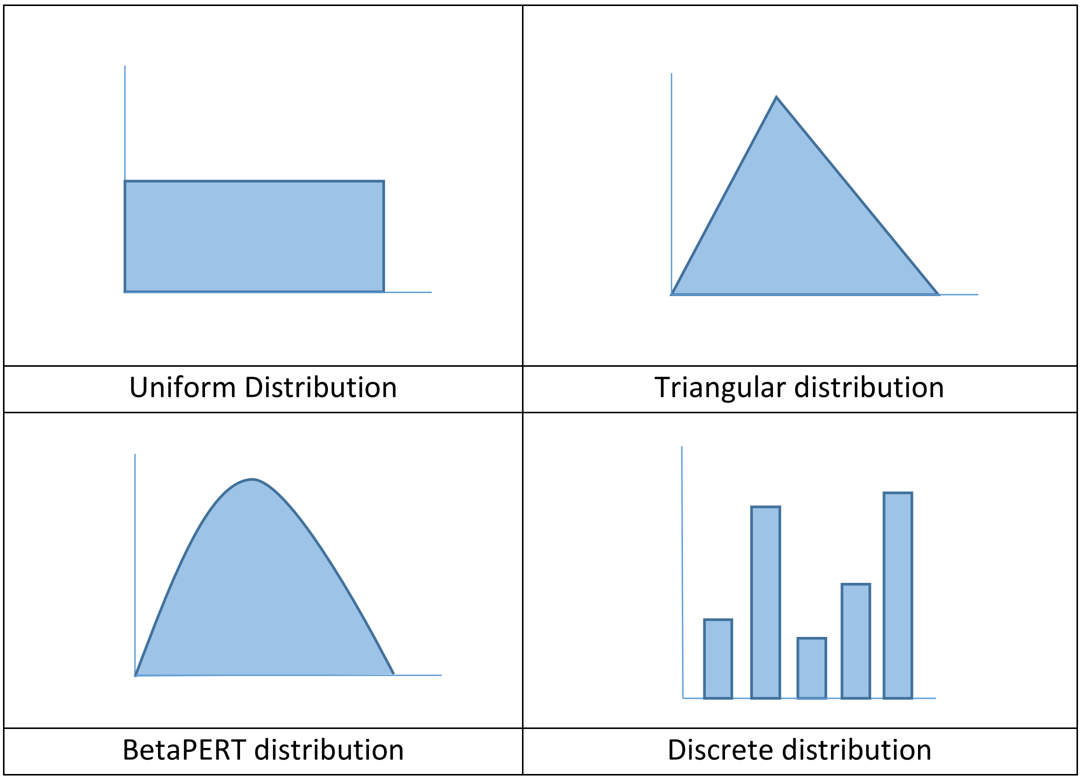


***Figure 6-1: Examples of probability distributions that may be used in stochastic simulation models.*** *Uniform distributions are useful for exploring all possible scenarios that could exist, and do not require prior knowledge of the system being modelled, but often do not reflect real-life situations. BetaPERT and Triangular distributions, where values closer to a defined point are most likely to be drawn, require knowledge of what the most likely value is, but often more accurately reflect the system being modelled. Discrete distributions are useful when modelling situations where there are several distinct outcomes.*

## 6.2 Aims

In Chapter 7, a simulation model consisting of five sub-models will be developed and described in detail. This chapter describes the process and results of a literature search required to specify the input distributions for the simulation model and define the influences that the variables in the model have on each other.

## 6.3 Methods

Input distributions were required in the areas listed in Table 6.1. in order to specify a simulation model of beef suckler herd production. This was then used to explore the relationships between physical measures of herd performance and financial performance of the enterprise. Due to the large number of areas to review during development of this simulation model, it was beyond the scope of this project to conduct a formal meta-analysis (i.e. using statistical methods to combine evidence from multiple sources) in each of these areas to inform model inputs. Literature was however searched in a structured way, and inputs were informed using evidence beyond individual or expert opinion. An initial literature search was conducted around modelling beef systems which helped to inform model structure. Searches were then conducted around each part of the planned simulation model to inform input distributions. Literature searches were conducted in Ovid® (using Medline and CAB databases), and the search terms displayed in Table 6-1 were used. An unqualified search was used with default fields, including title and abstract, and covering years 1946 to 2017.

Following searches, articles not in English were discarded. Titles were read initially, followed by abstracts, to identify relevant papers. Papers were discarded if they were not directly relevant to the area of production being modelled (for example the search returned technical articles on topics such as on managing dystocia and studies on specific causes of abortion. These did not include quantitative information and so were not of use informing input distributions. These were then used to both inform input distributions, i.e. what appropriate values (ranges, averages, fixed values etc.) should be input into the model to most closely reflect a suckler herd in England, and to determine the relationships between effector variables (variables which may influence another variable in the model) and outcome variables (variables which may be influenced by another variable in the model). For example, to determine the effect, if any, of dystocia on conception rate. Relevant papers were also used to inform model structure. Where several papers reported conflicting values or ranges, the context was considered and studies representing English systems most closely were prioritised.

*Table 6-1: Literature searches for simulation model input distributions*

| Search area | Search terms used | No. papers returned | Paper selection | Relevant papers identified |
|---|---|---|---|---|
| **Pre-weaning DLWG / calf birth weight** | Pre-weaning AND Calf AND (DLWG OR Daily Live Weight Gain OR Average Daily Gain) AND (Beef OR Suckler) | 16 | 4 papers were identified that were relevant by title and with full text available. | 4 |
| **Conception rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND (Conception OR Pregnancy) AND (UK OR England OR United Kingdom OR Britain) | 206 | 6 papers were relevant by abstract and in English. Full text was not available for 2 of these, and 2 were not relevant by abstract. | 2 |
| **Abortion rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Abortion$ | 521 | 27 papers were relevant by title and abstract, and were in English (lots of search results focussed on specific causes of abortion rather than herd rates). Full text was available for 5 of these. | 5 |
| **Stillbirth rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Stillbirth$ | 206 | 24 papers were relevant by title and in English. 15 were relevant by abstract and were not duplicates of papers already identified in the search. Full text was available for 4 of these. | 4 |
| **Twinning rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Twin$ | 442 | 58 papers were relevant by title and in English. 14 were removed as not relevant by abstract and 8 had been identified in previous searches. Of the remaining 36, full text was available from 21 | 21 |
| **Dystocia rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Dystocia | 577 | 90 papers were relevant by title and in English. After reviewing abstract 26 relevant papers were identified (lots of articles were on management and prevention of dystocia). 8 papers were duplicates of ones already identified, and full text was available for 9 of the remaining 18. | 9 |
| **Calf mortality rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Calf AND Mortality | 471 | 59 papers were relevant by title and in English. 4 were duplicates of papers already identified. No full text was available for 23 and 21 were not relevant by abstract. | 11 |
| **Cow mortality rate/culling rate** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Cow AND (Mortality OR Cull$) | 630 | 77 papers were relevant by title and in English. 27 papers were relevant by abstract. 7 were duplicates and full text was unavailable for 10. | 10 |
| **Diarrhoea /Pneumonia** | (Bovine OR Cattle) AND (Beef OR Suckler) AND Calf AND (Scour OR Diarrhoea OR Pneumonia OR Respiratory OR BRD) | 568 | 70 papers were relevant by title and in English. 35 were relevant by abstract. 1 was a duplicate and full text was unavailable for 11. 12 were not relevant on reading full text. | 11 |
| **Post-partum anoestrus interval (PPAI)** | Beef AND Postpartum | 73 | 20 papers were identified as relevant and in English (some were not relevant to UK systems, focussed on hormone profiles or were evaluating restricted suckling. Full text was available for all 20 of these papers. | 20 |

## 6.4 Results and discussion

The literature review identified many papers from across the world, some modelling complete beef systems (Sanders and Cartwright, 1979, Azzam et al., 1990, Tess and Kolstad, 2000), and others components of a system, for example growth (Amer et al., 1997). Some also focussed on specific interactions between components of the system using various other statistical techniques, such as using logistic regression to investigate risk factors for dystocia and stillbirth (Waldner, 2014a). Model inputs were selected using the evidence available where possible, although inevitably some arbitrary decisions had to be made where good evidence was not available, or where the evidence was conflicting. Some values were taken from other simulation studies, and some from evidence from field research. Where possible evidence from field studies was favoured over that informed by opinion, although often sample sizes were small and herd types were sometimes not applicable to the herd being modelled in this situation. Where evidence was conflicting, either the value from the study best representing a suckler herd in England was incorporated, or a compromise between the values reported was reached (for example a mean value). Model inputs were designed to reflect baseline values, i.e. values before the influence of any effector variables in the model (for example, conception rates assuming the cow did not experience dystocia at the last calving, or calf mortality rates assuming the calf did not suffer from pneumonia or diarrhoea). The interactions between parameters in the model were incorporated as additive where the literature supported this, or multiplicative if this is what the evidence suggested.

Evidence informing input distributions and effector influences was grouped into that describing cow features, and influencing reproduction, growth, herd health, and financial aspects of performance, as described in the following section.

### 6.4.1 Cow features sub-model inputs

Individual cow features included in the model were parity, BCS and weight. The herd level distributions for these inputs (as summarised in Table 6-2) were defined through consulting the literature and incorporating what was felt to be appropriate for a suckler herd in England.

**Parity**

Parity was split into four categories, with 0 representing parity 0 (breeding) heifers (at the first calving in the model), 1 representing first parity (i.e. animals calving for the first time during the first calving period in the model), 2 representing animals between parity 2 and 8, and 3 representing animals parity 9 or over. The distribution was determined so that on average 16% of animals would be breeding heifers, 16% of the herd would be first parity, 63% would be parity 2 to 8, and 5% would be parity 9 and over. This is in line with distributions seen by Wittum et al. (1994a) and suggested by Arthur et al. (1993).

**BCS**

It was felt that, as the distribution of BCS was unlikely to be the same across all herds, use of three distributions (low BCS, medium BCS and high BCS) would be more appropriate. Cow BCS was defined on a scale of 1-5 and drawn from a betaPERT distribution with a mode of 2 (low BCS), 2.5 (medium BCS) or 3 (high BCS), depending on the herd-level input distribution drawn. No usable evidence on BCS distributions in UK suckler herds was identified in the literature search, so these three scenarios were selected for evaluation in the simulation.

**Weight**

In the same way as BCS, it was felt that the distribution for weight was likely to vary between herds, so three herd-level betaPERT distributions were again created, again with equal probability of being drawn. Individual cow weights were then drawn randomly from the selected herd-level distribution. For the small herds weights ranged between 450kg and 650kg, with a mode of 550kg, for the medium herds weights ranged between 550kg and 750kg, with a mode of 650kg, and for large herds weights ranged between 650kg and 850kg, with a mode of 750kg. This reflects mature cow weights for different systems suggested by Roughsedge et al. (2005). Parity 0 heifers' weight was reduced to 65% of their adult weight, to reflect the target weight for parity 0 heifers, and first parity cows' weight was reduced to 80% of their adult weight. Cow weight was also modified by BCS, with a BCS of less than 1.5 resulting in a 100kg reduction in the cow's liveweight, and a BCS of over 3.5 resulting in an increase of 100kg. This is in line with each unit change in BCS being associated with a change in liveweight of around 100kg (Osoro and Wright, 1992), taking an overall average BCS of 2.5.

***Table 6-2: Input values and distributions for the cow features sub-model****. For discrete distributions, the percentage probability for each category is listed. For continuous, BetaPERT distributions, a minimum, mode, and maximum value are given. Effector variables (those that may affect main variables) are given, along with, effect sizes. References are also included in the table.*

| Variable | Model input value/distribution | References | Effector variable | Effect size | References |
|---|---|---|---|---|---|
| **Parity** | 4 categories (Discrete distribution):<br>0 = parity 0 heifers (16%)<br>1 = first parity (16%)<br>2=parity 3-8 (63%)<br>3=parity 9+ (5%) | (Wittum et al., 1994a, Arthur et al., 1993). | | | |
| **BCS** | 3 distributions:<br>BetaPERT (1,2,5)<br>BetaPERT (1,2.5,5)<br>BetaPERT (1,3,5) | | | | |
| **Cow weight** | 3 distributions:<br>BetaPERT(450, 550, 650)<br>BetaPERT (550,650,750)<br>BetaPERT (650,750,850) | (Roughsedge et al., 2005) | Parity | Parity 0 = 65% of adult weight.<br>First parity = 80% of adult weight. | |
| | | | BCS | BCS<1.5 = 100kg deduction.<br>BCS>3.5 = 100kg addition. | (Osoro and Wright, 1992) |

### 6.4.2 Reproduction sub-model inputs

Reproduction model inputs include 21-day pregnancy rate, post-partum anoestrus interval, abortion rate, dystocia rate, stillbirth rate and twinning rate. The model input distributions and effector variables are summarised in Table 6-3. Literature used to inform inputs referred to conception rates as well as pregnancy rates. Conception rate is the number of serves required for a cow to become pregnant, whereas pregnancy rate is the proportion of eligible cows that become pregnant over a time period (Cook, 2009, Cook, 2010). In this simulation model it was expected that all eligible and cycling cows would be served every 21 days until they were pregnant or until the breeding period finished (i.e. heat detection rate was assumed to be 100%). So it was assumed that pregnancy rate would be largely determined by conception rate (with post-partum anoestrus interval also having an influence).

**21-day pregnancy rate**

In a bioeconomic model evaluating different breeds and mating systems (Roughsedge et al., 2003a), conception rate was assumed to be normally distributed and to be affected by first calving age, cow weight, weight change in the three weeks up to calving and calving difficulty at the previous calving. In a simulation model of reproduction in beef cows, a mean single service conception rate of 0.7 was assumed (Johnson and Notter, 1987), whereas in a model of reproductive management systems for beef cattle, first service conception rates of 0.5 to 0.8 were used (Azzam et al., 1990). In a model of the impacts of reproductive technologies on beef production, a single service conception rate (with a natural mating) of 0.67 was assumed (Smeaton, 2001). Based on the above evidence, a 21-day pregnancy rate with a betaPERT distribution, a minimum value of 0.5, a maximum of 0.8 and a mode of 0.65 was felt to be appropriate. This baseline value was then modified by the following effector variables:

- **Parity:** First lactation heifers have been shown to have reduced conception rates compared to mature cows (Fike et al., 1996, Notter et al., 1979a, Doren et al., 1985), although, some studies failed to find such an association (Vosough Ahmadi et al., 2017). A 15% difference in pregnancy rates between cows and first lactation heifers served by AI over a 23 day period was reported by Fike et al. (1996) (53% in cows and 38% in heifers). These were control animals in a study investigating the effect of fence-line bull exposure, and so did not take into account any potential confounding factors such as dystocia or cow BCS. Using a model simulating a suckler herd and investigating the effect on milk production of the cow, Notter et al. (1979a) simulated the effect of milk production potential on conception rates. With medium genetic milk potential of dam and constant weight of calf, 2 year old animals were modelled to have a conception rate over a 1 month period of 57%, 3 year old animals 59%, and 8 year old animals 67%, indicating a 10% increase between 2 year old and 8 year old animals. Although this model takes into consideration the condition of the animal, previous dystocia is not accounted for. Doren et al. (1985), report total pregnancy rates rather than 21day or first serve rates, but parity 0 heifers still showed a 10% reduction compared to 3 year olds (78.4 vs 88.2), although interestingly parity 0 heifer conception rates were similar to those of 4 to 10 year old animals. This was using a variation of the model used by Notter et al., and so again dystocia was not accounted for. The only report identified to take into account the effect of parity, dystocia and BCS on pregnancy rate used a dynamic programming model to investigate consequences of replacement and management decisions (Vosough Ahmadi et al., 2017). Conception rate in each of the four 21-day periods after post-partum anoestrus showed no association with parity in this report. Therefore, it was felt that parity should have no effect on 21-day pregnancy rate in the current model.

- **Dystocia:** Dystocia is associated with a reduction in conception rate at the following breading season of around 10%: Tess and Kolstad (2000) describe a model of suckler cow production in which dystocia leads to a 10% drop in conception rate, and in a deterministic model reported by Notter et al. (1979c), dystocia reduced conception rate over a 30 day period by up to 10%. Although these studies take into account the effect of parity, there may be some confounding with twinning as this is not accounted for in either study.
- **BCS:** Cows with a low BCS have been shown to have lower conception rates (Vosough Ahmadi et al., 2017). This was quantified by Kunkle et al. (1998), using a 1-9 score, who showed that a BCS of 3 (roughly equivalent to 1.5 on a 1-5 scale) resulted in a pregnancy rate of 43%, a BCS of 4 (equivalent to 2 on a 1-5 scale) resulted in a pregnancy rate of 61%, a BCS of 5 (equivalent to 2.5), resulted in a pregnancy rate of 86% and a BCS of 6 (equivalent to 3) resulted in a pregnancy rate of 93%. As higher BCS appears to have less effect on conception rate, just the effect of a low body condition score was accounted for in the current model, and 15% was deducted from the 21-day pregnancy rate if a cow was below BCS 2. This is a conservative value based on the evidence described, but factors that may influence conception rate and be influenced by BCS (such as dystocia) were not taken into account in the study referenced, and so it was felt to be appropriate for this model where effects on an outcome are additive.
- **Twinning:** Twinning has been shown to reduce conception rates in the following breeding season (Echternkamp and Gregory, 1999b, Gregory et al., 1990, Cummins et al., 2008, Echternkamp et al., 2007). Some studies investigating the effects of twinning involve animals that are induced to twin. These were avoided when informing the influence on 21-day pregnancy rates, as the effects of inducing twinning on conception rate cannot be accounted

for. Some of the studies also used herds that had been undergoing selection over time to have higher than average twinning rates (Cummins et al., 2008, Echternkamp et al., 2007), and so this was also considered. All studies measured overall breeding season conception rates or pregnancy rates rather than 21d rates, but it was felt that these would still be indicative of the effect of twinning on single cycle conception rates. Some studies also identified animals carrying twins and fed them a higher plane of nutrition pre and post-partum (Echternkamp and Gregory, 1999b, Cummins et al., 2008, Echternkamp et al., 2007), whilst others just provided this post-partum (Gregory et al., 1990). Some studies considered other factors with the potential to affect conception rate, such as parity and dystocia (Echternkamp and Gregory, 1999b, Gregory et al., 1990), whilst some did not. The range of effects (absolute variation in pregnancy rate or conception rate between twin and single births) reported were 10% to 14%, with a mean and a median of 12%. None of the studies referenced take into account all the variables in the current model, and with the two reports accounting for the most variables (parity and dystocia) reporting the two maximum figures in the range (it would be expected that twinning would account for less variation in conception rate when other factors were taken into account), it was decided that the average figure of an absolute reduction of 12% in 21-day pregnancy rate with twins at the previous calving was appropriate.

- **Oestrus number:** Studies have suggested that conception rates may be reduced at the first oestrus post-partum (Amer et al., 1996), and that rates reduce with the number of services a cow has (Azzam et al., 1990, Blanc and Agabriel, 2008). In the current model the number of serves a cow has is equivalent to the oestrus number, as it is assumed that if a cow is eligible she is served (i.e. oestrus detection is not taken into account). In a partially stochastic model of reproductive efficiency in a beef herd (Blanc and Agabriel, 2008), conception rate at the first service after calving was related to post-partum anoestrus interval (PPAI), and following that it was related to the service and oestrus number: when the first serve was at a later oestrus conception rate increased, but as services increased with oestrus number conception rate decreased up to 3 serves, and then increased slightly for the 4$^{th}$ serve. These variations are very small (3% to 4%), but similar to the 2% to 4% reduction per service referenced by Azzam et al. (1990). In a model of calving distribution of a suckler herd, conception rates to first post-partum oestrus inseminations were 0.4, and were 0.55 - 0.7 to subsequent cycles, suggesting a 15% to 30% reduction in conception rate at the first oestrus (Amer et al., 1996). First oestrus is not synonymous with first service which may explain the differences in these values. In the current model, it was assumed that the cow had fully resumed cyclicity when eligible for service, and so it was decided that a 3% reduction in 21-day pregnancy rate per serve would be assigned from second service onwards.

The effects of these variables on 21-day pregnancy rate are additive, i.e. a cow which had twins and dystocia at her previous calving, with a BCS <2, would have a conception rate reduced by 37% (10% for dystocia plus 15% for BCS<2 plus 12% for twins). Many of the studies used to inform the inputs take into account multiple factors with the potential to influence conception rate, and where sufficient evidence was available, studies that only looked at individual effector variables were excluded. This was allowed for when defining the effect size, i.e. the aim was to allocate an effect size for an individual effector variable (e.g. dystocia) on the outcome variable (21-day pregnancy rate), whilst accounting for other potential effector variables (e.g. twinning or parity). Therefore, it was felt the in the case of two effector variables influencing the outcome, that the effects should be additive.

**Post-partum anoestrus interval**

Post-partum anoestrus intervals (PPAI) reported in the literature vary and appear to be influenced by many factors including environmental, management and physiological factors. The method of measuring PPAI also varies, with some studies measuring the time until standing oestrus is observed (Smith et al., 1996, Doornbos et al., 1984) some monitoring ovulation by ultrasound examination (Stagg et al., 1995), and others measuring hormone levels (Wheeler et al., 1982). Minimum intervals reported (some at the individual cow level) start at around 20 days, with maximum figures above 100 days (Johnson and Notter, 1987, Greer et al., 1990, Lamb et al., 1999, Denham et al., 1991). Mean figures used in previous studies vary between 40 and 80 days (Azzam et al., 1990, Villalba et al., 2006, Blanc and Agabriel, 2008). Therefore, a betaPERT distribution was used to represent post-partum anoestrus interval with a minimum of 4 weeks, a maximum of 12 weeks, and a mode of 9 weeks; there is a high degree of uncertainty in the literature and so a wide distribution was chosen to reflect this. PPAI is then modified by parity, and the presence of dystocia, twinning or stillbirth. Although photoperiod can influence PPAI, it was felt to be appropriate to ignore this effect as the majority of UK herds are spring calving (Gates, 2013), and so the current model reflects this. Breed of animal, the BCS of the animal and the effect of bull exposure were also not taken into account, although they may all have an effect on PPAI. The effect of BCS on PPAI in the literature is varied, with some reports citing it as the main determinant of PPAI (Villalba et al., 2006), and some reporting it not to be associated (Blanc and Agabriel, 2008, Houghton et al., 1990). The subjective nature of body condition scoring, the variety of different scoring scales used in the literature, and the different times in the production cycle that this is carried out can make interpreting effects in different studies challenging. The reports on the significance of any effects of BCS on PPAI are also conflicting, therefore this is not accounted for in the current model. BCS has been taken into account for 21-day pregnancy rate however, so does have an influence on fertility in the model.

- **Parity:** Animals in their first parity tend to have an increased PPAI (Azzam et al., 1990, Fike et al., 1996, Greer et al., 1990, Doornbos et al., 1984, Echternkamp and Gregory, 1999b, Yavas and Walton, 2000, Tervit et al., 1977). In the literature the range of effect size was 5 days to 4 weeks. Studies that take into account other potential factors that may influence PPAI, such as dystocia (Azzam et al., 1990), and twinning (Echternkamp and Gregory, 1999b), tended to report shorter PPAI (5 and 10 days respectively), suggesting a smaller effect size of parity than the full range reported in the literature. As in this model the effects of variables on PPAI are additive, a conservative value of one week was added to PPAI if the animal was in parity one.
- **Dystocia:** The presence of dystocia at a previous calving is associated with an increase in PPAI, with values of 1 to 35 days reported (Notter et al., 1979c, Azzam et al., 1990, Tess and Kolstad, 2000). The study reporting a one day increase in PPAI in cows also took into account many variables around forage quality and intake, and metabolism and growth. This may account for dystocia being responsible for less of the variation seen in PPAI, but as these factors are not included in this model, a larger value was considered more appropriate. Parity is accounted for in both other studies, but the effect of twinning was not. Therefore, a conservative value of two weeks was added onto PPAI in the event of dystocia in this model.
- **Stillbirth:** Suckling a calf has been shown to increase PPAI (Kahn and Lehrer, 1984, Lamb et al., 1999, Tervit et al., 1977). Therefore, if a calf is stillborn (we assume no calf is fostered on) PPAI may be reduced. If a calf dies shortly after birth the effect may be the same, however exactly when a calf dies before weaning cannot be determined in this model, therefore just the effect of stillbirth is accounted for. The effect sizes reported in the literature vary between 10 and 54 days, some figures being those used in other models of beef production (Kahn and Lehrer, 1984), and some being data from individual experiments (Lamb et al., 1999). The figure used in the model of beef production was 10 days and was incorporated in an additive way, as is the case in this model, whilst considering other factors that may affect PPAI. Therefore, it was decided that two weeks would be deducted from the PPAI in the event of a stillbirth, a figure at the lower end of this range but allowing for the additive effect of other variables accounted for in the model. As stillbirth is more likely to occur with dystocia and twinning, and these result in an increase in PPAI, it may be that these effects cancel each other out to some degree in the model.

- **Twinning:** Twinning is associated with an increase in PPAI of around two weeks (Echternkamp and Gregory, 1999b, Guerra-Martinez et al., 1990). However, there are some reports finding no significant effect (Wheeler et al., 1982). This may be due to several confounding factors such as dystocia and parity, which will affect PPAI as well as twinning rates. As twins also tend to have a shorter gestation period (Guerra-Martinez et al., 1990, Gregory et al., 1990, Echternkamp and Gregory, 1999a, Davis and Bishop, 1992, McCutcheon et al., 1991, Rose and Wilton, 1991, Owens et al., 1985), it has been suggested that this may cancel out any effects of a longer PPAI (Echternkamp et al., 2007). However, the reduction in gestation period seen with twins appears to be around a week (the average of the above references is six days). Taking this into account, in the current model one week has been added to PPAI in the event of twinning.

