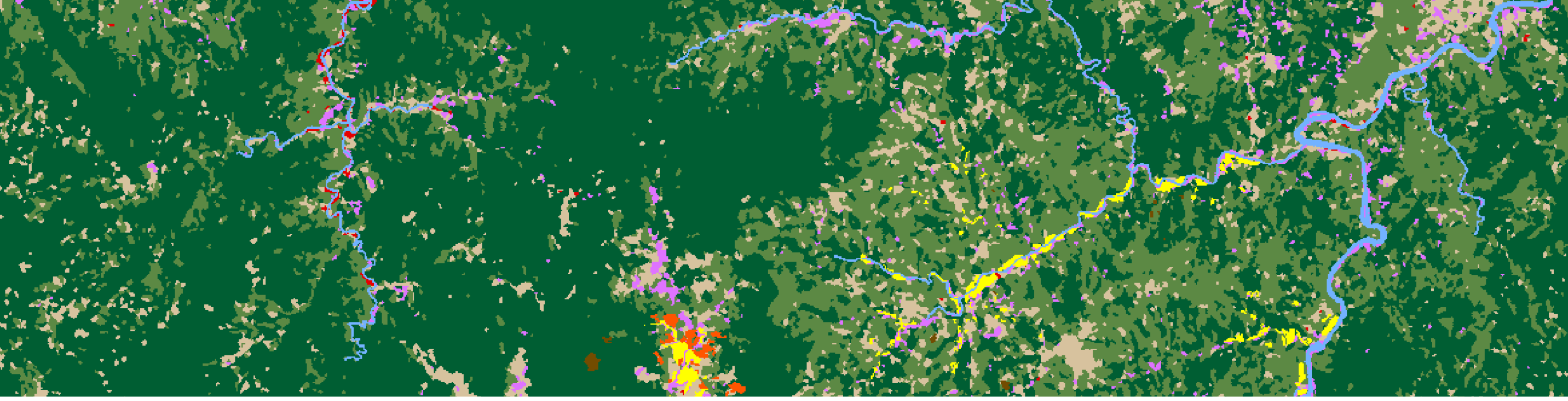
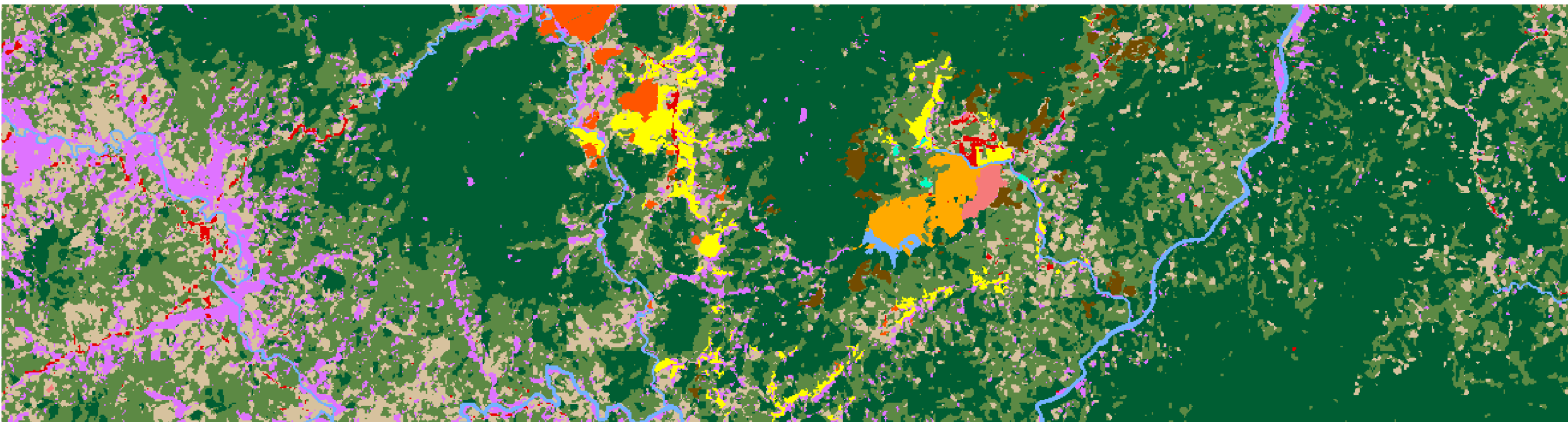


Characterising Socio-Environmental Mining Impacts using GIS and Remote Sensing: A Case Study in Didipio, Philippines

Michelle Ang Li Ern

November 2022

The work presented herein was submitted to the University of Nottingham Malaysia as fulfilment of the conditions and requirement for the degree of Master of Philosophy.



The members of the Supervisory Committee are as follows:

Prof Alex Lechner

Monash Indonesia;

School of Environmental and Geographical Sciences

Faculty of Science and Engineering

University of Nottingham, Malaysia

Prof Christopher Gibbins

School of Environmental and Geographical Sciences

Faculty of Science and Engineering

University of Nottingham, Malaysia

Statement of Word Count

This thesis including references and appendices contains 33474 words

Abstract

Mining results in significant land cover changes, directly and indirectly affecting local communities and the natural landscape via complex, interrelated and often long-lasting impacts. With the impending increase in demand for mineral resources, the need for robust analyses and clear reporting of data on the local and regional changes is considered essential for mining companies to effectively detect, track, sustainably manage and mitigate impacts. Remote sensing and GIS methods hold the potential to assist and improve conventional social science approaches; they provide the means to spatially capture and triangulate data from the dynamic mining landscape to study past and ongoing socio-environmental impacts. This thesis aims to investigate the use of spatially explicit GIS and Remote Sensing methods for assessing the social and environmental impacts of mining. To achieve this, the chapters (1) extensively reviewed prior studies that integrated GIS and remote sensing with social science methodologies to evaluate socio-economic and environmental mining impacts, (2) compile recommendations on how the integration of GIS, Remote Sensing, and Social Science can be enhanced for future research on the socio-economic and environmental implications of mining, and (3) characterise the land cover changes in a mining landscape in Didipio, Philippines, and its concurrent impacts on socio-environmental land uses.

Chapter 1 of this thesis introduces the importance of this research and its relevance to present societal concerns. The aim and scope of the thesis are also outlined here.

Chapter 2 comprehensively examines past research efforts by providing a systematic review of how GIS and remote sensing approaches have been integrated with social science approaches to assess socio-economic and environmental impacts of mining on local communities. We found that the integration of GIS and remote sensing applications with social science methods is a functional step and often the only means to spatially capture and coherently assess the various and complex dimensions of mining impacts. Overall, more research is still needed to improve interdisciplinary data capture and analysis, particularly to analyse less tangible socio-economic impacts. Concerted efforts must also be made to improve data availability, quality, geographic categorisation, consistency, validation, and transparency to achieve a more spatially integrated evaluation of socio-economic mining impacts.

Multidimensional approaches involving interdisciplinary methods and coordinated efforts from all stakeholders are required to effectively capture and coherently analyse the various data types needed for a full understanding of mining impacts.

In Chapter 3, land use and land cover changes in a Philippines