**Abortion rate**

Abortion rates in beef herds vary in the literature between 1% and 2% (Waldner, 2014b, Rogers et al., 1985, Segura-Correa and Segura-Correa, 2009, Caldow et al., 2002). In the current model a baseline abortion rate of 1% was used. This was then modified by the effector variables below which will increase the risk of abortion for an individual cow, resulting in an overall rate in the 1-2% range reported.

- **Parity:** Heifers have been shown to have a higher probability of aborting (Waldner, 2014b, Rogers et al., 1985). In the first study an odds ratio (OR) of 1.5 ($p = 0.03$) is seen in first calving heifers, whilst taking into account BCS and twinning. This is converted into a risk ratio (RR) using the non-exposed prevalence (i.e. the abortion rate in cows, or where this is not available the overall abortion rate), which is 1.61%, leading to a RR of 1.49, as described by Grant (2014). The second study reported abortion rates in parity 0 heifers and cows at 2.7% and 1% respectively, indicating a 1.7% increase in heifers. With the herd rate set at 1% in this model, multiplying this by 1.5 in the case of parity 0 heifers would lead to a 1.5% abortion risk in this age group, whereas using a 1.7% increase would lead to an abortion risk of 2.7% in parity 0 heifers. As the first study also takes into account other variables such as BCS and twinning, it was felt that multiplying abortion risk by 1.5 times for parity 0 heifers was most appropriate in the current model.
- **BCS:** Having a low BCS has been shown to be associated with increased risk of abortion (Waldner, 2014b). Using a nine-point scale, a BCS of less than 5 at pregnancy testing was shown to be associated with increased risk of abortion ($P=0.003$, OR = 1.56, RR = 1.55). This was extrapolated for use with a 5-point BCS scale, and a BCS of less than 2 was assigned an increased risk of abortion of 1.5 times the baseline.

- **Dystocia:** Cows that had dystocia at the previous calving were associated with increased risk of abortion with an OR of 2.1 (p=0.02) (Waldner, 2014b). This also results in a risk ratio of 2.1 (as the non-exposed prevalence is low). Therefore, the risk of abortion in the current model is doubled if there was dystocia at the previous calving.
- **Twinning:** Abortion rate has been shown to be higher when cows are carrying twins (Echternkamp and Gregory, 1999b, Waldner, 2014b). These studies respectively showed a 9% increase in abortion rate with twinning (3.5% versus 12.4%), and a RR of abortion with twins compared to abortion with no twins of 1.8 (OR = 1.82). The second study took factors such as parity and BCS into account, whereas the first study looked at the association between twinning and abortion in isolation. In the current model twinning was set to double abortion rate, as it was felt that this was an appropriate compromise between these two studies.
- **Previous stillbirth:** For cows that had a stillborn calf in the previous calving season, the risk of abortion has been shown to be increased with an OR of 2.2 (RR = 2.16) (Waldner, 2014b). In the current model, a stillbirth in the previous calving season leads to doubling the risk of abortion.
- **Previous abortion:** Having an abortion in the previous calving season was also associated with an increased risk of abortion in the current calving season (OR = 2.1, RR = 2.1). (Waldner, 2014a). In the current model, an abortion in the previous calving season leads to doubling the risk of abortion in the current calving season.

**Dystocia rate**

Herd dystocia rate may be affected by many factors, such as breed, BCS, average herd age and management factors (Nix et al., 1998). The definition of dystocia also varied between studies, with some categorising levels of dystocia using a scoring system (Basarab et al., 1993, Holland et al., 1993, McDermott et al., 1992, Nix et al., 1998), and some just recording normal or abnormal calving course (Citek et al., 2011), parturition as assisted or unassisted (Wittum et al., 1994a), or calving ease as normal or with dystocia (Bleul, 2011, Wittum et al., 1990, Waldner, 2014a, Rogers et al., 2004). Some studies also use data from teaching herds. This has been suggested as a possible cause of increased reported levels of dystocia, due to increased numbers of early interventions (Holland et al., 1993). These variations lead to a wide variety of dystocia rates being reported, up to 26.5% for a herd comprising only heifers and where dystocia was classed as any assistance (Basarab et al., 1993), to 3.5% in a study that defined dystocia as any assistance, but that used producer recorded data (Wittum et al., 1990), which has been suggested to lead to lower levels of dystocia event recording (Wittum et al., 1994a). In the current model dystocia was considered a binary event (i.e. different levels of dystocia were not considered), so studies reporting dystocia in a binary way were consulted. Dystocia rates in these studies were 3.5% to 7%, with an average of 5%. As the herd input values in the current model are baseline values, and so are moderated up by other factors, e.g. parity, previous dystocia, twinning and calf sex, the input value was set at 2%. Cow weight has not been used as an effector variable for dystocia, as it is assumed that appropriate bull selection has been used for smaller cows.

- **Parity:** Parity has been shown to be significantly associated with calving difficulty (Vosough Ahmadi et al., 2017). The size of the effect of being a heifer calving for the first time on the risk of dystocia in the literature ranges from a 4.7% increase to 16.2% increase (these are absolute not relative values) (Morris, 1980, Nix et al., 1998, Bleul, 2011, Waldner, 2014a, Rogers et al., 2004). The median of these figures was taken for the current model, giving an absolute increase in dystocia rate for first calving heifers of 12%.
- **Previous dystocia:** Dystocia in the previous calving season has been shown to be associated with increased risk of dystocia in the current season (Waldner, 2014a, McDermott et al., 1992). These papers report odds ratios of 2 and 3.71 respectively, which equate to risk ratios of 1.8 and 3.2. The average of these (2.5) was taken for the current model, and so in the event of previous dystocia, dystocia risk at the current calving was multiplied by 2.5.
- **Twinning:** Twinning has also been shown to increase dystocia rates by varying degrees (Gregory et al., 1990, Echternkamp and Gregory, 1999a, White et al., 2015, Bleul, 2011, Waldner, 2014a). Absolute values of 1% to 26.3% are reported, which equate to a 1.2 to 3 fold increase. The variation in values reported in the literature may be due to the different variables with the potential of affecting dystocia rates accounted for in different analyses, as well as the different ‘baseline’ levels of dystocia between herds studied. In the current model, twinning was assigned a 5% increase in the risk of dystocia (absolute value).
- **Calf sex :** Calf weight has been suggested as the most important predictor of dystocia (King et al., 1993), sex being less important when weight is accounted for (McDermott et al., 1992). In the current model, calf sex was used as a proxy for weight. Male calves were assumed to have a 5kg increase in birthweight over female calves (40kg and 35kg respectively). Dystocia has been suggested to increase by 1.8% (absolute value) per kg of calf birthweight (Morris, 1980), which for 5kg would be an increase of 9%. A second study showed a similar increase of 13% in dystocia between male and female calves (Echternkamp and Gregory, 1999a). In the current model 10% was added to the dystocia risk if the calf was male.

**Stillbirth rate**

In the current model, the definition of a stillbirth was taken to be a calf that was near full term (within 1 month) and was born dead or died within 1 hour of birth (Waldner, 2014a). Alternative definitions are used in other studies, such as calves that are born dead or die within 24 hours of birth (Segura-Correa and Segura-Correa, 2009), or any calf that is born dead (Wittum et al., 1990), and it is accepted that there are variations in the definition of stillbirth (Lovell and Hill, 1940). Despite these differences, the figures in the literature are generally similar at between 1% and 3 % (Waldner, 2014a, Rogers et al., 1985, Motus and Emanuelson, 2017, McDermott et al., 1992, Segura-Correa and Segura-Correa, 2009), with a single study (Citek et al., 2011) reporting a higher rate of 6.98% ( although data in the latter study was from only 50 herds). In the current model, a stillbirth rate of 1% was set. Again, this was a baseline level, and was increased in first parity heifers and in the event of dystocia or twinning.

- **Parity:** Stillbirth rates have been shown to be higher in first parity heifers (i.e. heifers calving for the first time) than in cows by between 0.3% and 5.6% (Morris, 1980, Rogers et al., 1985, Motus and Emanuelson, 2017, Waldner, 2014a). In the current model, heifers were assigned a 2% greater risk of having a stillborn calf, a conservative average as many of these studies do not take into account the effect of dystocia on stillbirth.
- **Dystocia:** Dystocia increases the risk of stillbirth (Citek et al., 2011, McDermott et al., 1992, Bleul, 2011). These studies used logistic regression models and quoted regression coefficients, odds ratios and risk ratios. Regression coefficients and odds ratios were converted into risk ratios for comparison (as previously described), and these risk ratios were 11.6, 12.2 and 18.5 respectively. Due to the varying definition of stillbirth, with some studies including calves dying up to 24hrs after birth, and the varying combinations of 'predictors' included in the different studies, a conservative level of a 10 times increase in the risk of stillbirth with dystocia was included in the current model.
- **Twinning:** Twinning is associated with an increased risk of stillbirth (Waldner, 2014a, Gregory et al., 1990, Cummins et al., 2008, Davis and Bishop, 1992, Karlsen et al., 2000, Smeaton and Clayton, 1998). The literature includes reports looking at the effect of twinning on stillbirth alone (Smeaton and Clayton, 1998, Cummins et al., 2008), or in conjunction with other factors associated with stillbirth rate, such as dystocia and parity (Waldner, 2014a, Gregory et al., 1990). It also includes reports using cattle induced to twin (Davis and Bishop, 1992), as opposed to cattle that have twinned naturally. The size of the effect of twinning on stillbirth risk varies in the literature, likely, at least in part, due to the different nature of the reports discussed. There is also the potential for confounding; when the effect of individual factors on stillbirth rate is considered in isolation, for example twinning, the effect seen may in

part be due to another factor, for example dystocia. Studies that looked at the effect of twinning alone on stillbirth rate (i.e. did not include other variables that may be associated with stillbirth rate), found absolute increases in stillbirth rate of around 15% with twin births (Smeaton and Clayton, 1998, Cummins et al., 2008). A study using logistic regression investigated associations between stillbirth rate, parity, dystocia and twinning (Waldner, 2014a). Here, a relative risk of 5.7 (odds ratio of 6.58) was reported for stillbirth with twinning. With the current model stillbirth rate set at 1%, this would equate to a 5.7% absolute increase in stillbirths with a twin birth. This is lower than the effects reported in studies looking at the effect of twinning on stillbirth in isolation, which is to be expected as other variables, such as dystocia, which are not accounted for, may be responsible for some of the increase reported. In the current model, the effect of twinning, parity and dystocia on stillbirth rate are calculated separately, with the effects being additive. Therefore, it was felt that the value that takes into account the effect of parity and dystocia was the most appropriate, and a 5 times increased risk of stillbirth with twinning was assigned.

- **Calf sex:** Some studies suggest that male calves are more likely to be stillborn (McDermott et al., 1992), however, it was felt that this is likely to be through an indirect effect on dystocia. Other studies suggest that calf sex in itself is not a significant predictor of stillbirth (Waldner, 2014a). This factor is therefore not included in the current model.

**Twinning rate**

The twinning rate in beef cattle in 2013 in the UK was reported as 2.47% (Gates, 2013). This is higher than other studies reporting rates of between 0.36% and 1.2% (Segura-Correa and Segura-Correa, 2009, Wittum et al., 1994b, Karlsen et al., 2000, Wittum et al., 1994a). Rates have been shown to vary by breed (Cobanoglu, 2011), and the lowest twinning rate of 0.36% was recorded from zebu cattle and their crosses (Segura-Correa and Segura-Correa, 2009). As these studies were not carried out in the UK, it was felt that the study using data from the UK would be most appropriate to use for determining this input. Interestingly, a report from Ireland also reported a higher twinning rate of 1.74% (Fitzgerald et al., 2014). In the current model twinning rate was set at 2%, but was increased in older animals (parity category 3) and if the cow had had twins previously. It was also decreased by 1% in first parity heifers. Some studies evaluating twinning in beef cattle use herds selected for twinning, or induce twinning by superovulation; these studies were discounted when determining the twinning rate for this model.

- **Parity:** Twinning rate has been shown to increase with parity (Fitzgerald et al., 2014, Cobanoglu, 2011, Davis and Bishop, 1992, Karlsen et al., 2000). A study quantifying this showed that the predicted probability of a first parity heifer having twins was 0.69%, parity 2 was 1.56%, parity 3 was 1.92%, parity 4 was 2.10% and parity 5+ was 2.34% (Fitzgerald et al., 2014). The herd twinning rate in the current model is 2%, therefore 1% was deducted if the animal was a first parity heifer, and 1% was added for parity category 3.

- **Previous twins:** Cows that have had twins previously are 11% more likely to have twins again (Karlsen et al., 2000). Therefore, if a cow in the model had twins at the previous calving, 11% was added to the baseline twinning rate for that cow.

**Birthweight**

In this model birthweight is set at 35kg for female calves and 40kg for male calves. Birth weights in the literature varied between 42kg and 33kg, with males being heavier than females (Motus and Emanuelson, 2017, Bellows et al., 1987). It was felt that 35kg for female calves and 40kg for male calves was representative of the breeds commonly seen in English suckler herds. Factors other than sex of calf will affect birthweight, such as parity of dam, BCS of dam and twinning. Although not incorporated at this stage in the current model, these have been made to influence weaning weights and so are taken into account.

**Male:Female ratio (of calves born)**

This was set at 0.5 male and 0.5 female, as is seen in other models of beef production (Azzam et al., 1990). This means that the effects of calf sex on variables in the model are likely to cancel each other out, however by including calf sex in the model, this ratio could be adjusted in the future if required.

*Table 6-3: **Input values and distributions for reproduction sub-model**. For discrete distributions, the percentage probability for each category is listed. For continuous, BetaPERT distributions, a minimum, mode, and maximum value are given. Effector variables (those that may affect main variables) are given, along with, effect sizes. References are also included in the table*

| Variable | Model input value/ distribution | References | Effector variable | Effect size | References |
|---|---|---|---|---|---|
| **21-day pregnancy rate** | BetaPERT (0.5, 0.65, 0.8) | (Roughsedge et al., 2003a, Johnson and Notter, 1987, Azzam et al., 1990, Smeaton, 2001). | Parity | No effect of parity on 21-day pregnancy rate incorporated in model. | (Vosough Ahmadi et al., 2017, Fike et al., 1996, Notter et al., 1979a, Doren et al., 1985). |
| | | | Dystocia | Dystocia at the previous calving results in a 10% reduction in 21-day pregnancy rate | (Tess and Kolstad, 2000, Notter et al., 1979c) |
| | | | BCS | BCS<2 results in a 15% reduction in 21-day pregnancy rate | (Vosough Ahmadi et al., 2017, Kunkle et al., 1998) |
| | | | Twinning | 12% absolute reduction in 21-day pregnancy rate with twinning at the previous calving | (Echternkamp and Gregory, 1999b, Gregory et al., 1990, Cummins et al., 2008, Echternkamp et al., 2007). |
| | | | Oestrus number | 3% reduction in 21-day pregnancy rate per serve | (Amer et al., 1996, Azzam et al., 1990, Blanc and Agabriel, 2008) |
| **Post-partum anoestrus interval (PPAI) (weeks)** | BetaPERT (4,9,12) | | Parity | First parity heifers are assigned a 1 week increase in PPAI | (Azzam et al., 1990, Fike et al., 1996, Greer et al., 1990, Doornbos et al., 1984, Echternkamp and Gregory, 1999b, Yavas and Walton, 2000, Tervit et al., 1977) |
| | | | Dystocia | PPAI is increased by 2 weeks for cows experiencing dystocia at the previous calving | (Notter et al., 1979c, Azzam et al., 1990, Tess and Kolstad, 2000) |
| | | | Stillbirth | Stillbirth reduces PPAI by 2 weeks (reflecting the absence of a suckling calf) | (Kahn and Lehrer, 1984, Lamb et al., 1999, Tervit et al., 1977) |

| | | | | | |
|---|---|---|---|---|---|
| | | | Twinning | Twinning increases PPAI by 1 week | (Echternkamp and Gregory, 1999b, Guerra-Martinez et al., 1990, Wheeler et al., 1982, Gregory et al., 1990), (Echternkamp and Gregory, 1999a, Davis and Bishop, 1992, McCutcheon et al., 1991) (Rose and Wilton, 1991, Owens et al., 1985, Echternkamp et al., 2007) |
| **Abortion rate** | 1% | (Waldner, 2014b, Rogers et al., 1985, Segura-Correa and Segura-Correa, 2009, Caldow et al., 2002). | Previous dystocia | Risk of abortion doubles with previous dystocia | (Waldner, 2014b) |
| | | | Previous stillbirth | Risk of abortion doubles with previous stillbirth | (Waldner, 2014b) |
| | | | Previous abortion | Risk of abortion doubles with previous stillbirth | (Waldner, 2014b) |
| | | | Parity | Increased risk of abortion of 1.5 times in heifers | (Waldner, 2014b, Rogers et al., 1985) |
| | | | BCS | Increased risk of abortion of 1.55 times if BCS<2. | (Waldner, 2014b) |
| | | | Twinning | Risk of abortion doubles with twins | (Echternkamp and Gregory, 1999b, Waldner, 2014b) |
| **Dystocia rate** | 2% | (Nix et al., 1998, Basarab et al., 1993, Holland et al., 1993), (McDermott et al., 1992, Citek et al., 2011, Wittum et al., 1994a), (Bleul, 2011, Wittum et al., 1990), (Waldner, 2014a, Rogers et al., 2004). | Parity | Increase in dystocia of 12% in first parity heifers | (Vosough Ahmadi et al., 2017, Morris, 1980, Nix et al., 1998, Bleul, 2011, Waldner, 2014a, Rogers et al., 2004). |
| | | | Twinning | 5% increase in dystocia with twinning | (Gregory et al., 1990, Echternkamp and Gregory, 1999a, White et al., 2015, Bleul, 2011, Waldner, 2014a). |
| | | | Previous dystocia | Increase in dystocia risk of 2.5 times with previous dystocia | (Waldner, 2014a, McDermott et al., 1992) |

| | | | | | |
|---|---|---|---|---|---|
| | | | Calf sex | Increase in dystocia risk of 10% with male calves | (King et al., 1993, McDermott et al., 1992, Morris, 1980, Echternkamp and Gregory, 1999a) |
| **Stillbirth rate** | 0.5% | (Waldner, 2014a, Segura-Correa and Segura-Correa, 2009, Wittum et al., 1990). | Parity | First parity heifers assigned a 2% greater risk of stillbirth | (Morris, 1980, Rogers et al., 1985, Motus and Emanuelson, 2017, Waldner, 2014a). |
| | | | Dystocia | 10 times increased risk of stillbirth with dystocia | (Citek et al., 2011, McDermott et al., 1992, Bleul, 2011) |
| | | | Twinning | 5 times increased risk of stillbirth with twinning | (Waldner, 2014a, Gregory et al., 1990, Cummins et al., 2008, Davis and Bishop, 1992, Karlsen et al., 2000, Smeaton and Clayton, 1998) |
| **Twinning rate** | 2% | (Gates, 2013, Segura-Correa and Segura-Correa, 2009, Wittum et al., 1994a, Wittum et al., 1994b), (Karlsen et al., 2000, Cobanoglu, 2011, Fitzgerald et al., 2014). | Parity | Parity category 1 = 1% reduction in risk of twinning.<br>Parity category 3 = 1% increase in risk of twinning | (Fitzgerald et al., 2014, Cobanoglu, 2011, Davis and Bishop, 1992, Karlsen et al., 2000). |
| | | | Previous twinning | Previous twinning results in an 11% increase in risk of twinning in the current calving season | (Karlsen et al., 2000) |
| **Calf birthweight** | 35kg for females, 40kg for males. | (Motus and Emanuelson, 2017, Bellows et al., 1987). | None | | |
| **Male:female ratio** | 1:1 | (Azzam et al., 1990) | None | | |

### 6.4.3 Growth sub-model inputs

Input distributions for pre-weaning DLWG were defined for the growth section of the model. From this weaning weights (actual and adjusted to weight at 200 days) were calculated. DLWG baseline values were modified by dam parity, dam BCS, calving block, calf sex, twinning and disease incidence, as summarised in Table 6-4.

**Pre-weaning DLWG**

This varies considerably in the literature due to the different breeds and systems reported. For example, average daily gain (ADG) in Hereford and Hereford cross calves varied between 0.58kg/day and 0.95kg/day depending on whether they and their dam were on low, medium or high quality pasture (Arthur et al., 1997). Breed of dam can also affect calf ADG, varying between 1.03kg/day and 1.20kg/day in a study evaluating the effect of cow genotype on calf growth (McGee et al., 2005), and in a study on Simmental calves assessing their growth with and without a supplement, control animals had an ADG of 1.41kg (Jensen et al., 1999). Other models of cattle growth use experimental results to inform inputs, for example Amer et al. (1997), where ADG up to 16 months rather than weaning was reported, and varied by breed between 0.83kg/day and 0.92kg/day. In a stochastic model of a mountain beef cattle system in the Spanish Pyrenees, a mean calf ADG value of 0.95kg/day was used (Villalba et al., 2006). This was validated using real herd data from the area, and observed values varied between 1.12kg/day and 0.69kg/day. A dataset from English suckler herds including DLWG to weaning values was obtained from AHDB. In this dataset, herd average values were normally distributed and varied between 0.5kg/day and 1.6kg/day, with a mode of 1.1kg/day. This largely agrees with the literature, and so the herd level model input distribution was defined as betaPERT (0.6, 1.1, 1.6), i.e. a minimum value of 0.6kg/day, a mode of 1.1kg/day, and a maximum of 1.6k/day. As there will also be DLWG variation between individual calves within the herd, the herd value was taken as the mode for defining individual calf DLWG distribution as follows: betaPERT (0.3, herd mode, 1.8). These values were chosen after consulting farm data, and during testing and refining of the simulation model to ensure that the outputs reflected our real herd dataset. Calf DLWG baseline value is modified in the model by the following variables:

- **Dam parity:** Calves from first parity heifers have been shown to have lower pre-weaning DLWG values than calves from cows (Fiems et al., 2008), and previous models of beef production have incorporated this (Azzam et al., 1990). Figures quoted are 0.05kg/day and 0.11kg/day reduction, therefore a conservative 0.05kg/day was deducted from a calf's DLWG in the current model if the dam is a first parity heifer, as the effects of all variables on overall calf DLWG are additive in this model.
- **Dam BCS:** Cow lactation yield has been shown to explain most variation in calf DLWG, and when this was taken into account BCS only explained 1.1% of DLWG

(Arthur et al., 1997). However, lactation yield was correlated with cow weight and BCS in that study, and as milk yield is not included in this model (and would be difficult to measure in normal suckler farm circumstances), dam BCS (which moderates weight) was used as a proxy in the current model. The effect of dam BCS on calf DLWG was quantified in another study (Kunkle et al., 1998). In this study a 1-9 BCS scale was used, therefore each score was halved to become the equivalent score on a 1-5 scale. This study showed decreases of 0.05 – 0.06kg/day with dam BCS of 1.5, 2, and 2.5. Therefore, if a dams BCS was less than 2, 0.05kg/day was deducted from the calf's pre-weaning DLWG in the current model.

- **Calving block:** It has been suggested that calves born earlier in the calving season tend to grow faster due to superior hygiene at calving and resulting better health. Some studies have not found any evidence of this, for example Funston et al. (2012) found no effect of calving date within calving period on calf DLWG. Other studies however show a significant effect, for example Pang et al., (1998) reported that DLWG to weaning was 0.05kg greater in early (April born) versus late (May/June born) calves. This figure was used in the current model, with 0.05kg being deducted for calves born in the last 3 weeks of the calving period.
- **Calf sex:** Male calves have been shown to grow faster than females (Doornbos et al., 1984, Azzam et al., 1990, Jensen et al., 1999). Figures quoted in these studies are 0.07kg/day (8.5%) difference, 0.04kg/day (5%) and 0.11kg/day (7.3%) respectively. An average of 7% was taken and a calf's DLWG was reduced by 7% if it was a female calf.
- **Twinning:** Twins have been shown to have reduced weaning weights compared to single calves (Wittum et al., 1994b, Davis and Bishop, 1992, Hennessy and Wilkins, 2005, Rose and Wilton, 1991, Guerra-Martinez et al., 1990). Other studies however found no significant difference (McCutcheon et al., 1991), although small groups sizes and large variation of weights within groups, along with the possibility of some cross suckling in the study, suggests that incorporating an effect of twinning on weaning weight is appropriate in the current model. Where differences in weaning weights between singles and twins were quoted in studies, these were converted into DLWG differences using average weaning ages. This resulted in a range of 0.23kg/day reduction to 0.13kg/day reduction with a mean of 0.17kg/day and a median of 0.16kg/day. A reduction in DLWG of 0.165kg/day was incorporated into the model for twin calves. As these are largely calculated from weaning weights and ages, the difference in birth weights between twins and singles will also be taken into account here, and so is not accounted for elsewhere in the model.
- **Disease incidence:** The presence of diseases such as diarrhoea and pneumonia within a herd can effect calf growth and weaning weights (Wittum et al.,

1994b, Stokka, 2010, Engelken, 1997). Weaning weight differences were provided in the studies used to inform these inputs, and so these were converted into DLWG reductions using weaning age where available, or assuming a 200d weaning age. Reductions in DLWG in the presence of pneumonia reported were 0.08kg/day (Stokka, 2010, Wittum et al., 1994b), with diarrhoea reported to cause around 0.05kg/day reduction (Wittum et al., 1994b). These effects were incorporated into the current model.

***Table 6-4: Input values and distributions for the growth sub-model.*** *For continuous, BetaPERT distributions, a minimum, mode, and maximum value are given. Effector variables (those that may affect main variables) are given, along with, effect sizes and references.*

| Variable | Model input value/distribution | References | Effector variable | Effect size | Refs |
|---|---|---|---|---|---|
| **Pre-weaning DLWG** | Herd level: BetaPERT (0.6, 1.1, 1.6)<br>Calf level: BetaPERT (0.3, herd mode, 1.8) | (Arthur et al., 1997, McGee et al., 2005, Jensen et al., 1999, Amer et al., 1997, Villalba et al., 2006). | Dam parity | Calves from first parity heifers were assigned a DLWG reduction of 0.05kg/day | (Fiems et al., 2008, Azzam et al., 1990) |
| | | | Dam BCS | Calves from dams with a BCS<2 were assigned a DLWG reduction of 0.05kg/day | (Arthur et al., 1997, Kunkle et al., 1998) |
| | | | Calving block | Calves born in the last 3 weeks of the calving period had 0.05kg/day deducted from their DLWG | (Funston et al., 2012, Pang et al., 1998) |
| | | | Calf sex | Female calves were deducted 7% from their DLWG | (Doornbos et al., 1984, Azzam et al., 1990, Jensen et al., 1999) |
| | | | Twinning | Twins were assigned a DLWG reduction of 0.165kg/day. | (Wittum et al., 1994b, Davis and Bishop, 1992, Hennessy and Wilkins, 2005, Rose and Wilton, 1991, Guerra-Martinez et al., 1990, McCutcheon et al., 1991) |
| | | | Disease incidence | Reductions in DLWG in the case of diarrhoea were 0.05kg/day, and in the case of pneumonia were 0.08kg/day. | (Wittum et al., 1994b, Stokka, 2010, Engelken, 1997) |

### 6.4.4 Health sub-model inputs

Input distributions in the health section of the model were defined for cow cull rate, cow mortality rate, pre-weaning mortality rate and disease incidence (pneumonia and diarrhoea). These are summarised in Table 6-5.

**Adult suckler cow cull rate**

This is likely to vary substantially between herds, and even within a herd year on year, as it is sensitive to external factors such as market prices. The average cull rate (voluntary and involuntary) in the UK in 2013 was 20.1% (15% sold or slaughtered and 5% dies on farm) (Gates, 2013). The average culling rate in Ireland (measured as an exit from the national herd so either slaughter/death on farm) was reported as 18% in 2008. Replacement rates of 14, 18 and 22% were considered low, medium and high for North American beef herds (Roberts et al., 2015), and cull rates in Western Canada were reported as 14% (Waldner et al., 2009). In the current model, voluntary cull rate was set as a betaPERT distribution, with a minimum value of 0%, a maximum value of 20% and a mode of 10%. If a cow was barren in the current model (failed to become pregnant during the 12-week breeding period) she was culled. This was classed as an involuntary cull. Voluntary culls were determined by the baseline herd cull rate, parity, whether or not the cow weaned a calf and whether or not she experienced dystocia.

- **Parity:** The decision whether to cull a cow or not depends on many factors, and although age has been shown to be a significant predictor of culling (Waldner et al., 2009, Tronstad and Gum, 1994), market prices also play an important part in the decision (Vosough Ahmadi et al., 2017), to the point where it may sometimes be viable to keep open cows to re-breed at the next opportunity (Tronstad and Gum, 1994). Cows over 10 years of age have been shown to be significantly more likely to be culled than other age groups (Waldner et al., 2009), with the odds of culling 2.4 times greater in cows over 10 years old compared to other mature cows (this was converted to a RR of 2). Therefore, a cow in parity category 3 in the current model had double the risk of being culled.
- **Dystocia:** Dystocia (at any point in the animals life) has been shown to increase the risk of being culled by around 1.5 times (Rogers et al., 2004), and to reduce longevity (Szabo and Dakay, 2009). In the current model dystocia leads to a doubling of the risk of a cow being culled.
- **Weaning rate:** In a study evaluating risk factors of longevity in beef cows, it was shown that cows not weaning a calf were twice as likely to be culled (Rogers et al., 2004). Therefore, this effect has been included in this model.

The occurrence of twinning and stillbirth do not influence cull rate in this model as they already influence weaning rate and dystocia rate (which both influence cull rate) and cow mortality rate. It was felt that twinning would mainly influence cull rate through its effect on dystocia, and that stillbirth rate would mainly have an effect through weaning rate. BCS and cow weight do not influence cull rate directly in the current model, although BCS does influence conception rate so will have an indirect effect on involuntary cull rates.

It has been suggested that animals with a higher BCS are more likely to be culled voluntarily due to their higher cull value, and that involuntary culls should incur a 3% weight loss when calculating kg of cull cow produced (Vosough Ahmadi et al., 2017). In this model, involuntary culls are barren animals, and so it was felt that reducing their weight by 3% would not be appropriate. Voluntary culls were determined according to the herd voluntary cull rate, parity, dystocia and weaning rate. Although the BCS of an animal may play a part in culling decisions, it was felt that this would be a minor factor in determining if an animal was to be culled or not, and so was not included in the model. Calving time within the calving period has also been associated with culling decisions (Vosough Ahmadi et al., 2017), however in this model the breeding period is only 12 weeks, and so it was felt to be unlikely that an animal would be culled due to calving 'late' within this period.

**Cow mortality rate**

Cow mortality rates reported in the literature vary between around 1% and 3% (Motus and Emanuelson, 2017, Oishi et al., 2013, Waldner et al., 2009). In the current model this input was assigned a betaPERT distribution with a minimum of 0%, a maximum of 3% and a mode of 0.25%. This has the potential to be increased by abortion, stillbirth, dystocia and parity. Twinning was not included as a risk factor as it was felt that it would mediate most effect on cow mortality through its effect on dystocia. Some studies have also failed to demonstrate a significant association between twinning and mortality rate (Motus and Emanuelson, 2017). Parity was also not included as it is included as an effector of cull rate, and no literature supporting the incorporation of BCS was identified.

- **Abortion:** Abortion has been associated with an increased risk of cow mortality (Motus and Emanuelson, 2017). The hazard ratio, produced using a multivariable model taking into account other factors such as breed, dystocia, parity and stillbirth, was 4.14, i.e. a cow that aborts is 4.14 times more likely to die. This effect was incorporated into the current model.
- **Stillbirth:** Stillbirth has been shown to be associated with an increase in cow mortality rate (Motus and Emanuelson, 2017). As part of a multivariable model, which included variables such as dystocia and parity, the hazard ratio was 2.24. In the current model, cow mortality rate is multiplied by 2.24 in the event of stillbirth.
- **Dystocia:** Dystocia has been shown to be associated with increased cow mortality rates (Motus and Emanuelson, 2017), with an increase of 2.07 per

100 cow years (2.12 in heifers) following dystocia. When analysed in a multivariable model, including stillbirth, abortion and parity, the hazard ratio was 10.3, i.e. a cow experiencing dystocia was 10.3 times more likely to die in the seven days following calving than one not experiencing dystocia. The hazard ratio reported represents risk at a particular time point (within 7 days of calving in this case), and so it was felt that an effect size closer to that seen in the bivariate analysis would be more appropriate. In the current model, in the presence of dystocia the mortality rate is doubled.

- **Parity:** Parity has been shown to be significantly associated with cow mortality rate (Motus and Emanuelson, 2017, Gates, 2013, Waldner et al., 2009), with the first study reporting a mortality rate hazard ratio of 1.65 for cows over parity 7 compared to those in parity 2, and the second study reporting an odds ratio of 1.8 (also 1.8 when converted into a RR) for mortality in cows over 10 years old compared to other mature cows. Therefore, in the current model, cows in parity category 3 were assigned a mortality rate of 1.7 times the baseline rate.

**Pre-weaning mortality rate**

Pre-weaning mortality rate can be affected by multiple environmental and management factors, leading to differing rates being reported in the literature. The definition of pre-weaning mortality may also vary, with there being the potential for some overlap with the definition of stillbirth. In the current model, pre-weaning mortality included any deaths over one hour after birth and up to weaning (Waldner et al., 2010, Waldner, 2014a). Some reports differentiate between perinatal and neonatal mortality (Wittum et al., 1994a), and some report calf mortality rate up to 45 days (Wittum et al., 1994a) or four months (Nix et al., 1998), rather than weaning. Calf mortality rates (excluding stillbirths) vary between 2% and 5.5% (Waldner et al., 2010, Withers, 1952, Lovell and Hill, 1940, Axelsen et al., 1981, Gates, 2013, Murray et al., 2016, Tarres et al., 2005, Elghafghuf et al., 2014, Oishi et al., 2013). In the current model this input was assigned a betaPERT distribution with a minimum of 0%, a maximum of 5% and a mode of 0.05%. This is slightly lower than rates reported in the literature, but as previously it has been designed to represent a baseline level. This then has the potential to be increased by other factors such as parity, dystocia, twinning, disease incidence (pneumonia / diarrhoea) and when the calf was born within the calving period. Cow BCS has been reported as an insignificant predictor of calf mortality and so was not added as an effector in the current model (Elghafghuf et al., 2014).

- **Parity:** Calves from first parity heifers have been shown to have higher mortality rates (Gates, 2013, Patterson et al., 1987, Wittum et al., 1994a, Nix et al., 1998, Azzam et al., 1993, Elghafghuf et al., 2014). Relative risk ratios reported in these studies vary between 1.3 and 2, whereas studies that report a percentage increase in pre-weaning mortality rate from first parity heifers vary between 3% and 4% increase. The studies that report risk ratios tend to take more factors into account, such as dystocia and twinning, so it was felt that multiplying the risk of pre-weaning calf mortality by 1.5 in the case of first parity heifers was appropriate in the current model.

- **Dystocia:** Dystocia has been shown to increase pre-weaning mortality rate (Morris, 1980, Wittum et al., 1994a, Nix et al., 1998, Tarres et al., 2005, Ganaba et al., 1995, Azzam et al., 1993, Wittum et al., 1990, Elghafghuf et al., 2014). Risk ratios (or odds ratios that have been converted into risk ratios) are often used to report the effects of dystocia on calf mortality, and these range from 1.5 to 10.3 in these studies. Different definitions of dystocia, for example yes/no binary classification versus scoring systems, and time periods over which calf mortality is measured, are likely to be at least in part responsible for this variation. Potential confounders in this model are parity and twinning, so studies which also took these factors into account were favoured, however a large variation in reported effect sizes was still seen. There is likely to be large variation between farms and years when it comes to calf mortality, due to management and environmental factors, so a large variation is to be expected. An increase in calf mortality risk of 4 times when dystocia is experienced was felt to be appropriate for the current model, and largely agrees with previous studies.
- **Twins:** Calf mortality rates are higher in twins than single born calves (Gates, 2013, Wittum et al., 1994a, Elghafghuf et al., 2014). Ganaba et al. (1995) found no increase in mortality rate with twinning, but this may be due to very few twin born calves being in the dataset. Relative risks reported in these studies were between 1.6 and 3.7 (Gates, 2013, Wittum et al., 1994a). Potential confounders here are dystocia and parity. These were taken into account in a study reporting hazard ratios between 3.8 and 1.06, depending on the age of the calf when it died (3.8 = 1 day old, 1.06 = 60 days old) (Elghafghuf et al., 2014). A hazard ratio represents a risk at a particular time, whereas relative risk is the cumulative risk over a period of time, which it was felt would be more appropriate for this simulation model. Therefore, it was felt that multiplying calf mortality rate by 2.5 in the event of twins was appropriate.
- **Calving Block:** Calf mortality rate increases as the calving date within the calving period increases (Morris, 1980, Tarres et al., 2005, Smith, 2012, Elghafghuf et al., 2014), and as the calving period extends (Murray et al., 2016). Elghafghuf et al. (2014) demonstrated an increase in hazard ratio for calf mortality of 0.74 for calves born in the last 10% of the calving period (HR = 1.64) compared to those born in the first 10% (HR = 0.9), both compared with the 50$^{th}$ percentile. The calving period in this model is 12 weeks, 10% of this

would only be the final week, therefore calves born in the final block (weeks 10-12) were assigned a 1.5 times increase chance of mortality in the current model.

- **Pneumonia/diarrhoea:** Pneumonia and diarrhoea have both been shown to increase mortality rates in calves (Ganaba et al., 1995); diarrhoea resulted in an increased neonatal mortality risk of 3.8 times a calf with no incidence of diarrhoea, whereas pneumonia resulted in an increased risk of 5.8 times. Parity is not taken into account in the referenced study however, so there is the potential for confounding. Therefore, a conservative tripling of mortality rate with diarrhoea and 4 times with pneumonia was felt to be appropriate in the current model.

**Disease incidence**

Many management and environmental factors will affect diarrhoea incidence, with rates in the literature varying between 1% and 22% (Wittum et al., 1994b, Murray et al., 2016, Wittum et al., 1994a, Schumann et al., 1990). In this model this is defined by a betaPERT distribution with a minimum of 0, a maximum of 20% and a mode of 5%, with the baseline level having the potential to be increased by parity, twinning and calf sex.

In a similar way to diarrhoea rate, many factors will affect pneumonia rate in calves, and this is reflected in the literature with rates between 1% and 11% reported (Wittum et al., 1994b, Murray et al., 2016, Woolums, 2010, Woolums et al., 2013). In the current model pneumonia rate is also defined by a betaPERT distribution with a minimum of 0, a maximum of 20% and a mode of 5%, again with the potential to be increased by parity, twinning and calf sex.

Although it would be expected that dystocia would also affect the risk of disease, no literature was identified to support this, so this was not added to the model. Likewise with the effect of calving period on disease incidence. Both of these factors were however included in determining calf mortality risk. Having one disease has also been shown to increase the likelihood of having the other (Murray et al., 2016), however determining cause and effect here is difficult, so this effect was also not included in the model.

- **Parity:** Calves from first parity heifers were shown to be more likely to have an episode of diarrhoea in a study evaluating risk factors for diarrhoea (Schumann et al., 1990) by around a factor of 2 (51% vs 28% in case herds and 20% vs 8% in control herds). In the current model, calves from first parity heifers were assigned twice the risk of diarrhoea than calves from cows.
- **Twins:** Neonatal respiratory disease has been shown to be more likely to occur in twins than singles (Wittum et al., 1994a). The OR reported was 15, with a non-exposed prevalence of 1% (overall neonatal respiratory disease

incidence), and a RR of 13.2 was calculated. Calf sex was also accounted for in the multivariable model used to calculate this RR, so twins were assigned 13.2 times the risk of pneumonia.

- **Calf sex:** Male calves have been shown to be three times as likely to suffer from respiratory disease as female calves (RR = 3.1) (Wittum et al., 1994a). Therefore, male calves were assigned 3.1 times the risk of respiratory disease than female calves in this simulation model.

***Table 6-5: Input values and distributions for the health sub-model*** *For continuous, BetaPERT distributions, a minimum, mode, and maximum value are given. Effector variables (those that may affect main variables) are given, along with, effect sizes and references*

| Variable | Model input value/distribution | References | Effector variable | Effect size | References |
|---|---|---|---|---|---|
| **Cull rate (voluntary) (%)** | BetaPERT (0, 10, 20) | (Gates, 2013, Maher et al., 2008, Roberts et al., 2015, Waldner et al., 2009). | Parity | Cows in parity category 3 have double the risk of being culled | (Waldner et al., 2009, Tronstad and Gum, 1994, Vosough Ahmadi et al., 2017) |
| | | | Dystocia | Cows with dystocia have double the risk of being culled | (Rogers et al., 2004, Szabo and Dakay, 2009) |
| | | | Weaning rate | Cows not weaning a calf have double the risk of being culled | (Rogers et al., 2004) |
| **Cow mortality rate (%)** | BetaPERT (0, 0.25, 3) | (Motus and Emanuelson, 2017, Oishi et al., 2013, Waldner et al., 2009). | Abortion | Abortion increases risk of cow mortality by 4 times | (Motus and Emanuelson, 2017) |
| | | | Stillbirth | Stillbirth doubles risk of cow mortality | (Motus and Emanuelson, 2017) |
| | | | Dystocia | Dystocia doubles risk of cow mortality | (Motus and Emanuelson, 2017) |
| | | | Parity | Cows in parity 3 category have a mortality rate of 1.7 times the baseline rate | (Motus and Emanuelson, 2017, Gates, 2013, Waldner et al., 2009) |
| **Pre-weaning mortality rate (%)** | BetaPERT (0, 0.5, 5) | (Waldner et al., 2010, Waldner, 2014a, Wittum et al., 1994a, Nix et al., 1998, Withers, 1952, Lovell and Hill, 1940, Axelsen et al., 1981, Gates, 2013, Murray et al., 2016, Tarres et al., 2005, Elghafghuf et al., 2014, Oishi et al., 2013). | Parity | Calves from first parity heifers have increased pre-weaning mortality risk of 1.5 times | (Gates, 2013, Patterson et al., 1987, Wittum et al., 1994a, Nix et al., 1998, Azzam et al., 1993, Elghafghuf et al., 2014) |
| | | | Dystocia | Dystocia leads to 4 times increase in calf mortality rate | (Morris, 1980, Wittum et al., 1994a, Nix et al., 1998, Tarres et al., 2005, Ganaba et al., 1995, Azzam et al., 1993, Wittum et al., 1990, Elghafghuf et al., 2014) |

| | | | | | |
|---|---|---|---|---|---|
| | | | **Twins** | **Twinning leads to doubling pre-weaning mortality rates** | **(Gates, 2013, Wittum et al., 1994a, Elghafghuf et al., 2014, Ganaba et al., 1995).** |
| | | | Calving block | Calves born in the last 3 week block are assigned a 1.5 times increase in risk of pre-weaning mortality. | (Morris, 1980, Tarres et al., 2005, Smith, 2012, Elghafghuf et al., 2014, Murray et al., 2016). |
| | | | Pneumonia | Pneumonia leads to a 4 times increase in pre-weaning mortality risk | (Ganaba et al., 1995) |
| | | | Diarrhoea | Diarrhoea leads to a 3 times increase in pre-weaning mortality risk | (Ganaba et al., 1995) |
| **Diarrhoea rate (%)** | BetaPERT (0, 5, 20) | (Wittum et al., 1994b, Murray et al., 2016, Wittum et al., 1994a, Schumann et al., 1990). | Parity | Calves from first parity heifers were assigned double the risk of diarrhoea than those from cows | (Schumann et al., 1990) |
| **Pneumonia rate (%)** | BetaPERT (0, 5, 20) | (Wittum et al., 1994b, Murray et al., 2016, Woolums, 2010, Woolums et al., 2013). | Twins | Twins were assigned 13.2 times the baseline risk of pneumonia | (Wittum et al., 1994a) |
| | | | Calf sex | Male calves were assigned 3.1 times the baseline risk of pneumonia | (Wittum et al., 1994a) |

### 6.4.5 Financial herd inputs

The model was run twice, once with financial herd inputs fixed and once with them varying according to the input distributions. When run using stochastically defined variables, the model was able to represent economic uncertainty, but physical performance indicators, which ultimately farmers tend to have more control over, tended to be associated less strongly with net margin. In order to further investigate the relationship between physical performance indicators and net margin in a given financial situation, the model was also run with fixed financial herd inputs. The inputs were largely defined through consultation with AHDB, market reports, and the Stocktake dataset discussed in Chapter 5, and are summarised in Table 6-6.

**Fixed costs**

Fixed costs were set at £85,000 in the fixed financial variables model, in line with figures for herds of around 200 breeding cows in the Stocktake dataset. In the model where financial inputs varied, fixed costs were defined by a betaPERT distribution with a minimum of £70,000, a maximum of £100,000, and a mode of £85,000, again in line with figures in the Stocktake dataset.

**Variable costs**

Variable costs were allocated on a per breeding cow basis, so in the fixed financial variables model this was set at £160/cow or £32,000 per herd. In the model where financial inputs varied, variable costs were defined by a betaPERT distribution with a minimum of £60/cow, a maximum of £260/cow, and a mode of £160/cow. This again approximates the figures in the Stocktake dataset.

**Replacement costs**

This was incorporated to allow for the cost of getting a retained replacement heifer from weaning (where they would exit the model if they were being sold) to calving. It was set at £300/replacement in the fixed financial variables model and was defined according to a betaPERT distribution with a minimum of £100, a maximum of £500 and a mode of £300 in the variable financial variables model. Again, this is in line with figures in the Stocktake dataset.

**Heifer sale value**

The output of the model is kg of weaned calf, which is determined for heifers and steers. The number of replacements required was deducted from the number of heifers weaned to give the number of heifers available for sale. These were allocated a sale value of £620/heifer in the fixed model and defined by a betaPERT distribution with a minimum of £300, a maximum of £1000 and a mode of £620 in the variable model. This again was defined using values in the Stocktake dataset.

**Steer sale value**

Where actual sale values are not available, the Stocktake dataset uses values of 1.96/kg for native sired calves and 2.35/kg for continental sired calves (AHDB, personal communication). The values extracted from the dataset (2015 only) were a minimum of £1.43/kg, a maximum of £2.57/kg and a median of £2.05/kg. These values were used in the variable financial variables model, with the mode value of £2.05 being used in the fixed financial variable model.

**Cull cow sale value**

This was defined by £/kg culled using weekly market prices for 2017 taken from AHDB market reports (AHDB Beef and Lamb, 2018). There was some seasonal variation observed, but it was assumed that cull animals were sold year-round and so a minimum value of £0.95, a maximum of £1.28 and a mode of £1.11 were used. In the fixed financial costs model, cull cow sale value was set at £1.11/kg.

***Table 6-6: Input values and distributions for the financial sub-model****. The model was run twice, once with financial herd inputs fixed and once with them varying according to the input distributions*

| Variable | Model input value/distribution | References |
|---|---|---|
| **Fixed costs (£)** | Fixed model: 85,000.<br>Variable model: BetaPERT (70,000, 85,000, 100,000) | Stocktake, (AHDB Beef and Lamb, 2018) |
| **Variable costs (£/cow)** | Fixed model: 160<br>Variable model: BetaPERT (60, 160, 260) | |
| **Replacement costs (£/replacement)** | Fixed model: 300<br>Variable model: BetaPERT (100, 300, 500) | |
| **Heifer sale value (£/heifer sold)** | Fixed model: 620<br>Variable model: BetaPERT (300,620, 1000) | |
| **Steer sale value (£/kg)** | Fixed model: 2.05<br>Variable model: BetaPERT (1.43, 2.05, 2.57) | |
| **Cull cow sale value (£/kg)** | Fixed model: 1.11<br>Variable model: BetaPERT (0.95, 1.11, 1.28) | |

### 6.4.6 Conclusion

The simulation model (which will be described in Chapter 7) has been designed to represent spring calving suckler herds in England. Inputs have been informed using data from the literature and available datasets. Where evidence is conflicting, data most appropriate to the system being modelled has been used. However, the literature was generally consistent and an overall consensus could usually be drawn. Where there was no available data, inputs were determined by drawing on expert opinion where possible. Much of the data used is from small field trials, or from herd types that may differ from a typical suckler herd in England. Therefore, the outputs were compared to the available dataset from English suckler herds (obtained from the AHDB Stocktake service as previously described), in order to validate the model.

# Chapter 7: Developing a simulation model to evaluate KPIs for beef enterprises

## 7.1 Introduction

In the previous chapter, literature and available datasets were consulted to inform input values and distributions for the construction of a simulation model, representing a beef production system. The influence different variables in the model had on each other was also considered and incorporated into the design. In this chapter, the structure of the simulation model will be described, and how it has been verified and validated will be discussed. The data produced by the model was analysed and used to further investigate the associations between performance indicators and overall beef enterprise success, defined as net margin/cow bred.

Simulated data is useful when investigating complex systems with many interacting variables, such as farm systems. Associations between variables may be difficult to determine because of 'noise' generated by these interacting variables, many of which may be unrecorded or unrecordable. Simulated data can account for these variables, keeping them constant, and allowing closer examination of associations between recorded variables. Simulation models have been used to investigate various aspects of beef production, for example the economic impact of calving intervals (Raboisson and Citerne, 2018), the effects on biological and economic efficiency of different cross breeding systems (Notter et al., 1979c), the effect of breeding season length on net income (Werth et al., 1991), and the effects of different feeding strategies (Villalba et al., 2006). Some of these models are stochastic (Villalba et al., 2006), some are deterministic (Raboisson and Citerne, 2018, Notter et al., 1979c), and some incorporate aspects of each, for example using outputs of a stochastic model as inputs in a deterministic model (Werth et al., 1991). In stochastic models, inputs are drawn from pre-defined probability distributions. The calculations or algorithms in the model then use these to produce an output, or if this is done multiple times (often referred to as multiple iterations), a set of outputs. In a deterministic model a single set of inputs is used to generate the outputs, with either the 'most likely' values being used, or a small set of alternative values. This is of less use when modelling systems where the inputs are uncertain, which they commonly are. As a result, some studies have built on models previously developed, and deterministic models have been further developed to incorporate more stochastic elements (Kahn and Lehrer, 1984).

The process of running multiple iterations of a stochastic model is commonly referred to as Monte Carlo simulation. Here numbers are drawn from probability distributions for each stochastic variable over many iterations, resulting in output distributions (Kristensen and Jorgensen, 1998). 'Monte Carlo' refers to the similarity between this method and the probability aspect of casino games which was recognised by its developers (Metropolis, 1987). Use of the method is now widespread, largely due to its flexibility and the increased availability of computers with sufficient processing capacity.

Stochastic simulation is of particular use when modelling farming systems, as it allows incorporation of the many uncertainties in a complex system of events that interact to determine an output (i.e. the many variables in a beef production system that can combine to determine net margin/cow bred) (Stygar and Makulska, 2010, Kristensen and Jorgensen, 1998). Analysis of data from stochastic simulation models allows evaluation of how each explanatory variable is associated with an outcome variable, whilst allowing for the uncertainties present in the 'real' system. Here, they will be used to ascertain how different performance metrics are associated with net margin/cow bred.

### 7.1.1 Simulation models and decision support tools

Simulation models allow assimilation of data from multiple sources, and it has been suggested that this is a main advantage of using them to inform decision making as opposed to a (human) 'expert', such as a vet or farm adviser. Farm systems are complex and multi-factorial, and so 'outcomes' are inherently uncertain. Dealing with uncertainty is an area where it has been suggested that the human brain has limited capacity, and incorporating stochastic elements into a simulation model can allow for that (Kristensen and Jorgensen, 1998). These techniques can therefore be used to aid decision making on farm, and indeed in other sectors; they have been used extensively in the financial sector to aid risk management (Evans and Jones, 2009).

Different types of mathematical model are referred to when discussing development of decision support tools, most commonly simulation models and optimisation models (Stygar and Makulska, 2010, Plà, 2007). Simulation models are developed to better understand a system, and enable the user to investigate a series of questions about a system, whereas optimisation models are used to provide optimal outputs for a set of inputs (Stygar and Makulska, 2010). Both may be either deterministic or stochastic in nature. Both optimisation and simulation techniques have been used to model herd management, however such models tend to be used mainly as research or teaching tools, with application in supporting herd management decision making on farm less common (Stygar and Makulska, 2010, Plà, 2007). The uptake of decision support tools in agriculture has been investigated, and factors that may lead to increased uptake identified (Rose et al., 2016). These include performance (providing up to date information and be updated regularly), ease of use (providing instantaneous information), peer recommendation, cost, and habit (for example the farmer using technology in other aspects of life, e.g. mobile phones). Despite current use being relatively low (although increasing), this is a clear area of overlap between research and practice, and an area where an interdisciplinary approach could be beneficial.

### 7.1.2 Simulation model structure and data analysis

The structure of simulation models of beef production may vary depending on their intended use. For example, nutrition research may focus on the metabolic processes of an individual animal (Williams and Jenkins, 2003), whereas simulations developed to compare different production systems may often model at the group or herd level (Sanders and Cartwright, 1979, Johnson and Notter, 1987). Models with herd level outputs may generate these through modelling at the individual cow/calf level (Tess and Kolstad, 2000, Azzam et al., 1990), and herd level models can also be adapted to perform calculations at an individual animal level in order to increase the complexity of the system modelled, for example by adding more variables (Kahn and Spedding, 1983).

The variables included in a simulation model will also vary between studies, depending on the aspects of interest: some models focus on biological variables, for example growth or reproduction (Amer et al., 1997, Azzam et al., 1990), some financial (Werth et al., 1991), and some a combination of both (Oishi et al., 2013, Doren et al., 1985, Werth et al., 1991). Others incorporate genetic (Davis et al., 1994, Tess and Kolstad, 2000) or environmental aspects (Oishi et al., 2013). Models may focus on individual aspects of the production cycle, for example growth (Hoch and Agabriel, 2004), or the overall system (Sanders and Cartwright, 1979, Pang et al., 1999) (with or without financial factors incorporated). Often models of overall systems use several sub-models to separate different aspects of production e.g. growth, fertility and financial variables (Sanders and Cartwright, 1979, Pang et al., 1999), and can be used to evaluate specific areas or answer specific questions (Notter et al., 1979a, Notter et al., 1979b, Notter et al., 1979c).

Mathematical models can produce huge amounts of data, and there are many ways this can be analysed to further understand the system modelled. Results of beef herd simulation models are often analysed in a bivariate way, i.e. investigating relationships between two variables in a model, often in a variety of different situations (Notter et al., 1979a, Notter et al., 1979b, Notter et al., 1979c, Azzam et al., 1990). Simulations may be run a number of times and the outputs compared for the different situations or management options simulated (Doren et al., 1985, Werth et al., 1991). Alternatively, a single situation may be modelled and the data analysed in a multivariable way, for example multiple regression or ANOVA models, allowing associations between variables to be evaluated whilst accounting for all other variables. No examples of this using beef herd simulation models were identified in the literature at the time of writing, but examples exist using dairy models (Kristensen et al., 2008, Hudson et al., 2014).

Probabilistic sensitivity analysis (PSA) is a technique that may be used to assess the relative importance of simulation model inputs in influencing the output (Oakley and O'Hagan, 2004), for example by increasing or decreasing by a set amount certain elements of the model and comparing the effects on the outcome (Amer et al., 1997, Pang et al., 1999, Villalba et al., 2006, Blanc and Agabriel, 2008). This allows further understanding of the influence of certain inputs on an output variable, and is clearly of great interest when investigating to what extent different factors are associated with enterprise success. The technique has been used extensively in human medicine for cost-benefit analysis, and is in fact required by the National Institute for Health and Clinical Excellence in order for them to make policy decisions (Andronis et al., 2009). There are also some veterinary examples, for example using PSA to analyse dairy herd data, and investigate the relationship between a lameness event occurring and the risk of the cow becoming pregnant (Hudson et al., 2014). Studies such as this illustrate how these techniques can be used to help inform herd management decisions on farm.

## 7.2 Aims

In Chapter 6 a literature search was conducted to inform input distributions for a simulation model of a typical beef suckler system. The aims of this chapter were to develop the structure of that simulation model and to analyse the data produced to investigate associations between performance indicators and overall beef enterprise success.

## 7.3 Methods

During development of the current simulation model, literature around various aspects of suckler production was consulted to inform model inputs, as described in Chapter 6. Existing literature also informed the relationships between the various parts of the production cycle, and how one variable may affect another. Input values were drawn randomly from the distributions informed by the literature, providing the stochastic element of the model. Input values represented a baseline level of production, before the influence of any effector variables. In order to ensure that values used were appropriate, simulation model outputs were validated against the Stocktake dataset analysed in Chapter 5. Herd-level input values were drawn initially (where these varied between herds). Cow and calf values were then drawn for each cow-calf unit. This was repeated 200 times to create a 'herd' of 200 cows with calves. The whole process was then repeated 10,000 times to produce data for 10,000 herds of 200 cows. Analysis of this dataset was used to explore the relationship between inputs and outputs of the system, and to further evaluate associations between the performance indicators discussed at earlier stages of the project, and overall enterprise success (net margin/cow bred).

### 7.3.1 Simulation model structure and implementation

Simulation was carried out in Microsoft Excel 2016 using Visual Basic for Applications (Microsoft Corp.). Macros are provided in Appendix 3. Individual cows were modelled over a two year period. The first year provided a 'burn in' period for each cow, so that aspects of her previous calving (calving 1) were able to influence the current calving period (calving 2). For example, a cow who had dystocia at calving 1 would have a prolonged PPAI at calving 2, and so would not be eligible to be served until later in the breeding period. The output of the model was kgs produced, which included weaned calves and cull cows (although the financial value of these differed). The overall structure of the simulation model is represented diagrammatically in Figure 7-1. The production system was broken down into reproduction, growth, health and financial sub-models, as discussed in the previous chapter. A cow inputs sub-model included any potential influences from the previous calving season, as well as individual cow features such as parity category, BCS and weight.

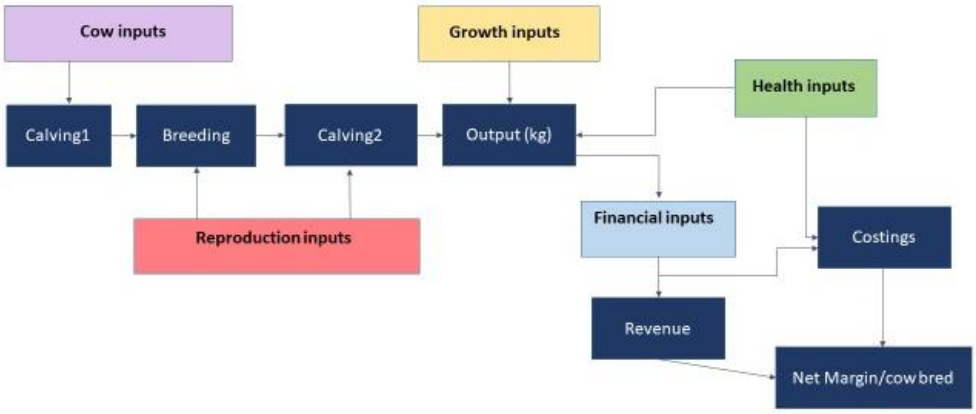


***Figure 7-1: Overview of simulation model structure****. Cow, reproduction, growth, health and financial sub-models all contributed to simulate a net margin/cow bred output. Two calvings were included in the model so that calving 1 could influence breeding and calving 2. Output of the cow, reproduction, growth and health sub-models (kg produced) was fed into the financial sub-model to generate revenue, and costings were used to convert this to net margin.*

For each calculation of a continuous variable in the model, values were drawn randomly from the distributions provided. For calculation of binary variables, i.e. whether an event happened or not, a binomial distribution was used based on the probability of the event occurring, which was either a fixed value or drawn from a distribution informed by the literature (see discussion of input distributions in Chapter 6).

The model operated at cow/calf level and herd level. Values were drawn at different levels depending on the literature available and what was felt to be most plausible for that variable:

- Some variables were set across all herds (for example abortion, twinning, dystocia and stillbirth rates), i.e. the baseline value was the same across all herds in the simulation and they were only altered by effector variables.
- Some variables were defined at the herd level i.e. the baseline value was the same for all animals in an individual herd, but varied between herds according to a defined distribution, for example mortality rates.

- Some variables were defined at the individual cow level, for example parity, resulting in the age distribution varying between different herds, but following the defined distribution across the population as a whole.
- Some variables were drawn at both cow and herd level, for example calf DLWG. Herds were randomly assigned either a high, medium or low DLWG, and values for individual calves were drawn from the appropriate herd distribution.

Baseline variable values drawn had the potential to be modified by effector variables in the model, for example if dystocia occurred at calving 1, the post-partum anoestrus interval (PPAI) for that cow was increased by two weeks. These effects were incorporated for binary variables by modifying the probability of the binomial distribution as appropriate, thus making it more or less likely to occur. For continuous variables they were incorporated by altering the value drawn for that variable by a specified amount.

#### *7.3.1.1 Cow sub-model*

The cow inputs section, represented diagrammatically in Figure 7-2, provided the model with individual cow features such as parity, BCS and weight. It also included previous calving season information (calving 1) including dystocia, twinning, stillbirth and abortion events, and calving time within calving period. This was required to calculate calving interval, and to ascertain when the animal would be eligible for breeding in the current breeding period. Some of these distributions were defined at the herd level (BCS, weight and calving week), so individual cow values were drawn from a herd specific distribution, whereas some were defined at the cow level (for example parity). Values drawn at the cow level had the potential to be influenced by effectors when determining the final value or probability of an event occurring.

Changes in BCS were not accounted for in the model, and the stochastically determined BCS value for an individual cow remained the same throughout the two calving seasons. Weight however was adjusted for parity zero heifers and first parity cows to ensure that when calculating cow efficiency (weaning weight as a proportion of cow weight), weight closer represented weight at weaning rather than weight at bulling, and so that if the animal became a cull cow her cull weight would better reflect age at culling. Time of calving in the previous calving season (calving 1) was determined through drawing first the calving block (i.e. the 3 week block during the 12 week calving period), and then the week within that block that calving occurred. Calving block was drawn from a BetaPERT distribution with a minimum value of 1 (i.e. block 1, or the first 3 weeks of the calving period), a mode value determined at the herd level, and a maximum value of 4 (i.e. block 4 or weeks 10-12 of the calving period). This was followed by drawing the week of calving within that block from a uniform continuous distribution with a minimum value of 1 and maximum value of 3. As calving patterns are likely to be more similar within herds than between different herds, the mode value for the BetaPERT distribution of calving block at the cow level was drawn at the herd level from a discrete distribution in which 65% of the herds would have a mode value of 1, 30% a mode of 2 and 5% a mode of 3. It was felt that it would be unlikely for most cows in a herd to calve in the final 3 week block of the calving period (block 4), and so this scenario was excluded.

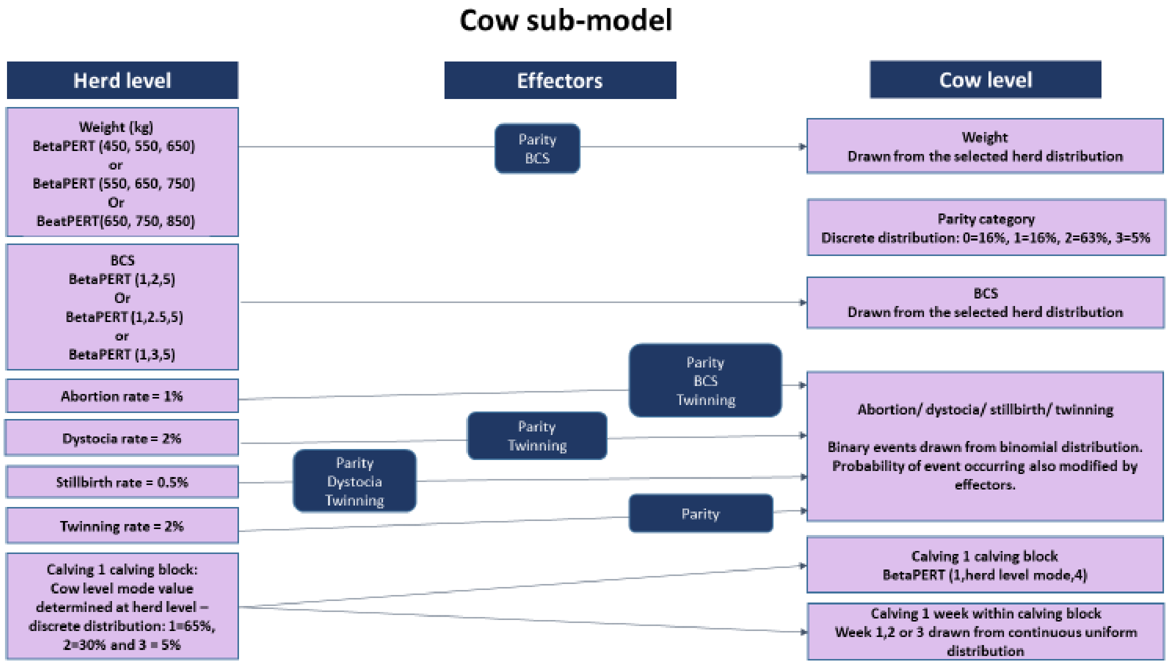


*__Figure 7-2: Cow sub-model__. Herd level variables are displayed with distributions or set values. Effector variables, which help inform the individual cow variables, are also displayed. The individual cow variables were used to inform the reproduction sub-model.*

### *7.3.1.2 Reproduction sub-model*

The reproduction sub-model, represented diagrammatically in Figure 7-3, provides the model with information for the current breeding season and calving 2. PPAI was selected at the individual cow level through drawing values from a defined distribution. The number drawn could also be altered by the effector variables.

Eligibility for service was then determined by the number of weeks calved at the beginning of the breeding period (calculated from the calving week in calving 1) and the PPAI, with cows becoming eligible for breeding once the animal's PPAI had finished. Herd 21-day pregnancy rate was drawn at the herd level, and whether an individual cow became pregnant or not was determined in a binary way for each three week cycle in the 12 week breeding period, with effector variables having the potential to alter the event threshold (herd pregnancy rate). Abortion, dystocia, stillbirth and twinning rates were included in the reproduction sub-model in the same way as for the cow inputs model, but effectors included events from the previous calving (calving 1), which had the potential to influence reproductive performance at the current calving (calving 2). Calving 2 calving block was determined by the breeding cycle the animal became pregnant in, as determined by her eligibility and 21-day pregnancy rate. Calving week within the 3-week block was drawn from a uniform continuous distribution so that weeks 1,2 or 3 were equally likely to be drawn. Calving 1 calving week and calving 2 calving week could then be used to calculate a calving interval in weeks. The number of calves born alive was also determined in this sub-model, and was defined by the pregnancy rate, abortion rate, stillbirth rate and twinning rate. The model did not allow for one calf in a set of twins to be stillborn (or for individual calves in a set of twins to behave differently in any way), but it was felt that, as the rates involved were low, the effect of this would be minimal. The output of the reproduction sub-model was the number of calves born alive. This was input into the growth sub-model to determine the weight gain of these calves up to weaning.

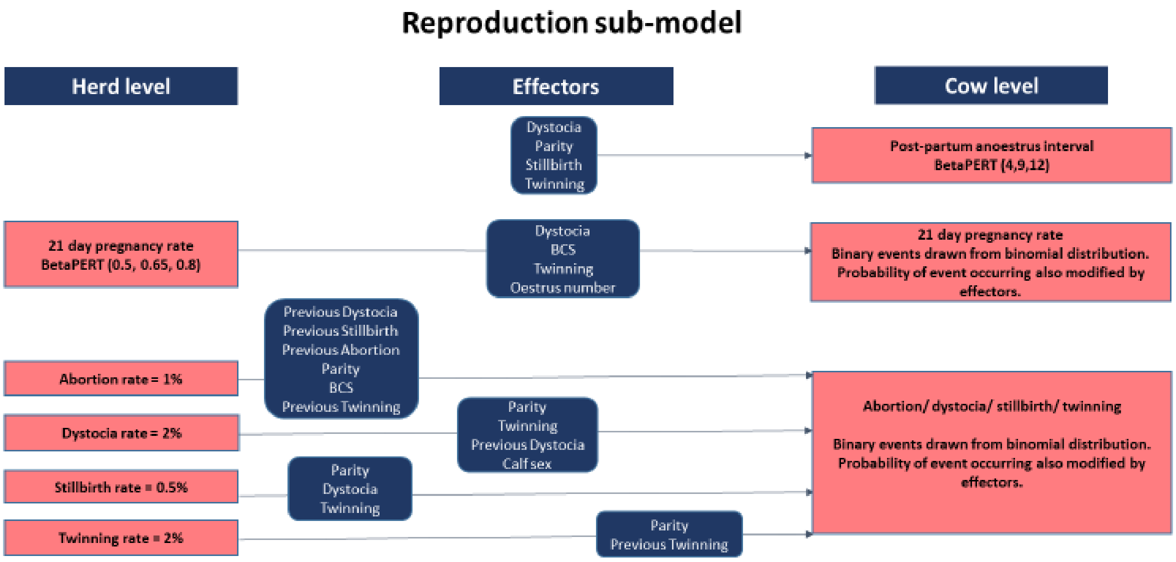


***Figure 7-3: Reproduction sub-model.*** *Herd level variables and distributions or set values are shown. Effector variables that will influence the cow level variables are also indicated. Cow level variables were used to determine the output of breeding and calving, which fed into the growth sub-model.*

### 7.3.1.3 Growth sub-model

The growth sub-model determined calf DLWG, from which actual and 200-day adjusted weaning weights were calculated, as outlined in Figure 7-4. A herd average (mode) was drawn at the herd level and used to define a distribution from which individual calf values were drawn. Effector variables were again able to influence an individual's DLWG value.

The output of the growth sub-model was weaning weights (actual and 200 day adjusted values), which were calculated from DLWG values. 200-day weaning weights are useful to compare between farms or years, as they are less affected by when the calf is born within the calving period. In comparison, actual weaning weights consider when a calf was born, with those being born earlier in the calving period being older, and therefore potentially heavier, at weaning. Weaning age was calculated to allow an actual weaning weight to be determined. It was assumed that calves born in week

9 were weaned at 200 days, those born in week 8 at 207 days, week 7 at 214 days etc. Actual weaning weight was then calculated considering calf sex, as this was modelled to influence birthweight. Cow efficiency was also calculated as the ratio between the 200-day weaning weight and the cow weight.

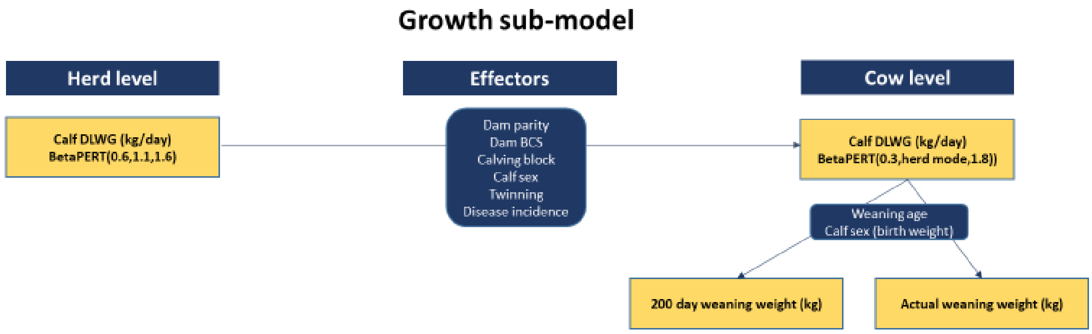


***Figure 7-4: Growth sub-model****. Herd level DLWG distributions are shown. Values drawn from this distribution may be influenced by the effector variables, before informing the individual cow level values. The output values from this sub-model are kg of calf (either quoted as 200 day weaning weight or actual weaning weight).*

### *7.3.1.4 Health sub-model*

The health sub-model provided information around mortality rates (cow and calf), cull rates (voluntary and involuntary) and disease incidence, as shown in Figure 7-5. These are all binary variables at the cow level, and occurrence was determined by drawing from a binomial distribution as previously described. The probability of each event occurring was defined by the herd rate, drawn from a defined distribution, as outlined in the diagram. The outputs of the health sub-model were the weight of cull cows to be sold, and in conjunction with the growth sub-model, the number and weight of calves weaned. Replacement rates were also calculated from cull and mortality rates: the herd was modelled to be in equilibrium, i.e. the herd size did not change, therefore the number of replacements required was the same as the number of breeding cows lost through mortality rates and culling. Voluntary culls were defined by the herd cull rate and effectors as shown in the diagram, and involuntary culls were barren cows (those that failed to become pregnant during the breeding period). These all fed into the financial sub-model to allow for revenue and costs to be determined.

### *7.3.1.5 Financial sub-model*

The financial sub-model was used to take outputs from the growth (kg of calf produced) and health sub-models (number of cull cows and replacement rates) and to calculate revenue and costs. All values were drawn at the herd level, and there was no individual animal variability (they were all herd average values), as outlined in Figure 7-6. Revenue from steer calves sold was calculated per weight of calf sold. However for heifers only number sold could be calculated in the model, as some were kept for replacements. Sale weights used were actual, rather 200-day adjusted, weaning weights.

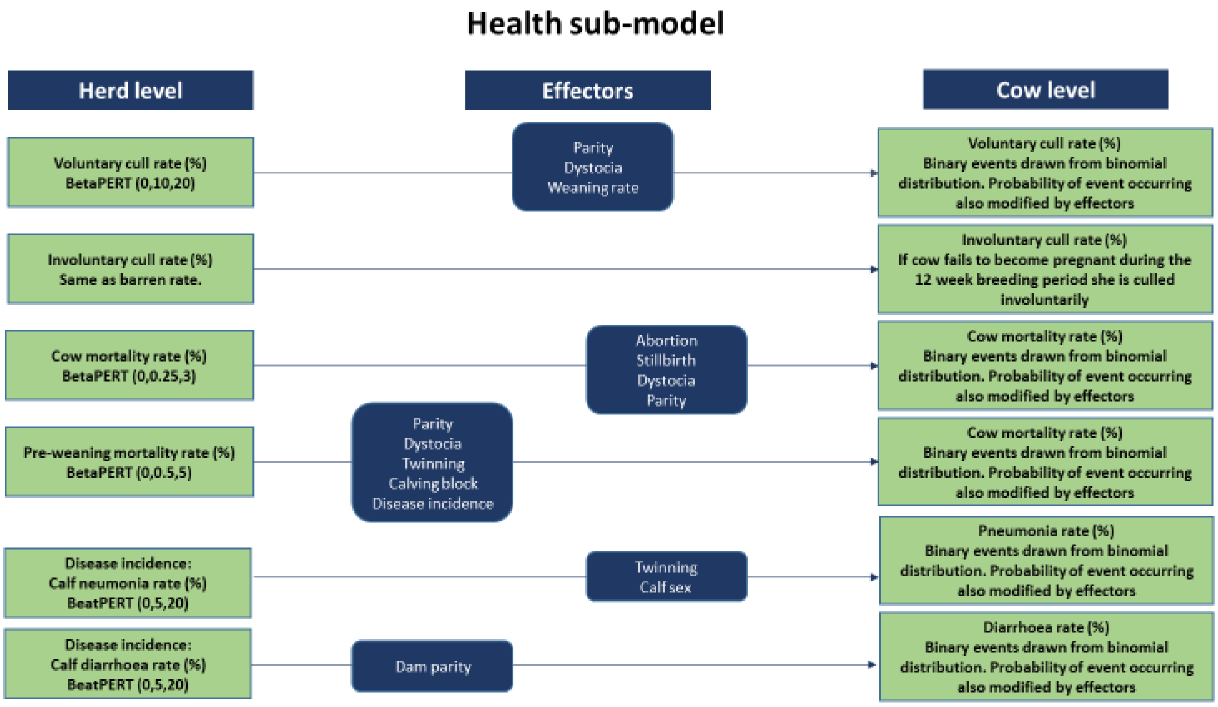


***Figure 7-5: Health sub-model:*** *Herd level variable distributions are shown. Effector variables that influence the individual animal level variables are displayed and the outputs from the health sub-model are fed into the growth sub-model to help determine overall kg of output.*

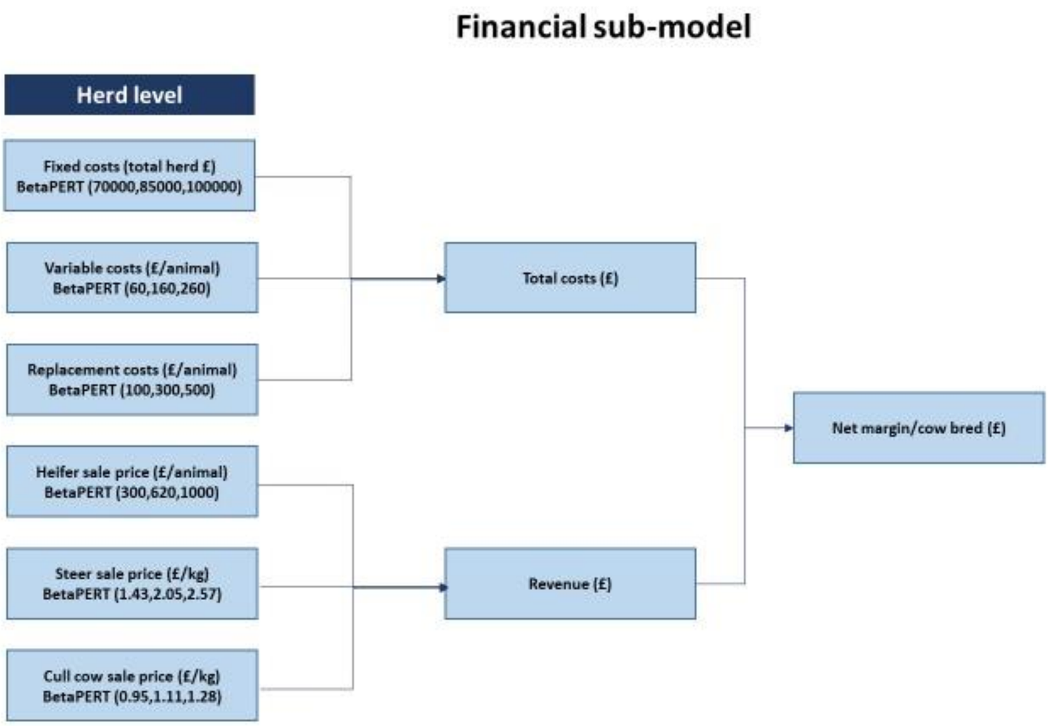


***Figure 7-6: Financial sub-model****. Herd level variable distributions are shown which determine total costs and revenue. These values determine the model output, net margin/cow bred.*

### 7.3.2 Model tuning and validation

The herd modelled was a spring calving herd, as this is the most common calving pattern in the UK (Gates, 2013). Herd size was set at 200 breeding cows, which although clearly larger than the average breeding herd in the UK, was felt to be large enough to reduce any 'noise' that may be created by chance events or outlier values in a smaller herd. In order to evaluate how appropriate a herd size of 200 was in the model, all random variables were fixed (at the mode value) at the herd level. This allowed some individual cow variation but prevented extreme values being drawn, and effectively the same 'average' herd of 200 cows was simulated 10,000 times. Herd averages and distributions of variables were comparable with the previous model (assessed visually using histograms and comparing mean values and standard deviations), indicating that the herd size of 200 was sufficient to prevent individual animal outlier values having a significant effect on the herd averages generated.

10,000 herds were modelled as it was felt that this would provide sufficient data for analysis. During model tuning the model was run with 20,000 herds, but the distribution of net margin was very similar to the 10,000 herd run, as were the results of some preliminary data analysis. Therefore, it was felt that the extra time taken for the larger dataset to be generated was not warranted, and that the 10,000 herd model would be more nimble to work with.

The final version of the model described was developed initially through consultation of the literature, but to ensure that the outputs were applicable to suckler herds in England it was validated against a pre-existing dataset. The Stocktake dataset, which contains a small sample or observed outputs for similar herds (as described in Chapter 5) was used. Minimum, maximum and median values of model outputs and equivalents from the Stocktake dataset were compared in tables. Distributions of model outputs such as pregnancy rate, mortality rate and DLWG were compared visually using histograms to ensure comparability. Where there was little available supporting evidence, consideration was also given to what was felt to be appropriate for an English suckler herd.

Some inputs were revised at this tuning stage and baseline rates were changed if outputs appeared much higher or lower than those reported in studies, or in the Stocktake dataset. For example, when calculating weaning age it was initially assumed that calves born in week 6 (the middle of the calving period) were weaned at 200 days of age, those born in week 5 were weaned at 207 days of age, those in week 4 at 214 days etc. This was modified after running the model as weaning weights and ages were lower than anticipated and did not fit well with the Stocktake dataset, despite DLWG values being similar. This suggested that although 200 days is commonly used for adjusting weights at weaning to allow comparisons, calves tend to be weaned older than this in reality (the median value in the Stocktake dataset was 235 days). This was altered in the final model so that calves born in week 9 were weaned at 200 days old, those born before this would be older at weaning and those born after would be younger. Tuning the model in this way was found to be particularly important where effector variables were influencing the baseline rate defined in the model; often assumptions had to be made when determining these baseline values from the literature, for example defining a calf mortality rate in the absence of any disease, dystocia, twinning etc. was challenging from the literature available. There are many reports of the challenges associated with validating simulation models where there is limited real farm data (Stygar and Makulska, 2010, Plà, 2007, Pang et al., 1999), and the described model tuning and validation stage was felt to be an effective way of ensuring plausibility of the model and application to English suckler herds.

### 7.3.3 Data analysis

The final model output was a set of performance indicators (or data from which performance indicators could be calculated) for 10,000 simulated herds. The performance indicators generated (and calculated) reflected those in the KPI toolkit (previously described in Chapter 2), and those available in the Stocktake dataset (used for analysis in Chapters 4 and 5), and included both physical and financial metrics. This was used to further explore the relationship between specific performance indicators and overall enterprise success, which was defined as net margin/cow bred. Initially, bivariate analysis of individual performance indicators with net margin/cow bred was done, and indicators were ranked by their level of association with this measure of enterprise success. A multiple regression model was then built in a forward stepwise fashion (as described in Chapter 4), adding indicators in the order of their ranking and retaining them in the model if they showed a significant association with net margin/cow bred ($p<0.05$). All variables were re-offered to the final model to check for significance.

As the regression model outcome variable was a financial metric, financial variables were found to explain most of the variation in net margin/cow bred when both physical and financial explanatory variables were added to the model. In order to better understand the relationships between physical metrics and net margin/cow bred, regression models were also built for physical and financial explanatory variables separately. This resulted in four regression models being constructed; the first including comprehensive financial variables, the second including comprehensive physical variables, and two further models exploring more specific physical variables. Model fit was assessed as previously, through evaluating the distribution of standardised residuals, leverage and influence values (Figure 7-7). A fifth model including both comprehensive physical and comprehensive financial variables was explored, but its fit was found to be unsatisfactory. This is likely to be due to the high correlation of the predictor variables in the model when both physical and financial variables are included.

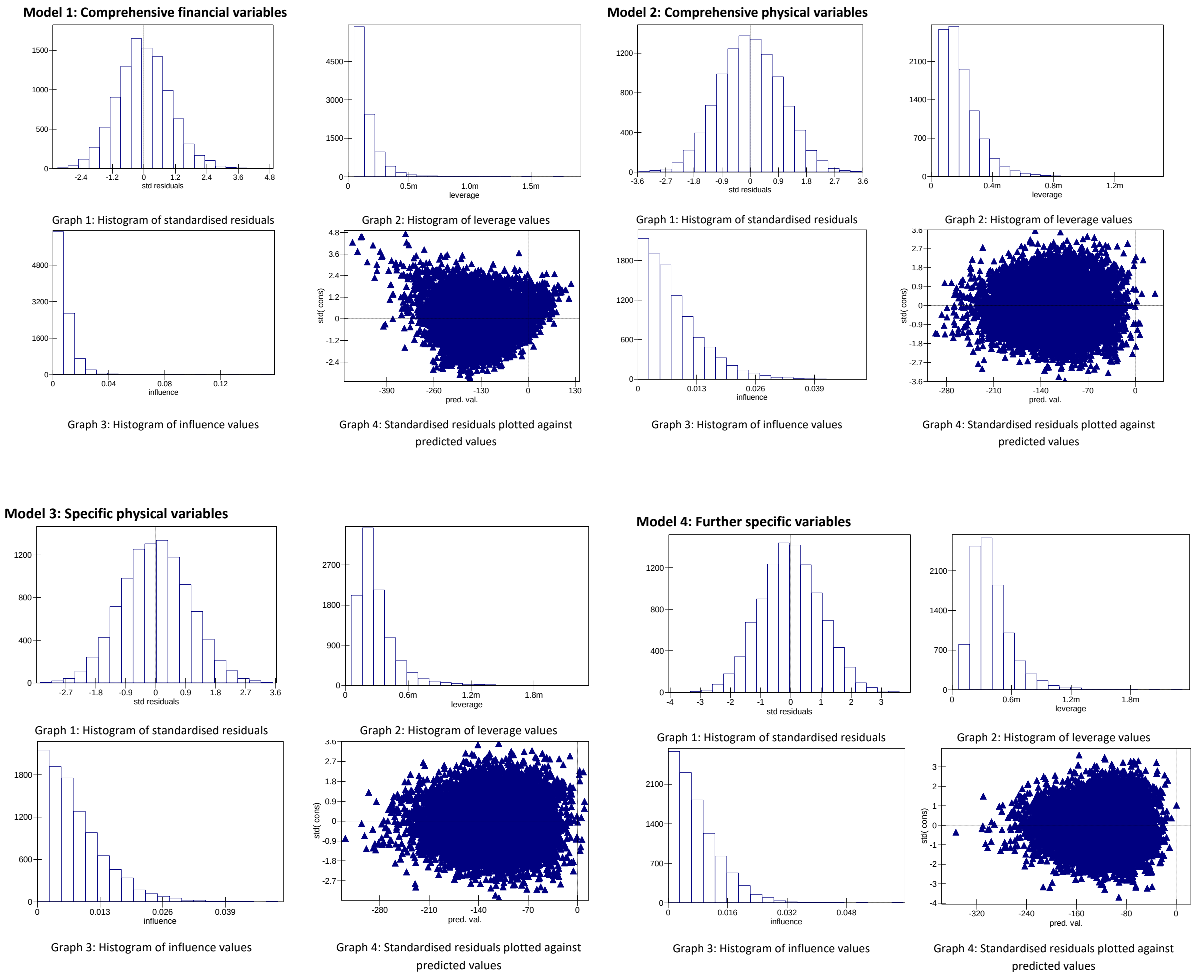


***Figure 7-7: Assessment of model fit, models 1-4.*** *Model fit was assessed by evaluating the distribution of the standardised residuals to check for approximation to a normal distribution (it would be expected that 95% of residuals would lie between -2 and +2). Leverage and influence values were also evaluated. Standardised residuals were plotted against predicted values to assess homoscedasticity.*

## 7.4 Results and discussion

### 7.4.1 Model tuning and validation

Following tuning, the model was validated against a pre-existing dataset as described in the previous section. Table 7-1 summarises the outputs from the model and compares the figures with the Stocktake dataset. Not all herds in the Stocktake dataset were included when calculating all the distributions, for example only block calving herds were used for the outputs relating to block calving (percent calving in the first 3, 6, or 9 weeks and calving period), and herds with zero values for pregnancy rate in Stocktake were removed (this reflects no use of pregnancy scanning rather than an actual pregnancy rate). The table is colour coded to reflect the area of the production cycle each performance indicator output measures: red sections contain reproduction metrics, orange reproduction and growth, purple reproduction and health, yellow growth, green health and blue financial.

Many of the suckler herds contributing to the Stocktake dataset are small, and so extreme values are to be expected and do not necessarily mean that the model should be revised substantially to reflect these (in fact, the aim of the model is to reduce the 'noise' associated with such outlier values). The larger inter quartile ranges (IQR) reported for the Stocktake dataset reflect this wider distribution. The 12 week calving period modelled also ensures very little variation in calving period and weaning age, which is reflected in the much lower IQRs reported for these outcomes in the simulated dataset as opposed to the Stocktake dataset. The IQRs for 200-day weaning weight are similar between the two datasets, despite actual weaning weight IQRs being very different. This suggests that lots of the variation seen in weaning weight in the stocktake dataset is due to variation in weaning age.

### 7.4.2 Bivariate analysis

Data was initially analysed in a bivariate way using Excel 2016 (Microsoft Corp.), evaluating the association between net margin/cow bred and each metric in turn. This allowed ranking of the metrics in order of their association with net margin/cow bred, as displayed in Table 7-2.Financial variables tended to explain the most variation in net margin as would be expected, and of these, gross margin ranked the highest (the only difference between gross and net margin was fixed costs). In this model, revenue explained more variation in net margin/cow bred than cost variables (as discussed in the multiple regression analysis section), and variable and fixed costs calculated per kg explained more than variable and fixed costs calculated per calf. However, total costs per kg and per calf weaned were very similar in the amount of variation in net margin/cow bred they explained

*Table 7-1:* ***Comparison of simulation model outputs and Stocktake dataset*** *for model validation (where available). Median and inter-quartile range (IQR) values given for comparison. Outputs are colour coded according to area of production they represent:* Red = reproduction, orange = reproduction and growth, purple = reproduction and health, green = health and blue = financial.

| Output | Simulation model | | Stocktake dataset | |
|---|---|---|---|---|
| | Median | IQR | Median | IQR |
| % calved in first 3 weeks | 29 | 7 | 33 | 39 |
| % calved in first 6 weeks | 72 | 15 | | |
| % calved in first 9 weeks | 91 | 6 | | |
| Overall pregnancy rate (%) | 92 | 5 | 91 | 7 |
| Calving period (weeks) | 12 | 0 | 13 | 11 |
| Barren rate (%) | 8 | 6 | 8 | 9 |
| % Born alive | 88 | 6 | 88 | 55 |
| % Stillborn | 2 | 2 | 2 | 4 |
| Twinning rate (%) | 2 | 2 | | |
| Abortion rate (%) | 2 | 1 | | |
| Dystocia rate (%) | 9 | 3 | | |
| Weaning age (days) | 226 | 9 | 235 | 99 |
| Median calving interval (weeks) | 53 | 0 | | |
| Median efficiency (kg calf weaned/kg cow) | 35 | 9 | | |
| Weaning rate (%) | 87 | 7 | 86 | 51 |
| DLWG (kg/day) | 1.02 | 0.16 | 1.08 | 0.99 |
| 200d weaning weight (kg) | 242 | 33 | 249 | 41 |
| Actual weaning weight (kg) | 267 | 37 | 290 | 133 |
| Pre-weaning mortality rate (%) | 2 | 3 | 2 | 4 |
| Cow mortality rate (%) | 1 | 1 | 2 | 3 |
| Replacement rate (%) | 16 | 7 | 17 | 22 |
| Cull rate (%) | 15 | 7 | 11 | 18 |
| Pneumonia incidence (%) | 14.5 | 11 | | |
| Diarrhoea incidence (%) | 7.5 | 6 | | |
| Total cost/kg (£) | 2.79 | 0.55 | 2.78 | 1.96 |
| Net margin/cow bred (£) | -119.78 | 101.44 | -166.46 | 870.90 |
| Variable cost/cow bred (£) | 160.21 | 49.36 | 166.67 | 212.88 |
| Fixed costs/cow bred (£) | 424.93 | 36.33 | 478.75 | 389.48 |
| Fixed costs/kg (£) | 1.87 | 0.35 | 1.91 | 1.58 |

The different denominators that may be used when calculating these performance indicator metrics (cows bred, kgs weaned or calves weaned) allow values to be standardised for comparison between enterprises or across years. Which one is used ‘on farm’ may often depend on what data is available, for example whether the total kgs of weaned calf is known. In this model, the number of cows bred did not vary between the herds (every herd bred 200 cows), and so when fixed and variable costs were expressed per cow bred, they explained less of the variation in net margin than when expressed per kg weaned or calf weaned (as these do vary). Expressing values per kg weaned tended to explain more variation in net margin than expressing them per calf weaned. This may be because kg weaned is determined by both the number of calves weaned and calf growth, and so may have greater potential to influence net margin than the number of calves weaned alone. (In this model, when kg was used as the denominator, this did not include kg of cull cows produced).

In contrast, the 'total cost' metrics explained the variation in net margin to the same degree, whether expressed per kg produced or per calf weaned. In this model, total costs were the sum of fixed, variable and replacement costs, and so it may be the influence of replacement costs that caused this difference. Replacement costs were calculated using barren and mortality rates (as these determined the number of replacements required to maintain herd size), and so incorporated fertility and health aspects of production. As the numerator in the 'total cost' metrics also incorporated fertility and health aspects, it may be that the effect of the denominator incorporating multiple aspects of production was reduced, and so the influence of the two metrics on net margin was more similar.

In general, more comprehensive metrics explained more variation in net margin in this dataset. This is reflected in the weaning weight/cow bred variables; these explain more of the variation in net margin than the fertility variables as they incorporate aspects of fertility and growth, rather than fertility alone. In a similar way, actual weaning weight values tended to explain more of the variation in net margin than 200-day adjusted values. This is due to actual values incorporating an element of fertility performance, as calves born earlier in the calving period will be older (and therefore likely to be heavier) at weaning. 200-day adjusted values however are more useful when a standardised value is required for comparison, for example between farms or across years. Surprisingly for a comprehensive performance indicator, cow efficiency explained less variation in net margin. This may be because this model did not take into account cow size when allocating costs, so allowances for larger cows taking up more room and eating more were not made. DLWG to weaning, as a more specific performance indicator, explained less variation in net margin.

For several metrics, both mean and median values were correlated with net margin. Mean values tended to correlate better in this dataset, probably because the net margin value used was also a mean. When analysing 'real' farm data, where outlier values may be liable to have more of an influence on means, median values may be more appropriate.

Of the fertility metrics, number of calves weaned/cows bred explained most variation in net margin. This is a more comprehensive performance indicator than many of the other fertility metrics investigated, as it also incorporates pre-weaning mortality rate, a health aspect of performance. This was a popular performance indicator with the TAG, as the data is readily available (the number of calvings and calf deaths is statutory to record), and the calculation is straight forward. Pregnancy rate and barren rate explained the same amount of variation in net margin, as in this model they are the reverse of each other (if a cow is not pregnant she is barren). The percent calving in the first 9 weeks of the calving period explained more variation in net margin than the percent calving in the first 6 weeks, which in turn explained more than the percent calving in the first 3 weeks. This suggests that in this model, how many cows calve overall has more influence on net margin than when in the calving period they calve. This may be because the calving period modelled is relatively short at 12 weeks maximum; if a herd with a longer calving period was modelled, calving earlier may become more important in explaining variation in net margin.

Health metrics tended to correlate less well with net margin than metrics measuring other aspects of performance in this modelled dataset. This may be in part because there was less available literature to inform the model inputs in this area. Of these metrics, replacement rate correlated to the greatest degree, which is to be expected as it is the most comprehensive; it is partly determined by barren rate and so has a fertility component.

### 7.4.3 Multiple regression analysis

Multiple regression models were built in a forward stepwise fashion as described in chapter 4. Separate models were constructed for financial and physical variables initially so as to avoid dominance of the financial variables in explaining variation in the financial outcome variable (as previously). As is inevitable with a dataset such as this, where many of the variables are calculated from each other, there were lots of highly correlated predictor variables. For example, number of calves born alive per 100 bred and number of calves weaned per 100 bred were highly correlated as they measure very similar aspects of performance; the only difference being that the latter metric incorporates pre-weaning mortality rate. This was particularly problematic with the comprehensive metrics (as they measure multiple aspects of performance) and made interpreting the regression model difficult. Therefore, separate regression models were constructed for comprehensive variables and more specific ones to minimise correlation between predictor variables. Model fit was assessed and found to be satisfactory (Figure 7-7). The total variation in net margin/cow bred explained by each model was also determined by plotting observed values against predicted values.

***Table 7-2: Bivariate analysis of simulated production metrics and net margin/cow bred**, ranked by order of association. Red = reproduction, orange = reproduction and growth, purple = reproduction and health, yellow = growth, green = health and blue = financial.*

| Performance indicator | Significant relationship with net margin/cow bred? | Proportion of net margin/cow bred explained ($r^2$) |
|---|---|---|
| **Gross margin/cow bred** | Yes ($p<0.01$) | 0.8303 |
| **Revenue/cow bred** | Yes ($p<0.01$) | 0.6304 |
| **Total cost/calf weaned** | Yes ($p<0.01$) | 0.57692 |
| **Total cost/kg weaned** | Yes ($p<0.01$) | 0.57691 |
| **Variable costs/kg weaned** | Yes ($p<0.01$) | 0.4204 |
| **Total cost/head/day** | Yes ($p<0.01$) | 0.4073 |
| **Fixed costs/kg weaned** | Yes ($p<0.01$) | 0.3888 |
| **Fixed costs/calf weaned** | Yes ($p<0.01$) | 0.337 |
| **Variable costs/calf weaned** | Yes ($p<0.01$) | 0.3126 |
| **Total weaning weight** | Yes ($p<0.01$) | 0.2842 |
| **Weaning weight/cow bred** | Yes ($p<0.01$) | 0.2841 |
| **200-day weaning weight/cow bred** | Yes ($p<0.01$) | 0.2667 |
| **Total 200-day weaning weight** | Yes ($p<0.01$) | 0.2667 |
| **Number calves weaned/cow bred** | Yes ($p<0.01$) | 0.2311 |
| **Percent of calves born alive** | Yes ($p<0.01$) | 0.2056 |
| **Variable costs/cow bred** | Yes ($p<0.01$) | 0.1958 |
| **Pregnancy rate** | Yes ($p<0.01$) | 0.1923 |
| **Barren rate** | Yes ($p<0.01$) | 0.1923 |
| **Percent calving in first 9 weeks of calving period** | Yes ($p<0.01$) | 0.1578 |
| **Average weaning weight** | Yes ($p<0.01$) | 0.1411 |
| **Percent calving in the first 6 weeks of the calving period** | Yes ($p<0.01$) | 0.1301 |
| **Fixed costs/cow bred** | Yes ($p<0.01$) | 0.1172 |
| **Percent calving in the first 3 weeks of the calving period** | Yes ($p<0.01$) | 0.1024 |
| **Average 200-day weaning weight** | Yes ($p<0.01$) | 0.0983 |
| **DLWG up to weaning** | Yes ($p<0.01$) | 0.0938 |
| **Percent pregnant in the first 9 weeks of the breeding period** | Yes ($p<0.01$) | 0.086 |
| **Replacement rate** | Yes ($p<0.01$) | 0.0799 |
| **Percent pregnant in the first 6 weeks of the breeding period** | Yes ($p<0.01$) | 0.076 |
| **Cull rate** | Yes ($p<0.01$) | 0.0713 |
| **Average calving interval (mean)** | Yes ($p<0.01$) | 0.0414 |
| **Average calving interval (median)** | Yes ($p<0.01$) | 0.0375 |
| **Average cow efficiency (mean)** | Yes ($p<0.01$) | 0.037 |
| **Average cow weight (mean)** | Yes ($p<0.01$) | 0.0367 |
| **Pre-weaning mortality rate** | Yes ($p<0.01$) | 0.0235 |
| **Average cow efficiency (median)** | Yes ($p<0.01$) | 0.0136 |
| **Cow mortality rate** | Yes ($p<0.01$) | 0.0123 |
| **Abortion rate** | Yes ($p<0.01$) | 0.0079 |
| **Dystocia rate** | Yes ($p<0.01$) | 0.0029 |
| **Percent stillborn** | Yes ($p<0.01$) | 0.002 |
| **Pneumonia incidence rate** | Yes ($p<0.01$) | 0.0016 |
| **Scour incidence rate** | Yes ($p<0.01$) | 0.0014 |
| **Percent pregnant in the first 3 weeks of the breeding period** | Yes ($p<0.01$) | 0.0012 |
| **Twinning rate** | Yes ($p<0.05$) | 0.0006 |

### 7.4.3.1 Model 1: Comprehensive financial variables

Comprehensive financial variables were added to the model with the aim of incorporating both a revenue and a cost aspect. This would allow the balance of cost versus return on influencing net margin to be assessed. Predictor variables to be included in the model were chosen according to their degree of bivariate correlation with net margin/cow bred; those with a greater degree of correlation were included in the model. For example, a metric including 'total cost' was required as this was the most comprehensive cost metric. Total cost/calf weaned was included as it explained more variation in net margin than total cost/kg weaned and total cost/head/day (the other total cost metrics available). Revenue/cow bred was the only revenue metric available and so was included in the model.

***Table 7-3: Model 1 - comprehensive financial variables****. Regression coefficients, standard errors, p-values and effect sizes for comprehensive financial explanatory variables. Financial explanatory variables highlighted in blue.*

| Model term | Coefficient | Standard error | p-value | Difference in net margin/cow bred between best and worst herds (£) | Value of 1 unit improvement in performance for average sized suckler herd (£) |
|---|---|---|---|---|---|
| **Net margin/cow bred (£)** | Outcome | | | | |
| **Revenue/cow bred (£)** | 0.773 | 0.00475 | <0.01 | 334.66 | 20.79 |
| **Total cost/calf weaned (£)** | -0.544 | 0.00367 | <0.01 | 359.14 | 14.58 |

Each pound increase in revenue/cow bred was associated with £0.77 increase in net margin/cow bred. The decrease in net margin/cow bred associated with the same increase in total cost/calf was -£0.54. There was a difference of £434.62 in revenue/cow bred across the simulated herds, which equated to a total difference in net margin/cow bred of £334.66. For an average sized English suckler herd of 27 cows (AHDB Beef and Lamb, 2019b) this would lead to an overall net margin increase of £20.79 for each pound increase in revenue/cow bred. The same figures for total cost/calf weaned are displayed in Table 7-3. This model demonstrated that just two financial performance indicators explained 88% of the variation in net margin/cow bred in the herds simulated.

The effect sizes of the associations in this model were large, with differences in net margin/cow bred of over £300 between the best and worst performing herds (with respect to these variables). For an average sized suckler herd of 27 breeding animals, this would equate to an overall net margin increase of £9000 if the herd with the worst revenue increased their revenue to match that of the best, and an increase of £9,700 if the herd with the highest total cost/calf weaned decreased their costs to equal that of the lowest. Although a high association between financial explanatory variables and a financial outcome variable are to be expected, it is of interest to quantify this and to explore the balance between cost and revenue on influencing net margin. Further work investigating more specific aspects of financial performance was done to investigate these relationships further.

Total cost metrics were broken down into replacement, fixed and variable costs. When fixed and variable costs/kg weaned were added to the model with total replacement costs, 86% of net margin was explained, whereas when fixed and variable costs/calf weaned were added to the model with total replacement costs, 91% of net margin was explained. This is in contrast to the bivariate analysis, where using kg weaned as the denominator for the cost metrics resulted in better correlation with net margin. This may be due to correlation in the model between revenue and the denominators of the cost metrics (calves or kgs weaned), making the results difficult to interpret.

As revenue in this model was determined by the number and weight of animals sold (including cull cows), it was felt that it may be correlated with replacement rate (and so replacement costs); The herd size was set to remain at 200, so a higher replacement rate would lead to more animals being retained in order to maintain herd size, fewer animals being sold, and so less revenue. Therefore, it was felt that it may be more appropriate to use fixed and variable costs metrics in the model and exclude replacement costs or metrics that incorporate replacement costs (such as total costs). When this was investigated however, it was found that revenue did not correlate to a great degree with replacement costs ($r^2$ was 0.0083), whereas when total cost metrics were correlated with revenue $r^2$ values were 0.1341 (total costs/calf weaned) and 0.3172 (total costs/kg weaned). This suggests that it may be the denominators (calves and kgs weaned) that correlate with revenue more than the replacement costs themselves, and that the number of kgs weaned correlates with revenue to a greater degree than the number of calves weaned. When revenue was removed from the model, only 41% of variation in net margin was explained. This type of correlation between components of explanatory variables is likely to be a challenge in any analysis where values in the dataset are calculated from each other, and needs to be considered when interpreting results.

#### *7.4.3.2 Model 2: Comprehensive physical variables*

A second model was constructed with the aim of investigating the relationship between physical predictor variables and net margin/cow bred (Table 7-4). The physical variables explaining the most variation in net margin/cow bred during bivariate analysis were added into the model. In order to avoid high levels of correlation, just one predictor variable from each area of production (fertility, health and growth) was included. Weaning rate (number of calves weaned/cow bred) was the fertility predictor variable that explained most variation in net margin during bivariate analysis (although it clearly incorporates pre-weaning mortality rates in addition to fertility aspects of performance). Weaning weight/cow bred rather than total weaning weight was used in the model; they both correlated at a very similar level in the bivariate analysis (and made very little difference to the overall variation in net margin/cow bred explained by the model), but weaning weight/cow bred was felt to be easier to interpret when applying to different farms, i.e. it would not be influenced by the number of cows bred. Of the health predictor variables, replacement rate explained the most variation in net margin (although this will also incorporate fertility aspects of performance as barren cows are culled and will therefore increase replacements required to maintain herd size). This model explained 35% of the total variation in net margin/cow bred observed across the simulated herds. This is clearly less than model 1 (as would be expected), however farmers are likely to have more control over their herd's physical performance indicators than the financial ones, and so be able to manipulate them more readily to increase net margin/cow bred.

***Table 7-4: Model 2 - comprehensive physical variables****. Regression coefficients, standard errors, p-values and effect sizes for comprehensive physical explanatory variables. The financial outcome variable is highlighted in blue, the reproduction and health* explanatory variable is highlighted in purple, the growth explanatory variable is highlighted in yellow and the health explanatory variable is highlighted in green.

| Model term | Coefficient | Standard error | p-value | Difference in net margin/cow bred between best and worst herds (£) | Value of 1 unit improvement in performance for average sized suckler herd (£) |
|---|---|---|---|---|---|
| **Net margin/cow bred (£)** | Outcome | | | | |
| **Weaning rate (%)** | 2.92 | 15.3 | <0.01 | 113.88 | 78.84 |
| **Weaning weight/cow bred (kg)** | 1.06 | 0.0282 | <0.01 | 210.34 | 28.62 |
| **Replacement rate (%)** | -2.53 | 0.129 | <0.01 | -84.76 | -68.31 |

This model demonstrated that each percent increase in weaning rate was associated with a £2.92 increase in net margin/cow bred, each kg increase in weaning weight/cow bred was associated with a £1.06 increase in net margin/cow bred, and each percent increase in replacement rate was associated with a £2.53 decrease in net margin/cow bred. The associated differences in net margin/cow bred between the best and worst performing simulated herds, and the overall net margin effect size for the average sized English suckler herd of 27 breeding cows (AHDB Beef and Lamb, 2019b) are also displayed in Table 7-4. The overall difference in net margin between the best and worst performing herds for an average sized herd was £3000 for weaning rate, £5,600 for weaning weight and £2,300 for replacement rate.

In order to assess the predicted net margin/cow bred change for an equivalent increase in each explanatory variable in the model, as opposed to a unit increase, a tornado plot was drawn illustrating the effect on net margin/cow bred of changing the explanatory variable from its median value to its 75$^{th}$ percentile value (Figure 7-8). This demonstrated the relative larger effect size of weaning weight/cow bred than weaning rate on net margin/cow bred in the simulated herds. Herds increasing their weaning rate from the median to the 75th percentile were associated with an increase in net margin/cow bred of £8.76, whereas those increasing their weaning weight/cow bred by the equivalent degree were associated with an increase in net margin/cow bred of £19.96. This is an important step in interpreting these results and using them to inform decision making on farm, as use of coefficients from the regression model alone suggest a greater influence of weaning rate on net margin (as it has the larger coefficient).

With the average net margin/cow bred of an English suckler herd reported as -£144.76 (AHDB Beef and Lamb, 2016b), or -£3,900 for a herd of 27 breeding cows, being able to influence net margin through focussing on these physical performance measures could help farmers towards an economically viable beef enterprise without the support of subsidy, alternative enterprises, or off farm income.

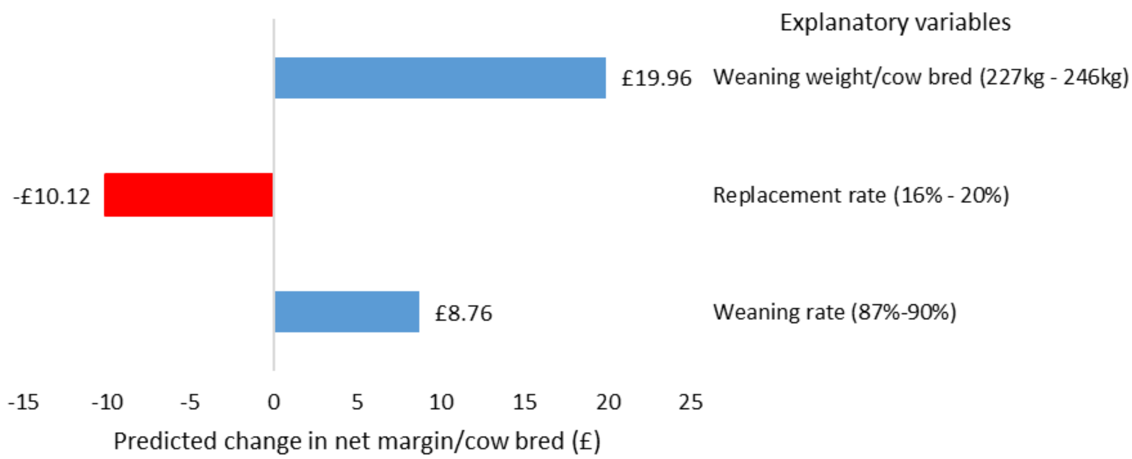


***Figure 7-8: Predicted effect of increases in explanatory variables on net margin/cow bred.*** *Tornado plot of the predicted effect of an equivalent increase (from the median to the upper quartile, values of which are given in brackets) in each explanatory variable on net margin/cow bred. Predictions are generated by taking the difference between the 50th and 75th percentile values, and multiplying this by the explanatory variable regression coefficient in Model 2.*

In Model 2 there is likely to be some correlation between weaning rate and weaning weight/cow bred, as both will be influenced by the number of calves weaned. This can make interpreting regression coefficients and effect sizes difficult. To investigate the relationship between weaning rate and weaning weight with net margin further, an alternative model (Model 2a) was created including average weaning weight (which will not be influenced by the number of calves weaned) in place of weaning weight/cow bred (Table 7-5).

*__Table 7-5: Model 2a - comprehensive physical variables__. Regression coefficients, standard errors, p-values and effect sizes for comprehensive physical explanatory variables. The financial outcome variable is highlighted in blue, the reproduction and health explanatory variable is highlighted in purple, the growth explanatory variable is highlighted in yellow and the health explanatory variable is highlighted in green.*

| Model term | Coefficient | Standard error | p-value | Difference in net margin/cow bred between best and worst herds (£) | Value of 1 unit improvement in performance for average sized suckler herd (£) |
|---|---|---|---|---|---|
| **Net margin/cow bred (£)** | Outcome | | | | |
| **Weaning rate (%)** | 5.555 | 0.125 | <0.01 | 113.88 | 149.99 |
| **Average weaning weight (kg)** | 0.888 | 0.024 | <0.01 | 145.75 | 23.98 |
| **Replacement rate (%)** | -2.57 | 0.129 | <0.01 | -84.76 | -69.39 |

Model 2a explains 34% of overall net margin/cow bred. This is slightly less than the previous model which is to be expected as, previously discussed, average weaning weight is not influenced by fertility in the same way as weaning weight/cow bred, and so this aspect of production will be 'missing' from this model compared to Model 2. This model is easier to interpret though, as there is less correlation between the weaning rate and weaning weight explanatory variables. In the same way as for Model 2, the effect of equivalent increases in explanatory variables on net margin/cow bred were investigated (Figure 7-9).

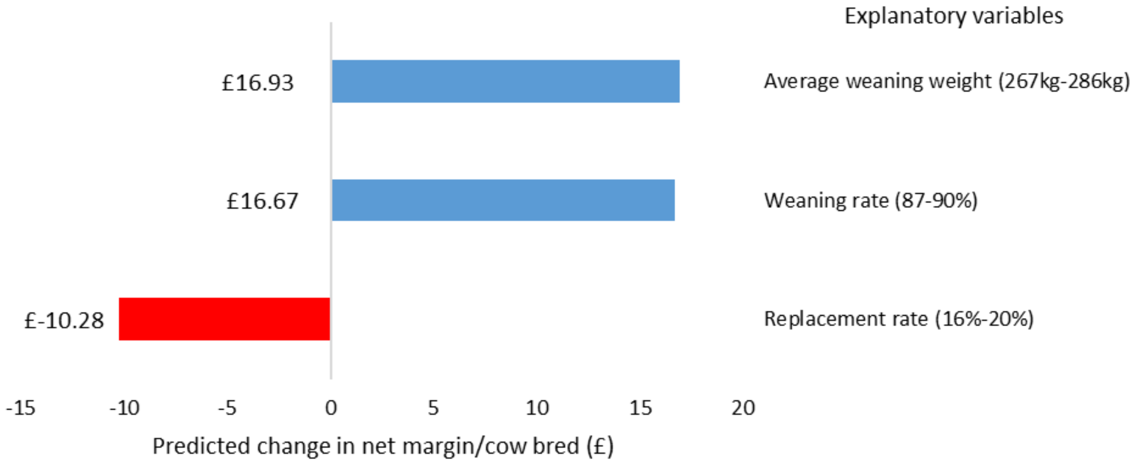


*__Figure 7-9: Predicted effect of increases in explanatory variables on net margin/cow bred__. Tornado plot of the predicted effect of an equivalent increase (from the median to the upper quartile, values of which are given in brackets) in each explanatory variable on net margin/cow bred. Predictions are generated by taking the difference between the 50th and 75th percentile values, and multiplying this by the explanatory variable regression coefficient in Model 2a.*

The overall effect of an equivalent change in weaning weight and weaning rate on net margin were found to be very similar; an increase in weaning rate from the median to the 75th percentile was associated with an increase in net margin/cow bred of £16.67, and the equivalent increase in average weaning weight was associated with an increase in net margin/cow bred of £16.93. This highlights the importance of identifying and accounting for correlation in explanatory variables when interpreting results. The previous model suggested that weaning weight had a greater equivalent effect size on net margin than weaning rate, but further investigation found that when weaning weight was investigated in isolation (i.e. when an average weight was used which will not be influenced by the number of calves weaned) the equivalent effect sizes were very similar.

#### *7.4.3.3 Model 3: Specific physical variables*

Models 1, 2 and 2a investigate the relationship between net margin and comprehensive performance indicators (physical and financial) available in the Stocktake dataset and highlighted as important during development of the KPI toolkit. Following this, more specific physical metrics were assessed in terms of their potential to impact net margin. These were again added to the model in order of their degree of correlation during bivariate analysis, and so as to avoid high levels of correlation between explanatory variables as previously. For the growth aspect of production, 200 day weaning weight/cow bred was incorporated. This 200-day corrected weaning weight metric (as opposed to an actual weaning weight value), does not account for when in the calving period the calf is born, and so was classed as a more specific metric measuring growth more than fertility (although when expressed per cow bred there is a degree of fertility and health performance reflected). For the fertility aspect of production, the percent of calves born alive was included. This is a more specific metric than weaning rate as it is not affected by pre-weaning mortality rates, and after weaning rate explained the highest proportion of net margin in the bivariate analysis. Three health metrics were included as replacement rate (the comprehensive health metric) had three components. Of these, cull rate explained most variation in net margin during bivariate analysis, followed by pre-weaning mortality rate, and then cow mortality rate. Model 3 (Table 7-6) explained 27% of the total variation in net margin/cow bred. This is less than the previous models, due to the more specific nature of the explanatory variables include

*Table 7-6: **Model 3 - specific physical variables**. Regression coefficients, standard errors, p-values and effect sizes for specific physical explanatory variables. The financial outcome variable is highlighted in blue, the reproduction explanatory variable is highlighted in red, the growth explanatory variable is highlighted in yellow and the health explanatory variables are highlighted in green.*

| Model term | Coefficient | Standard error | p-value | Difference in net margin/cow bred between best and worst herds (£) | Value of 1 unit improvement in performance for average sized suckler herd (£) |
|---|---|---|---|---|---|
| **Net margin/cow bred (£)** | Outcome | | | | |
| **200d weaning weight /cow bred (kg)** | 1.19 | 0.0321 | <0.01 | 193.34 | 32.13 |
| **Percent calves born alive (per cow bred)** | 3.87 | 0.161 | <0.01 | 135.45 | 104.49 |
| **Culling rate (%)** | -2.15 | 0.131 | <0.01 | -66.65 | -58.05 |
| **Cow mortality rate (%)** | -10.4 | 0.726 | <0.01 | -52.00 | -280.80 |
| **Pre-weaning mortality rate (%)** | -2.9 | 0.297 | <0.01 | -46.40 | -78.30 |

Model 3 demonstrated a £1.19 associated increase in net margin/cow bred for each kg increase in 200-day weaning weight/cow bred. For each 1% increase in percent of calves born alive (out of those cows bred), there was also an associated £3.87 increase in net margin/cow bred. For each percent increase in culling rate there was an associated £2.15 reduction in net margin/cow bred, and for the same increase in mortality rate for cows and calves, there was an associated £10.40 and £2.90 reduction respectively in net margin/cow bred. Values reflecting the difference in performance for each of these variables between the best and the worst herds are also displayed, along with the overall net margin change per unit increase in each variable for the average sized English suckler herd. Equivalent increases in each explanatory variable from the $50^{th}$ to the $75^{th}$ percentile were again investigated. This showed the largest equivalent effect size on net margin to be 200 day weaning weight/cow bred (£19.05), which is likely due to its incorporation of some fertility aspects of production. This was followed by the percent of calves born alive (£9.68), cull rate (-£7.53), cow mortality rate (-£5.21) and pre-weaning mortality rate (-£4.35).

A further model was constructed to include even more specific physical metrics and to investigate their influence on net margin. Again, variables were added to the model in order of correlation during bivariate analysis, and so as to avoid high levels of correlation between explanatory variables. Model 3a explained 32% of variation in net margin/cow bred, slightly more than model 3 which may be due to the inclusion of a larger number of explanatory variables. Again, the associated differences in net margin/cow bred between the best and worst performing herds, and the values for an average sized herd were calculated (Table 7-7).

*__Table 7-7: Model 3a - specific physical variables__ Regression coefficients, standard errors, p-values and effect sizes for specific physical explanatory variables. The financial outcome variable is highlighted in blue, the reproduction explanatory variable is highlighted in red, the growth explanatory variable is highlighted in yellow and the health explanatory variables are highlighted in green*

| Model term | Coefficient | Standard error | p-value | Difference in net margin/cow bred between best and worst herds (£) | Value of 1 unit improvement in performance for average sized suckler herd (£) |
|---|---|---|---|---|---|
| **Net margin/cow bred (£)** | Outcome | | | | |
| **Pregnancy rate (%)** | 7.33 | 0.144 | <0.01 | 248.20 | 197.91 |
| **DLWG to weaning (0.1 kg)** | 20.6 | 5.86 | <0.01 | 123.60 | 556.20 |
| **Abortion rate (%)** | -5.21 | 0.698 | <0.01 | 31.26 | -140.67 |
| **Dystocia rate (%)** | -1.47 | 0.323 | <0.05 | 23.52 | -39.69 |
| **Pneumonia rate (%)** | - 0.460 | 0.086 | <0.01 | 22.08 | -12.42 |
| **Twinning rate (%)** | 2.33 | 0.609 | <0.01 | 16.31 | 62.91 |

This model demonstrated significant associations between increases in net margin/cow bred with increases in pregnancy rate, DLWG and twinning rate. It also showed significant associated decreases in net margin/cow bred with increases in abortion, dystocia and pneumonia rate. Many of these effect sizes were small, for example decreasing the pneumonia rate by 10% (which clinically would represent quite a large reduction) was associated with an increase in net margin/cow bred of only £4.60. Likewise reducing the dystocia rate by 10% was associated with an increase in net margin/cow bred of only £14.70. It is likely that there are beneficial physical and financial effects of making such herd improvements that are not incorporated into this model, and so these values may appear artificially small. Increasing twinning rate was associated with an increase in net margin/cow bred, despite the associated complications that can come with twin births. There are many studies that have investigated the potential benefits of twinning (i.e. weaning two calves), compared to the potential complications (reduced weight gain, increased disease rates etc.), and it is not the purpose of this model to replicate those studies. However, both the negative and positive effects of twinning were taken into account in the model as far as possible (see Chapter 6). A 1% reduction in abortion rates was associated with an increase in net margin/cow bred of £5.21 in this model. Although a small effect size, values such as this may well cover the cost of vaccination, and illustrate the benefits of taking such preventative health measures. It is also worth noting that the positive effects of vaccination may well be greater than this in a herd where there is a specific disease problem. Further modelling of herds experiencing such disease breakdowns could be used to investigate this further. Greater effect sizes are seen for DLWG to weaning and pregnancy rate. The difference in net margin/cow bred for each 0.1kg increase in DLWG was large at £20.60 (or £556.20 across an average sized herd). Due to the 34% difference between the best and worst pregnancy rates simulated in the model, this metric also showed a large difference in net margin between the best and worst performing herds of £248.20. A 1% increase in pregnancy rate was associated with an increase in net margin/cow bred of £7.33. Values such as these, although small, may be of use when considering the cost efficiency of fertility treatments such as oestrus synchronisation and AI. DLWG and pregnancy rate also showed the largest effect sizes when investigating equivalent performance increases from the 50th to the 75th percentile (£16.48 and £14.66 respectively). This again was due to the large effect size of these explanatory variables coupled with wide variation in performance between herds.

#### *7.4.3.4 Model 4: Physical and financial variables*

A final model, incorporating both physical and financial comprehensive explanatory variables was investigated. However, due to inherently high levels of correlation between the explanatory variables, model fit was not satisfactory and it was felt that maintaining separate physical and financial models was preferable.

## 7.5 Conclusions

The simulation model developed during the current study allowed clearer evaluation of the relationships between various performance indicators, both physical and financial, and net margin/cow bred than the dataset previously used. Four regression models were developed, one incorporating solely financial variables (model 1), and four incorporating gradually more specific physical variables (models 2 to 4), in order to avoid high levels of correlation between explanatory variables. Two versions of model 2 are reported to highlight the challenges encountered when there is correlation between predictor variables. These models explained different amounts of overall variation in net margin/cow bred, reflecting the ability of the combination of explanatory variables in predicting the net margin/cow bred outcome, as displayed in Table 7-8.

***Table 7-8:*** *Total variation in net margin explained by regression models 1-4*

| Model | Variables included | Variation in net margin/cow bred explained by model (%) |
|---|---|---|
| **1** | Revenue/cow bred (£), Total cost/calf (£) | 88 |
| **2** | Weaning rate (%), Replacement rate (%), weaning weight / cow bred (kg) | 35 |
| **2a** | Weaning rate (%), Replacement rate (%), Average weaning weight (kg) | 34 |
| **3** | 200d weaning weight/cow bred, % born alive (per cow bred), culling rate (%), cow mortality rate (%), pre-weaning mortality rate (%) | 27 |
| **3a** | Pregnancy rate (%), DLWG to weaning, Abortion rate (%), Dystocia rate (%), Pneumonia rate (%) Twinning rate (%) | 32 |

Model 1, incorporating financial variables, explained the most variation in net margin/cow bred, as is to be expected as the outcome variable is also a financial metric, and so the explanatory variables are components of it. A cost and a revenue explanatory variable were included in this model, with the revenue variable showing the largest effect size. When equivalent increases in herd performance from the 50th to the 75th percentile were investigated, revenue still showed a larger effect size on net margin than cost. This is the opposite to what was found when analysing the Stocktake dataset, where costs appeared to have more influence on net margin. This is likely to be because the simulation model includes many aspects of performance that will affect revenue, such as the physical performance indicators, but not those that will affect cost. It has been designed this way as these physical variables are the metrics that farmers will tend to have more control over, so making these performance indicators more actionable. The denominators of the metrics may also help to explain this discrepancy, as revenue is calculated per cow bred in the same way as net margin is, whereas total cost is calculated per calf.

Various denominators for the different metrics were explored when analysing the simulation model data. Denominators for outputs from the simulation model were originally chosen to allow validation of the model against the Stocktake dataset, however incorporating predictor variables with different denominators in a regression model increases the potential for correlation between the variables, as highlighted in model 1. Models 2 and 2a also illustrate the potential difficulties in interpreting regression model coefficients where there is correlation between predictor variables.

Further exploration of financial predictor variables found that variable cost metrics tended to explain more variation in net margin than fixed cost metrics. This is contradictory to the dataset that was used to inform the input distributions (Stocktake dataset), where fixed costs explained more variation in net margin than variable costs (see chapter 5). This is likely to be because in this model fixed and variable costs are drawn randomly (from a distribution informed by the Stocktake dataset), and are not influenced by physical variables in the model which would influence variable costs in real life. The financial sub-model was included in this simulation model in order to allow the outcome variable (net margin/cow bred) to be calculated, and so the associations between physical explanatory variables and this financial outcome to be investigated. It is accepted however that the financial sub-model is a simplification of the complex interactions that will exist in 'real-life' beef enterprises.

Models including physical variables (models 2 and 3) explained between 27% and 35% of the variation in net margin, with model 2 (incorporating comprehensive physical indicators) explaining the most. This is in agreement with the opinion of the TAG originally consulted about the use of KPIs (see Chapter 2), who scored comprehensive KPIs more highly against characteristics of a 'good' KPI and felt that they were generally of most use in monitoring enterprise success (defined as net margin/cow bred). However, these regression models have also highlighted potential problems when using comprehensive performance indicators, as they may measure multiple aspects of performance simultaneously, and so be difficult to interpret if these multiple aspects are not broken down. This fits well with the use of a hierarchical structure also suggested during TAG meetings and used to develop the KPI toolkit (see chapter 3). Here, a small number of comprehensive KPIs were used to measure overall performance, and a series of more specific performance indicators were suggested to 'drill down' into data if required to investigate specific problems.

Assigning monetary values to performance metrics using this model can help in decision making on farm. Although many of the values appear small when expressed on a per cow basis, they may be of use in decision making, for example around the use of AI in fertility management, or in instigating a vaccination protocol (see model 4). When scaled up to reflect an average herd size, as reported for models 1 to 4, these values also become more significant.

Using PSA to investigate the effect on net margin of equivalent increases in various performance aspects allowed the outputs of the simulation model to be contextualised. This is a crucial step in using results of such models to inform decision making on farm, as highlighted by models 2 and 2a. In these models weaning rate has the largest regression coefficient, and so the largest effect size per unit of production. However, the larger variation in weaning weight values means that increasing performance from the median value to the upper percentile value results in a much larger (model 2) or very similar (model 2a) effect size on net margin. This contextualisation of the results also highlights the significance of the values at the whole herd level.

Combining the results of the simulation model data analysis with the KPI toolkit developed in Chapter 3, associated changes in net margin for each performance metric, when performance is increased from the median to the 75th percentile can be illustrated (Figure 7-10).

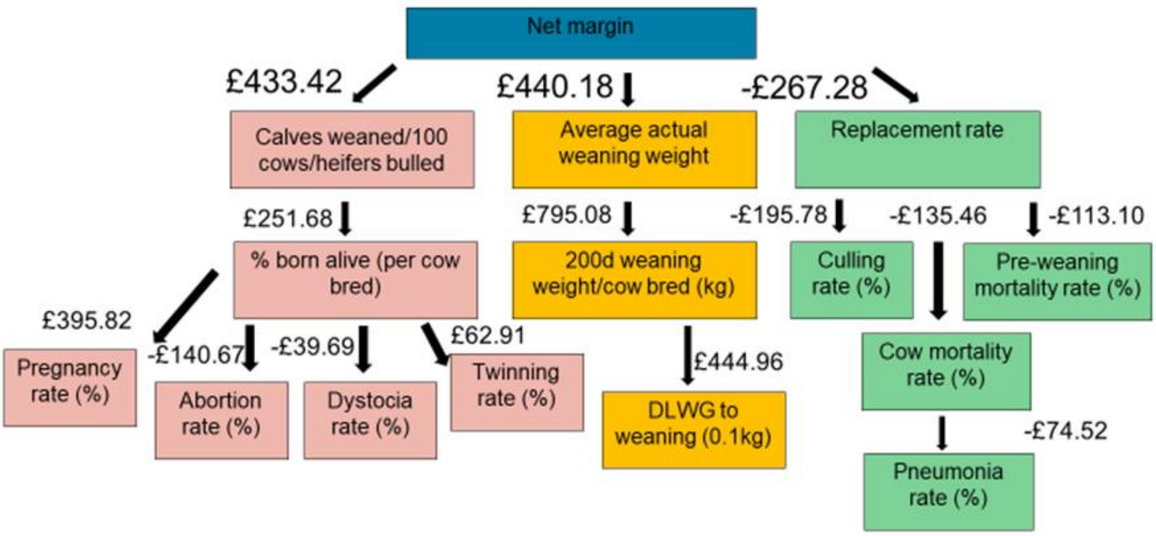


***Figure 7-10: Changes in net margin associated with a 25% increase in performance metrics included in the KPI toolkit***. *Fertility metrics are highlighted in red, growth metrics in yellow and health metrics in green.*

Assigning financial values to equivalent changes in performance metrics may be used to help farmers decide where to concentrate efforts in improving enterprise success (in this case net margin). More comprehensive measures can be used to provide an overview of performance and indicate areas where there may be potential for improvement. More specific metrics can then be used to investigate these areas in more detail. With any metric it is important to understand what is being measured, and to interpret the results correctly. This is particularly pertinent with comprehensive metrics, where several aspects of performance may be being measured simultaneously, and the source of any problem may not be immediately apparent. Regular dialogue between a farmer and their vet or adviser can aid in the correct interpretation of these figures, and in collection of data that will be of use in helping the enterprise achieve its goals. Misinterpretation of data may lead to poor decision making, and ultimately a loss of engagement with collecting and using data to inform management decisions and achieve enterprise goals.

# Chapter 8: Discussion

## 8.1 Introduction

Performance metrics used in the beef industry tend to have been largely derived through discussion between industry experts. They are often based on a 'common sense' approach to monitoring herd efficiency, or anecdotal evidence around metrics that have been useful on case study farms (Riddell et al., 2013, Caldow et al., 2007). This approach has its merits and may well result in improved production on many beef enterprises. However, increasing pressure on financial margins and environmental incentives to improve efficiency mean a greater understanding of the relationships between metrics used to monitor herd performance and overall enterprise success is warranted.

During this project a literature review (Chapter 1) was conducted to ascertain what metrics are currently used to monitor beef performance, and to compare these with metrics used in the dairy, pork and poultry sectors. Comparisons were also drawn with metrics used in beef enterprises in other major beef producing countries. A technical advisory group was co-ordinated to discuss aspects of performance monitoring in beef herds (Chapter 2), and this was furthered through distribution of a questionnaire (Chapter 3). A major output of the technical advisory group meetings was development of a KPI toolkit, with definitions and example calculations, allowing farmers and advisors to select appropriate KPIs for a given enterprise at a given time. Chapter 4 describes analysis of data from a beef herd and provided a case study illustrating how analysis of such data can be used to help inform herd management decision making. In Chapter 5, data from multiple herds over several years was used to further investigate the relationships between performance indicators and enterprise success. This dataset was also used to validate a simulation model, the development of which is described in Chapter 6. The data produced by the simulation model is analysed in Chapter 7, and the performance metrics found to be important in this analysis were compared with the KPI toolkit. The result is a set of performance metrics developed through reviewing relevant literature, consultation with the industry, and analysis of both farm and simulated data (Figure 8-1).

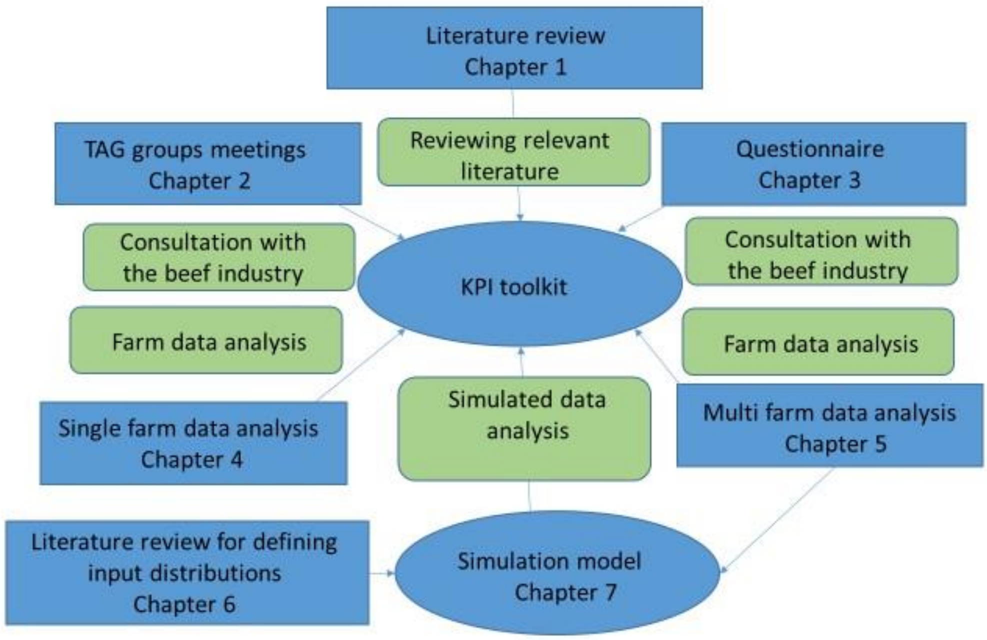


***Figure 8-1: Diagrammatic illustration of the inputs used in developing the KPI toolkit****, and the chapters in which they are described.*

The role of the farm animal vet is changing, and in recent years there has been increasing involvement in proactive, preventative and advisory aspects of herd management. However, this role change has only been partial so far, and it is widely accepted that further changes need to take place to avoid de-professionalisation of farm vets (Ruston et al., 2016). In order to maintain a significant advisory role, farm vets need to have good working relationships with their clients based on trust, and also have the skills necessary to exchange knowledge and influence behaviour change. On dairy farms, where visits will often be weekly or fortnightly, it could be argued that these relationships would be easier to maintain, and that there would be more opportunity for knowledge exchange. On beef and sheep farms however, where veterinary input is likely to be less frequent and often seasonal, these relationships may be harder to forge, and the opportunities for influencing behavioural change more limited. No literature was identified investigating the role of farm vets specifically with regards to beef farms, but studies have been done investigating this in the sheep sector (Bellet et al., 2015, Kaler and Green, 2013). These studies identified barriers to sheep farmers using veterinary flock health management services, such as a perceived lack of sheep specific knowledge by vets and an inability to demonstrate how flock health planning could benefit the sheep enterprise. However, the ability of vets to be involved with decision making on sheep farms, and thus gain experience in this area, was hindered by a lack of the financial and production data that would be required to demonstrate the potential benefits of farmers utilising such veterinary services (Kaler and Green, 2013). Vets also felt that a lack of data was contributing to them being less able to provide preventative services, and whilst they organised farmer meetings and saw these as an opportunity to engage with their clients, farmers often viewed these with suspicion, and saw them as a selling opportunity for the vets, rather than a knowledge exchange exercise. The levels of subsidy received by farmers in both the sheep and beef sector was also suggested as a cause of reduced engagement with data collection and preventative flock health planning. From the veterinary perspective, three factors were identified that were associated with the time a farm vet spent in an advisory role on a sheep farm (Bellet et al., 2015). These were motivation (the vet wanting to, and thinking that they do provide a good service), capability (the vet having the knowledge and resources required) and opportunity (the vet having support from their senior colleagues and clients). Beef and sheep enterprises are often present on the same farm, so it could be assumed that the opinions of beef farmers, and farm vets who carry our work on beef farms, would be similar. Further research into similar opinions in the beef sector would be of interest to investigate this further.

## 8.2 Evaluating performance indicators for beef herds

Data is required to use and evaluate performance metrics, and challenges around capturing data from beef herds may go a long way to explaining the limited evidence available around beef KPIs. 'Big data' is a common concept when considering data analysis to inform decision making, or to make predictions. Data qualities that are characteristic of big data can be summarised by considering the "four V's": volume, veracity, velocity and variety (Hudson et al., 2018), and these principles can be applied to data from beef herds. The volume of data available on beef farms is often less than that on dairy farms, where technology around milking systems and automated data capture increase the data available for analysis. The extensive nature of many beef enterprises, where cattle may be handled infrequently, could limit the opportunities for data collection, and the typically small size of beef herds in the UK reduces the size of the datasets commonly collected. However, statutory data, such as movement data, can be used to calculate some performance metrics, and this can allow a degree of performance monitoring in all beef herds (Hewitt et al., 2018). This data may also be used at a regional or national level, for example monitoring trends in calf mortality rates (Hyde et al., 2020) or the effects of infectious diseases (Gates et al., 2013). Veracity is important in big data, but poor or variable accuracy is often a feature of big data sets. This may be the case with data from beef herds, as manual data capture and fewer automated data collection routes mean that human error can lead to mistakes during data collection. However, the argument could be made that mistakes can also occur with automated data systems, and that if this happens they may be more likely to go unnoticed than with manual collection methods. Velocity of data can refer to the length of time taken to collect it, or the length of time taken for analysis. The long production cycle of the suckler cow, in comparison to the poultry or pork production cycle for example, limits the volume of data available in a set time period, and reduces its velocity. Monitoring performance indicators with a lower lag time however, such as growth rate, can increase the velocity of data. The diversity of the beef sector, and the multiple and varied ways in which data from beef herds is collected and stored, increases the variety of the data available, posing challenges around combining data sets in order to increase data volume. This is a common feature of big data, where there is often a wide variety of data types from multiple sources, and the ability to combine and integrate this data is key.

Accurate herd data is crucial in monitoring herd health and efficiency, however the way it is analysed and interpreted is also important. Research herds can often generate accurate data with which to draw conclusions, but care should be taken when applying these conclusions to commercial herds as they may be very different (Theurer et al., 2015). The diversity of the beef sector in Great Britain can also result in challenges when generalising results of analysis from one commercial farm to another. Confounding may occur if there are factors not included in the analysis that affect both the outcome and the explanatory variables, and attributing causality should be done with caution. Misinterpretation of data may also come from bias; selection bias results if the population being studied differs significantly from that which the results are being applied to, and information bias results if the accuracy of data is not consistent or if events are missed. An example when monitoring herd fertility would be if only cows that are known to have become pregnant, rather than all those served, are included when calculating average conception rates (Cook, 2010). Averages are often used when interpreting herd data, however it can be useful to evaluate the underlying frequency distributions in order to draw conclusions about appropriate management changes (Theurer et al., 2015). Temporal or seasonal distributions may also be useful to consider, as opposed to a yearly average summary figure.

Challenges associated with data capture and analysis have led to alternative methods of investigating application of performance indicators in beef herds, such as the use of expert opinion (Caldow et al., 2007). Alternative methods for generating datasets with which to evaluate performance indicators is another option; simulation modelling can be used to model systems and generate large datasets where obtaining and analysing 'real-life' data poses challenges. Incorporating a stochastic element is useful in complex systems where there is inherent uncertainty, such as farm systems. Both the use of expert opinion and consensus forming techniques, and generation and analysis of simulated data, have been employed in this project to evaluate performance indicators for beef herds.

## 8.3 Consensus methods versus simulation modelling

Where challenges with data capture and analysis exist there will often be a scarcity of evidence available with which to make informed decisions. In these cases, other techniques may be used to inform best practice. These may generate qualitative data, such as consensus forming methods, which can be used to collate expert opinion around best practice. Alternatively, techniques such as simulation modelling can be used to generate quantitative data, which can then be analysed to inform best practice. In a third option, a mixed-methods approach can be taken, in which both quantitative and qualitative methods are employed.

Commonly used consensus forming methods include the Delphi method, the nominal group technique (NGT), and the consensus development conference (like the consensus forming methodology of the NIH) (World Health Organisation, 2014). In this study, a combination of aspects of different consensus methods were used to investigate use of performance metrics in beef herds. These included small group meetings (like the NGT) of the TAG, sometimes with sessions for more open and unstructured discussion. Larger conference style meetings, incorporating a wider variety of beef industry representatives, were also held. These more 'conference style' meetings focussed more on presentation of project findings followed by open discussion. In addition, further opinion was gathered through distribution of a questionnaire.

Simulation modelling requires collation of information in a similar way, but this is often carried out by reviewing literature to inform input distributions for the model. It could be argued that this method allows a wider variety of information to be collated from multiple sources, as it does not rely on individuals completing a questionnaire or being present at a meeting. It should be recognised that some of the literature used to inform input distributions may itself use consensus forming techniques. In the absence of literature, expert opinion may also be used to inform input distributions, so the two methods are not mutually exclusive, and may in fact be complimentary. Conversely, reviews of relevant literature may form part of consensus forming techniques, for example with the NGT a review of the literature may be carried out to provide background information and inform initial discussion.

Although there are clearly differences between these methods, both consensus forming methods and simulation modelling use research outcomes to address a question, and they both produce data which is used to explain and develop theories. Both methods start by evaluating what evidence already exists, and end by discussing if, how and why any new findings fit with pre-existing knowledge. They both have strengths when a research question is broad and requires precise analysis (which quantitative data can provide) that can be applied in context (where qualitative data can be very useful).

Mixed-method approaches are commonly employed in situations where neither quantitative or qualitative methods can fully address the research question (Johnson and Onwuegbuzie, 2004). Quantitative methods are objective, precise, and tend to be more generalisable across different settings than qualitative methods. They are commonly used for testing hypotheses and making predictions or validations.

Qualitative methods on the other hand are considered more subjective, taking into account context, and useful for generating hypotheses. Mixed methods approaches aim to combine the two in a complimentary way, and have been suggested to be particularly useful in health sciences, when aiming to apply science to practice (NIH Office of Behavioral and Social Sciences, 2018). The different methods may be used simultaneously, or sequentially, and there may be an equal split between quantitative and qualitative methods, or a bias one way or the other. 5 main rationales for using mixed method approaches have been suggested (Greene et al., 1989)

1) Triangulation: combining results from different methods studying the same question, for example one method confirming the other.
2) Complementary: methods aiming to enhance or clarify each other.
3) Initiation: a combination of methods being used to gain a deeper understanding of the research question or generate new, related questions.
4) Development: findings from one method informing the other.
5) Expansion: a combination of methods used to expand the breadth/range of research, for example different methods used for different areas within a research question.

In this project, a sequential mixed-method model was used, with qualitative methods informing quantitative ones and vice-versa. Consensus methods were used to collect opinion and inform simulation model structure and inputs, along with a review of existing relevant literature. The quantitative simulation model outputs were then used to confirm the qualitative outcomes from the start of the project, as model results were used to validate the KPI tookit.

## 8.4 Simulated versus 'real' herd data

Multiple regression provides an insight into the effects individual predictors have on an outcome variable. Using data from one farm allows informed management decisions to be made on that farm. Combining datasets from multiple farms provides the prospect of making the results more generalisable across the sector. There are however still many variables that will affect the outcome (net margin/cow bred) that are un-measurable, and so limit the overall predictive ability of the regression models (as shown with the regression models in Chapters 4 and 5). Simulation modelling allows us to account for those un-measurable variables, as well as assisting with challenges around data set size and accuracy.

Development of simulation models involves some knowledge of the system, which in this project came from a combination of literature reviews described in Chapters 1 and 6, and discussion with a TAG described in Chapter 2. The KPI toolkit developed in Chapter 2 was used to provide structure for the simulation model, with sub-models of the simulation model reflecting the different sections of the toolkit (fertility, growth, health and financial). The results of simulated data analysis could then be used to validate the toolkit, and to support it with evidence beyond expert opinion derived through TAG discussion. The dataset used for analysis in Chapter 5, consisting of multiple English beef enterprises over several years, was used to validate the simulation model, and to check outcomes for plausibility and relevance to English beef enterprises.

Combining use of 'real' and simulated data allows studies to benefit from both approaches: 'Real' data can be used to inform (or validate) the simulation model, whilst the simulation model can help to account for some of the un-measurable variables inherent in 'real' data. For example in this study, during the tuning stage of model development the Stocktake dataset (Chapter 5) was used to 'sense-check' model outputs. In this study, the data was all from English beef enterprises, so was likely to be directly applicable to the sector. The data used to inform the simulation model however was more varied, with studies reporting many different types of beef systems, from different countries using different breeds, often measuring different metrics defined in different ways. This presented challenges when defining input distributions, particularly where there is likely to be large variation between herds, such as calf mortality rate (Bleul, 2011). Where possible UK studies were used, or those reporting systems comparable to those which might be found in the UK. Some studies used farmer reported data, whereas some used data from research herds or researcher collected data from commercial herds. Data from these different sources and collected via these different methods may yield different results, presenting challenges when deciding which values to incorporate into the simulation model. For example, there may be more inconsistencies with farmer reported data, but data from commercial herds may be more applicable than that from research herds. Incorporating a wider diversity of data could also be argued to allow more generalisation of the results between farms. However, there is a compromise to be drawn somewhere between making results generalisable across farms as far as possible, but also ensuring they are applicable to the sector in the UK.

When collecting and analysing real herd data, challenges deciding what to include and what to omit do not tend to be as prevalent as when determining input distributions for simulation models (although decisions around handling outlier values is similar). Likewise, decisions about which effector variables to include do not have to be made (all effector variables are inherently present in real data). In the simulation model in this study, some potential effector variables were identified which were not included in the model at this stage, but could be incorporated at a later date if required. For example, twinning rates have been shown to vary by breed, and tend to be lower in beef than in dairy breeds (Cobanoglu, 2011). An Irish study also showed twinning to peak between August and November (Fitzgerald et al., 2014). If the suitability of different breeds for beef systems modelled was being investigated, or comparisons between spring and autumn calving herds being made, these factors could be incorporated into the model in future. The sex of each calf born in the model was defined, as although the ratio was 50:50, and so any effects on overall productivity were likely to be cancelled out, it would allow the effect of altering the ratio (for example by using sexed semen) to be investigated in the future. This sort of flexibility in the data that can be generated is also a benefit of simulation models; in real life if the data was not captured initially, going on to answer further questions would involve collecting more data. However, generating simulated data can also pose challenges: in this study the simulation model was not able to follow individual cows through multiple years (two breeding seasons were used so that complications in a previous season could effect the 'current' season). This meant that analysis around the effect of age at first calving could not be done with the generated data, whereas this is something that would be relatively easy to record when collecting 'real' hard data.

The structure of the simulation model allowed many of the metrics in the KPI toolkit to be calculated, although age at first calving and cow efficiency could not be investigated in a meaningful way using this model. Including an aspect of feeding/keeping cost in relation to size, and relating calf size to cow size, may have enabled associations between cow efficiency and net margin to have been made. However, these costs will vary with different management systems and market volatility. In order to evaluate associations between age at first calving and net margin, a cost of rearing could be included, which would be higher for those calving at three than for those calving at two years. This would also require heifer calves to reach appropriate growth rates however. A deterministic model that takes into account both age at first calving and diet cost was used to investigate the costs and benefits of reducing calving intervals in French beef herds (Raboisson and Citerne, 2018). Diet costs were defined by the authors according to the market situation at the time, and depending on the type of system; two spring calving systems and two autumn calving systems were modelled, with one intensive (higher feeding costs) and one more extensive (forage based and lower feeding costs) within each calving system. Diet costs also varied according to the stage of production, for example it was different at calving to at weaning. Age at first calving was defined as either 24, 30, 36 or 40 months, and the cost of increasing the calving interval in these different systems, with different ages at first calving and culling ages, were evaluated. Comparing specific scenarios in this way, and focussing on a specific aspect of the production system, is very different to investigating associations between inputs and outputs of the whole system, which was the aim of the simulation model described in Chapters 6 and 7. Here, feeding costs were incorporated into the model under variable costs, but they were allocated at the herd rather than the cow level, and so did not vary by cow size or stage of production. In order to incorporate age at first calving into the model, an additional model could be added to the cow sub-model, to define each individuals age at first calving, and to include the associated management costs and required growth rates. More detail around the financial inputs to the model, including the possibility of varying these at the cow level, could be investigated in the future, however it was felt that it was beyond the scope of the current project.

## 8.5 Generation of evidence to support the KPI toolkit

The KPI toolkit was developed through a variety of consensus forming methods, and its hierarchical structure was reflected in the structure of the simulation model. Input distributions for the simulation model were developed through reviewing the literature, or expert opinion where this was not possible or where the literature was conflicting. Farm data was collected which could then be used to validate and 'sense-check' the simulation model outputs. These outputs were then analysed to validate the KPI toolkit, and to assign quantitative values to the association between net margin and individual performance indicators.

The four regression models used to analyse the simulated data in Chapter 7 reflect the different levels of the KPI toolkit developed in Chapter 2. They illustrate how comprehensive metrics can be used to give an overall impression of enterprise success (and show higher levels of association with overall enterprise success), whereas specific metrics can be used to interrogate the data further, but alone will be associated to a lesser degree with overall enterprise success. Generation of simulated data, although requiring some knowledge of the system being modelled, provides large datasets with minimal 'noise', allowing robust statistical interrogation. In this case, it has been used to further investigate associations between metrics suggested through focus group discussion, and a financial measure of overall enterprise success.

Analysis of the simulated data largely supported the KPI toolkit structure developed in Chapter 2, although there are some differences due in part to the nature of the calving system modelled. For example, no carcase quality data was generated in the simulation model as the output of the model was a weaned suckler calf, and certain metrics could not be calculated from the simulated data (such as age at first calving) as previously discussed. The comprehensive financial variables model included a measure of cost (total cost/calf weaned) and a measure of revenue (revenue/cow bred). These were identified as the combination which between them explained the most variation in net margin (88%). The two financial KPIs in the toolkit however are both cost measures, as this was highlighted as an area important for the farmer to monitor, and where they had a degree of control. Revenue performance indicators are unlikely to be as useful in a practical sense on farm. Financial performance indicators is an area where both the KPI toolkit and the simulation model could be further developed. In practice, vets often do not get heavily involved in financial aspects of herd management, likely at least in part due to a lack of knowledge and expertise in this area (although clearly management decisions have financial implications). There may also be a reluctance on the farmer's part to discuss financial aspects of their business. There are programmes available for farmers that provide financial insight, and although vets are not required to be specialists in this area, a knowledge of relevant terminology may facilitate discussion and decision making in this area. Vet school curricula are now starting to include more business skills teaching, and this may improve the confidence of vets when discussing financial implications of management decisions.

The comprehensive physical variables regression model included weaning rate, a measure of weaning weight, and replacement rate. Actual weaning weights were used, as opposed to 200-day corrected weights, as they explained more variation in net margin. This is due to the former metric also incorporating a fertility aspect, i.e. calves born earlier in the calving period will be heavier at weaning. The 200-day corrected value however will be of more use for benchmarking, as it allows for variation in weaning ages across farms, and is a more specific measure of calf growth. The most appropriate metric therefore depends on the aim of the data analysis, and this should be ascertained by the vet or adviser in consultation with the farmer. Comprehensive KPIs in the toolkit also included 200-day weaning weight/kg cow or heifer bred (cow efficiency), which could not be evaluated in a meaningful way with this simulation model as previously discussed, and the percent calving in the first 3/6/9 weeks of the calving period. In the simulation model data, overall pregnancy rate was found to be associated with net margin to a greater extent than pregnancy rate within each three week block of the calving period. This may be because the calving period was set at 12 weeks, and there was no scope for animals to calve beyond this. Modelling a longer calving period may allow associations between the timing of calving and net margin to be investigated further. In a block calving suckler herd, maintaining a tight calving pattern is clearly desirable. However, this will not be applicable to all suckler systems, as some are more suited to a year-round calving pattern. This highlights again why a toolkit type approach to performance indicator selection is appropriate in a diverse sector like the beef industry.

In addition to replacement rate, the other comprehensive KPI measuring health aspects of performance in the toolkit was the percent treated with antibiotics. Clearly this is an essential metric to record in practice. However, disease rates were included in the simulation model rather than treatment rates, as this is what the literature supported (and it is likely to be the disease rather than the treatment that is having the direct effect on production). Although pneumonia rate was found to be significantly associated with net margin, it was included in a later model as a more specific performance indicator.

Regression model 3 contained more specific metrics, including 200 day weaning weight/cow bred, the percent of calves born alive, culling rate, cow mortality rate and pre-weaning mortality rate. This again is largely in agreement with the toolkit, although 200 day weaning weight/cow bred was included as a growth metric rather than a fertility metric. Many of the growth/carcase metrics in the toolkit are based around carcase specifications and so were not included in the suckler herd simulation model (as the output was a weaned calf rather than a finished animal). Including weaning weight measures as growth rather than fertility was therefore considered more rational when structuring the regression models, as otherwise only more specific measures of growth (for example DLWG) were available. In practice, whether a metric is categorised as a 'fertility' or a 'growth' metric is of no consequence. It is important though to consider exactly what is being measured so that metrics can be interpreted appropriately. For example, an average 200-day weaning weight does not reflect fertility performance, whereas 200-day weaning weight/cow bred does incorporate this.

The final model, incorporating the most specific metrics, included pregnancy rate, abortion rate, dystocia rate, twinning rate, DLWG to weaning and pneumonia rate. Abortion rate, dystocia rate and twinning rate were not included in the original toolkit, but could all be monitored on farm and so may be useful additions. The association between BCS and dystocia was not included in the simulation model as no literature had been identified to support this. More recently however, a study has shown an association between low BCS and increased risk of dystocia in beef cattle (Bragg et al., 2021). DLWG was included in the original toolkit as a comprehensive KPI. This is because it was felt to be a very important measure of production (particularly for grower/finisher enterprises), but as it is a specific indicator measuring just one aspect of production, it was included in this way during simulated data analysis.

In addition to validating the structure of the toolkit, analysis of the simulated data allowed quantification of the associations between each metric and net margin. These figures can be expressed as an increase or decrease in net margin/cow bred for each unit change of a metric, as an increase or decrease in net margin/cow bred for a quartile increase in each metric (a change from the median to the 75$^{th}$ percentile), or as an increase or decrease in net margin for an average sized herd for a unit or a quartile change in each metric. Expressing changes in net margin for a quartile increase in each metric allows for the differences in scale of the units used to measure performance, for example a 1kg increase in weaning weight may well be easier to achieve than a 1% increase in weaning rate. However, figures expressed in this way may be harder to interpret on farm, where the net margin change per unit increase may be more helpful for decision making. Figure 8-2 shows a version of the KPI toolkit, structured according to the simulated data analysis. The net margin/cow bred value for a 25% increase in each KPI is quoted. For example, increasing the number of calves weaned per 100 cows/heifers bred by 25% (from the simulated median value to the 75$^{th}$ percentile value), was associated with an increase in net margin/cow bred of £16.67. A quartile increase in 200 day weaning weight/cow bred was associated with the greatest increase in net margin/cow bred. This may be due to its comprehensive nature incorporating fertility, growth and health aspects of production. In general, more specific performance indicators have lower values (as would be expected), however this is not the case for the growth/carcase performance indicators. This reflects the challenges previously discussed with having multiple metrics in a regression model that measure the same aspect of production, which resulted in a more specific growth/carcase metric being selected as a KPI (average actual weaning weight), and a more comprehensive metric being selected as a performance indicator (200 day weaning weight/cow bred). Although individual values illustrated in figure 8.2 are relatively small, these marginal gains may represent the difference between profit and loss in some beef enterprises. Overall, increases in growth appear to have the greatest impact on net margin, which is an important farmer message, and may be a motivation for greater monitoring of this aspect of production.

In general, the regression models reflected the different levels of the KPI toolkit, with the more comprehensive metrics explaining the most variation in net margin (as would be expected). All models (apart from the financial metrics model) included at least one measure of fertility, growth and health, to reflect the different sections of the toolkit. Including two metrics measuring the same aspect of performance was avoided where possible, which led to some differences in ordering of metrics within the toolkit, as discussed above. Further development of the simulation model to incorporate a growing/finishing phase of production, addition of more inputs at cow level and increased detail in the financial sub-model, may allow further metrics in the toolkit to be evaluated in future.

It has been suggested that mixed-methods studies, where some components of the study are qualitative and some quantitative, can be particularly useful when aiming to link research to practice. Qualitative methods can allow greater contextualisation, which is of benefit when aiming to make research outputs relevant in clinical practice. Here a toolkit has been developed which can be used as a decision-making tool, and to facilitate discussion with beef farmers around production monitoring. Associating changes in performance with changes in net margin/cow bred allows the potential economic benefits of different management changes to be evaluated, adding to the information available to farmers when making management decisions.

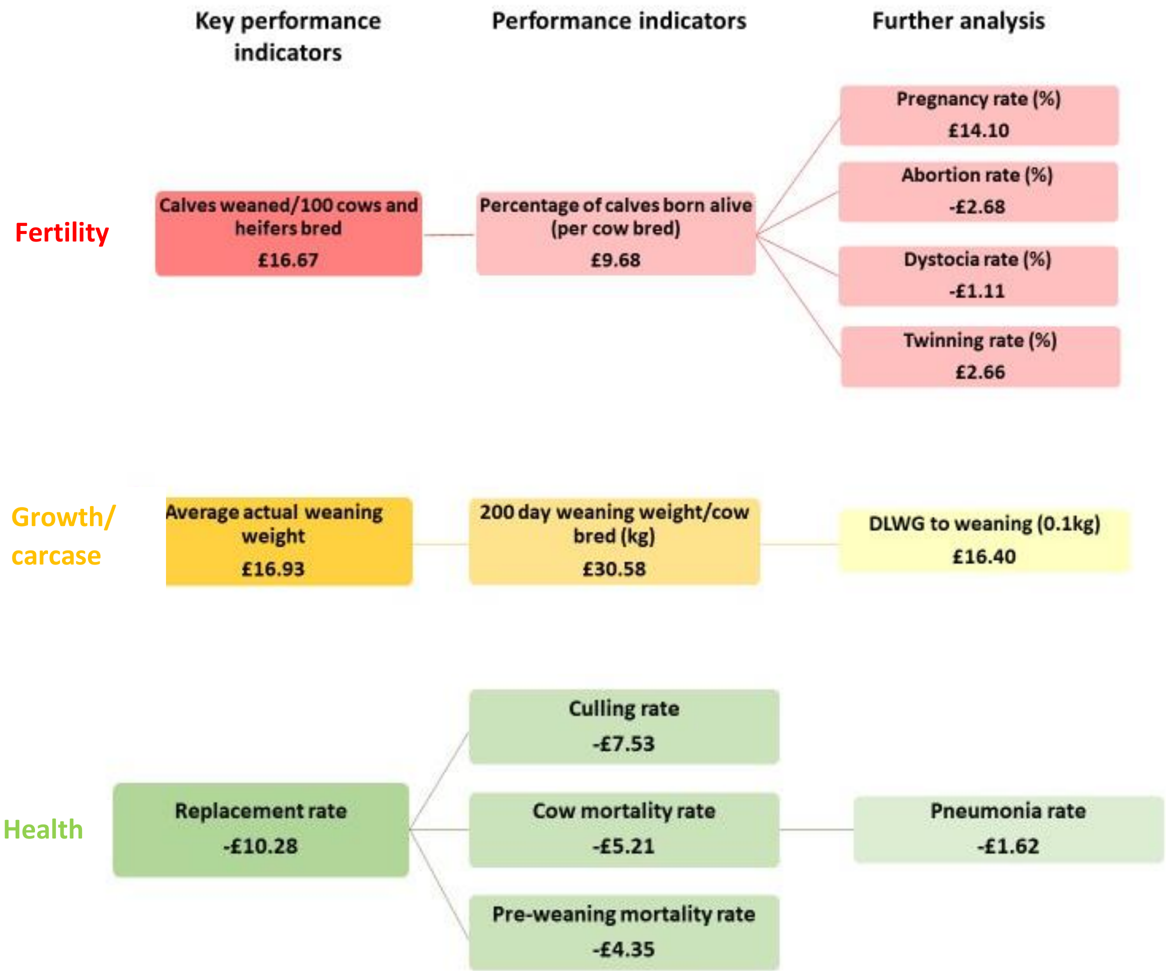


*Figure 8-2: **KPI toolkit structured according to simulated data analysis** with figures representing the difference in net margin/cow bred with a quartile change (from median to 75th percentile) of that metric.*

## 8.6 Future work

Use of herd data to make informed decisions on beef farms is less common than in the dairy sector, veterinary intervention on these enterprises is often less than in other farm types, and many beef enterprises fail to make a positive net margin. Although three separate issues, with many contributing factors, they are all inherently linked, and by engaging with farmers around data collection and analysis and increasing veterinary involvement with decision making, vets may be able to work with farmers to increase the efficiency of these enterprises. With uncertainty surrounding subsidies, the current volatile political climate, increased consumer concern around red meat production and beef production costs often exceeding sale prices, increases in efficiency in beef production are becoming more important.

This project used focus group discussions to reach a consensus on a list of appropriate metrics to monitor beef production, and went on to evaluate this list further using real herd and simulated data. Where no data is available on farm, statutory movement data could be used to monitor performance. BCMS data is available for all farms, with no data collection being required by the farmer other than what is statutory. Metrics such as calving interval, age at first calving and mortality rates can be calculated, along with evaluation of calving patterns. This may be a way of introducing benchmarking to farms that do not currently performance record, by providing an 'entry-level' set of performance indicators. Performance indicators that can be calculated from BCMS data are restricted mainly to those relating to fertility; no weight, financial, carcass or treatment data is available. However, this data could be added, allowing a farmer to build on what is recorded and monitored as required. For this to be of use to farmers and vets in practice, a tool could be developed to automate the process of calculating these metrics from BCMS data.

There is also potential to further develop the simulation model described in this project, for example by incorporating age at first calving and cow efficiency variables as previously discussed. Incorporating growing and finishing inputs and outputs would also allow evaluation of metrics used to monitor these types of system. The effects of specific diseases on production could be incorporated, for example BVD or Johne's Disease, which would allow the potential costs of these diseases to be evaluated. The role of the vet on beef enterprises could be investigated further, along with barriers to uptake of veterinary services offered in the sector. Different calving patterns or periods could be investigated (for example to further investigate the association of calving period with enterprise success), or the use of sexed semen to manipulate numbers of heifers and bulls born.

The diversity of the beef industry means that defining a blueprint of metrics applicable to all enterprises at all times is not helpful. Developing a toolkit of metrics with standardised definitions in a hierarchical structure, it is hoped will provide a structure through which farmers, vets and advisors can monitor beef herd production by selecting appropriate metrics at the relevant level for their enterprise aims.

## 8.7 Conclusions

Challenges exist around capturing and analysing data on beef farms, as well as interpreting analysis for informing management decisions. Despite this, there is an appetite amongst many beef farmers for more input from vets and advisors in this area. The current volatile political and economic climate could be seen as an additional incentive for farmers to monitor production efficiency, and to ensure that their enterprises are viable without support from subsidies. Advances in automated data collection technology, along with increases in EID use, may facilitate data capture in the future, and it is important that vets and advisors are able to analyse and interpret this data in the most effective way.

Using a combination of facilitated discussion, farm data analysis and simulation models, a set of performance indicators, structured into a toolkit, have been developed. The toolkit provides a decision-making pathway with comprehensive performance indicators broken down into more specific metrics, allowing broad aspects of herd performance to be monitored, and individual problems to be investigated in more detail as required. Simulation modelling provided a more robust evidence base for the structure of the toolkit, and assigned economic values to some of the performance indicators included. This provides a foundation for further simulation modelling, where other aspects of production could be included in more detail, to allow further evaluation of performance indicators in the toolkit.

Use of data to inform herd decision making relies on engagement with farmers, and on vets or advisors building up trusting relationships with farmers to allow decisions to be made collaboratively. These relationships are often harder to foster on beef and sheep enterprises as opposed to dairy, due to the seasonal and extensive nature of many of the enterprises. Exploring farmers perception of the role of farm animal vets on beef enterprises further, and how the profession can best meet the needs of the beef industry may help to address this in the future. This, coupled with increasing availability of data (either real or simulated), may help to place the beef sector in a place of economic, environmental, welfare, and public perception sustainability.

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# Appendix 1: Beef KPI project questionnaire

## Beef KPI project questionnaire

My name is Sarah Hughes and I am a postgraduate student at the School of Veterinary Medicine and Science at the University of Nottingham. This questionnaire is part of a collaborative project between the University of Nottingham and AHDB Beef & Lamb which aims to evaluate how measuring and recording information on farm can help farmers maximise the productivity of their beef enterprises. As part of this project we are keen to understand what data is routinely recorded on farm, how this information is captured and where it is stored. We are also interested in finding out more about the barriers preventing farmers recording and using data. I would be grateful if you would be willing to help with this study by completing the following questionnaire. This should take less than 15 minutes.

Participation in this research is entirely voluntary and there is no obligation to take part. Your details and the information you provide will be anonymised and this study has been approved by the School of Veterinary Medicine and Science's ethics committee*. The information I collect will be presented in my PhD thesis and used for publication and research presentations at conferences or meetings, as well as being fed back to AHDB Beef & Lamb (the project sponsors).

Your help is very important to the success of this study, so we would appreciate your time and interest. Further information about the study can be obtained by contacting Sarah Hughes (svxsah@nottingham.ac.uk).

Thank you in advance for your help.

* Data collected will be treated in the strictest confidence and will only be reported in anonymised form, but I will be forced to consider disclosure of certain information where there are strong grounds for believing that not doing so will result in harm to research participants or others, or (the continuation of) illegal activity.

**Questions**

1) Which county do you farm in? **……………………………………………………………….**

2) Which best describes your herd type *(Please select the single best answer)*
   i. Suckler
   ii. Calf rearer
   iii. Grower
   iv. Grower/finisher
   v. Finisher
   vi. Other *(Please specify)*

3) What is the size of your herd? *(Please state number of breeding cows for suckler herds and estimated average herd size for rearer/grower/finisher herd)*

……………………

4) Do you have any other enterprises within your business (For example sheep/arable/ tourism etc.)

   Yes/No

If yes go to question 5, if no go to question 6

5) What are they? ……………………………………………………………………………………………………………….

6) How many full-time equivalents work on the beef enterprise (including family labour)? ……………………

7) Do you use any herd management software for your beef enterprise?

   Yes/No

If yes go to question 8, if no go to question 11

8) Which one do you use? ……………………………………………………………………….

9) What do you like most about your herd management software? *(please select all that apply)*
   i. Ease of data entry
   ii. The way the data is displayed
   iii. The key performance indicators (KPIs) it calculates
   iv. The reports it generates
   v. Its compatibility with other software e.g. financial packages
   vi. Its ability to record data for other enterprises e.g. sheep
   vii. It allows benchmarking of herd performance
   viii. Other (please specify)

10) What, if anything would you like to change about your herd management software?…………………………………………………………………………………………………………………………………………………………………………………………………………………………… (Go to question 12)

11) What are your main reasons for this? *(please select all that apply)*
   i. Cost
   ii. Time
   iii. Unsure what is available
   iv. Concerned about losing data if software/computer fails
   v. Too complicated

vi. Cannot enter data into the computer outside i.e. crush-side
vii. Herd size too small
viii. Do not see the need
ix. Do not know
x. Other (please specify)

12) Do you use electronic identification (EID) in your herd?

Yes/No

If yes go to question 13, if no go to question 14

13) What do you find most useful about it?
……………………………………………………..........................
……………………………………………………………………………………………………………………(Go to question 15)

14) What are your main reasons for this? *(please select all that apply)*
i. Cost of equipment (for example tag reader and software)
ii. Cost of tags
iii. Unsure where to purchase tags
iv. It is not compulsory
v. Do not see the need
vi. I am hoping to in the future
vii. Other (please specify)

15) Please indicate with a cross where you record each category of data, or if you do not record it. If you record data in multiple places please indicate them all.

| | Herd management software | Paper based system | Online statutory recording system e.g. CTS | Do not record |
|---|---|---|---|---|
| Weights | | | | |
| Feed intake | | | | |
| Calving events | | | | |
| Bull in/out or AI dates | | | | |
| Pregnancy diagnosis results | | | | |
| Calving ease | | | | |
| Medicine use (including animal ID, substance used, withdrawal period and date of treatment) | | | | |
| Reason for medicine use (as above plus reason for treatment) | | | | |
| Lameness | | | | |
| Individual animal infectious disease status | | | | |
| Abattoir feedback (e.g. KO%, carcass classification, liveweight, deadweight etc.) | | | | |
| Movements (e.g. on/off/births/deaths) | | | | |
| Financial (e.g. cost of production, gross margin, net margin etc.) | | | | |
| Other (please specify) | | | | |

16) How difficult do you consider it to be to collect the data that you do?

……………………………………

(Scale 1-10)

17) How often do you use this data, for example running reports/analysing data? *(please select the most appropriate)*

i. At least once a month
ii. At least once a quarter
iii. At least every six months
iv. At least yearly
v. Less than once a year

vi. Never

18) What do you use the data for? *(please select all that apply)*

i. Individual animal management, for example identifying animals that aren't growing well.
ii. Monitoring herd performance, for example monitoring the percentage of the herd that calve in the first 3 weeks of the calving period.
iii. Financial management of the enterprise
iv. Key performance indicator (KPI) calculation
v. Deciding when to finish animals
vi. Benchmarking
vii. Making breeding decisions
viii. Other (please specify)
ix. I do not use data

19) How difficult do you consider it to be to use your data in the way that you do, for example does it involve complex analysis?............................................................
(Scale 1-10)

20) What, if anything, would you like to record that you currently do not?.......................................................

21) What currently prevents you from recording this?

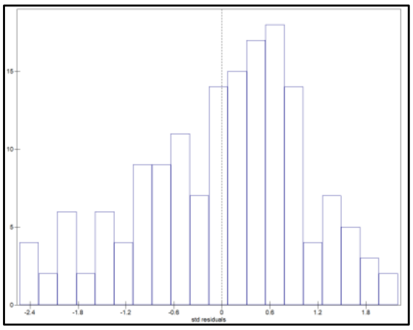
a) Cost
b) Time
c) Lack of technology
d) Other (please specify)……………………………………………………………………

22) How valuable do you feel using data is in managing your beef enterprise?....................................
(Scale 1-10)

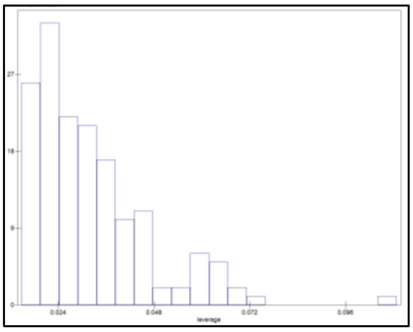
Many thanks for your time. The results of the project will be disseminated by AHDB Beef and Lamb and a summary of the results can be obtained by contacting Sarah Hughes at svxsah@nottingham.ac.uk.

# Appendix 2: Stocktake data model fit analysis

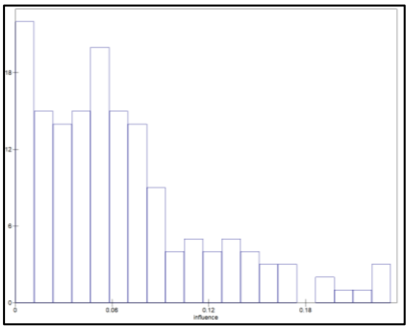
*Multiple regression of physical performance indicators and net margin/cow bred in the suckler dataset (section 5.4.2)*



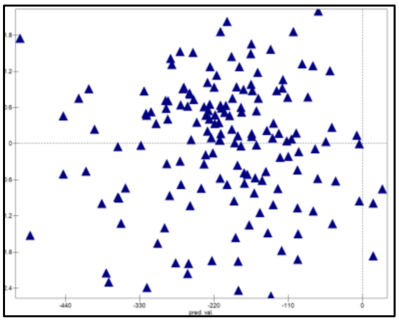
Histogram of standardised residuals



Histogram of leverage values

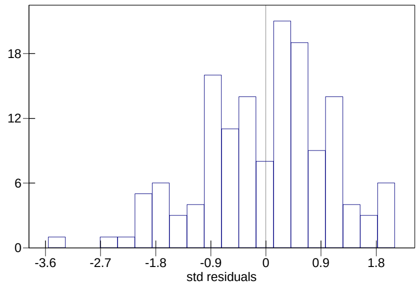


Histogram of influence values

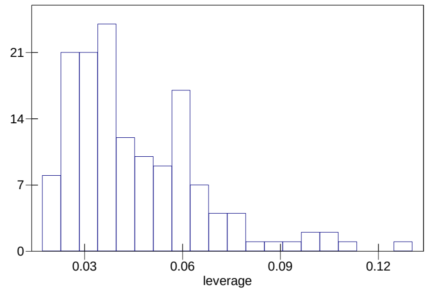


Standardised residuals plotted against predicted values

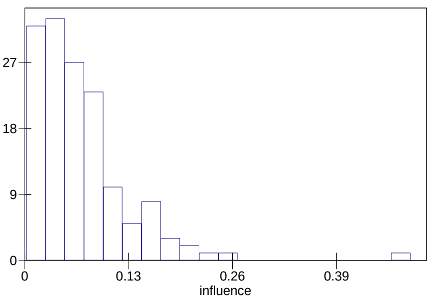
*Multiple regression of financial performance indicators and net margin/cow bred in the suckler dataset (section 5.4.3)*

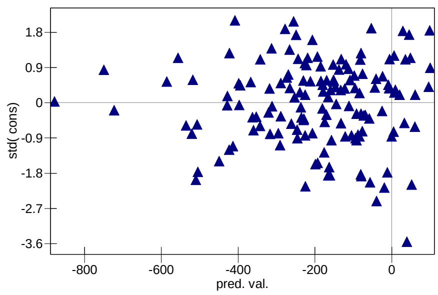



Histogram of standardised residuals



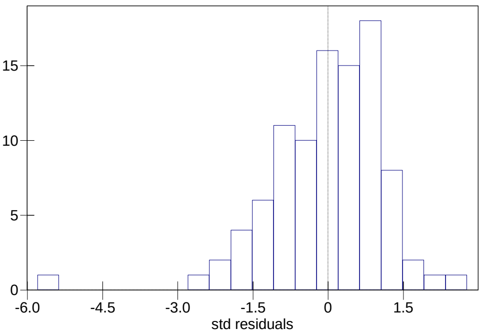

Histogram of leverage values

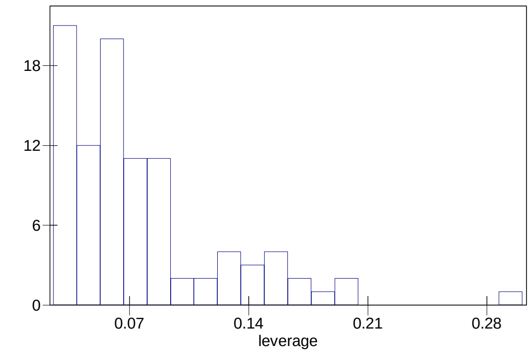


Histogram of influence values

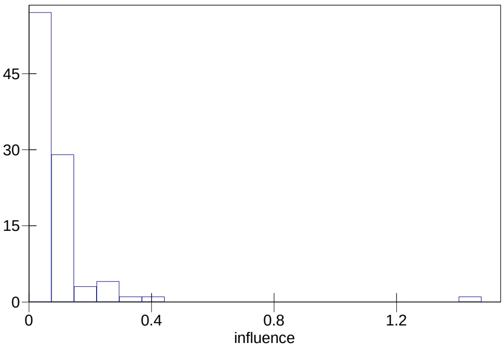
Standardised residuals plotted against predicted values

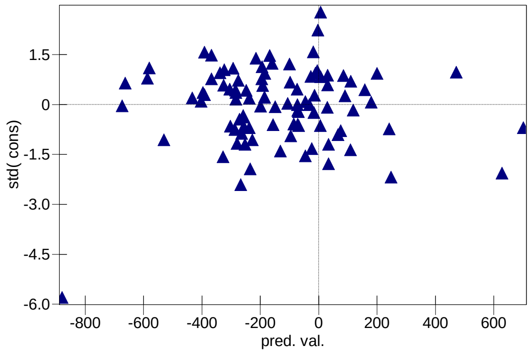



Histogram of standardised residuals

Histogram of leverage values




Histogram of influence values

Standardised residuals plotted against predicted values

*Multiple regression of the Stocktake grower/finisher dataset (section 5.4.5)*

# Appendix 3: Macros used for data simulation

**Herd simulation**

```
Public Sub SimulateHerd()

Application.ScreenUpdating = False

Application.Calculation = xlCalculationManual

For j = 1 To 10005

   Sheets("herd").Calculate

      For i = 1 To 200

         Sheets("cow").Calculate

         CowCount = i + 22

         Sheets("herd").Range("b" & CowCount & ":AA" & CowCount).Value =
Sheets("cow").Range("a52:z52").Value

      Next i

   HerdCount = j + 1

   Sheets("herd").Calculate

   Sheets("world").Range("b" & HerdCount & ":ah" & HerdCount).Value =
Sheets("herd").Range("a12:ag12").Value

   Sheets("world").Range("ai" & HerdCount & ":bh" & HerdCount).Value =
Sheets("herd").Range("a20:z20").Value

Next j

Application.ScreenUpdating = True

Application.Calculation = xlCalculationAutomatic

End Sub
```

**Uniform distribution**

```
Public Function Unif(dMin, dMax As Double)

Application.Volatile (True)

Dim randy As Double

   randy = Rnd()

   Unif = dMin + (randy * (dMax - dMin))

   End Function
```

**Triangular distribution**

```
Public Function Triang(dMin, dMode, dMax As Double)
Application.Volatile (True)
Dim dRand, dc_a, db_a, dc_b As Double
'adapted (stolen really!) from www.sulprobil.com
   If dMode <= dMin Or dMax <= dMode Then
      Triang = CVErr(xlErrValue)
      Exit Function
   End If
   dc_a = dMax - dMin
   db_a = dMode - dMin
   dc_b = dMax - dMode
   dRand = Rnd()
   If dRand < db_a / dc_a Then
      Triang = dMin + Sqr(dRand * db_a * dc_a)
   Else
      Triang = dMax - Sqr((1# - dRand) * dc_a * dc_b)
   End If
End Function
```

**BetaPERT distribution**

```
Public Function Betapert(a, m, b As Double)
'draws from a betaPERT distribution on each refresh
'using min (a), mode (m) and max (b) as defining params
Application.Volatile (True)        'recalculates on each sheet refresh
Dim alp, bet, helpy, randy As Double
   'calculate helper variables before calculating beta shape params
   randy = Rnd()
   helpy = 1 + (4 * (((m - a) * (b - m)) / ((b - a) ^ 2)))
   'calculate beta shape params
```

```
    alp = ((2 * (b + (4 * m) - (5 * a))) / (3 * (b - a))) * helpy

    bet = ((2 * ((5 * b) - (4 * m) - a)) / (3 * (b - a))) * helpy

    'make random draw using shape params

    Betapert = Application.WorksheetFunction.Beta_Inv(randy, alp, bet, a, b)

End Functio
```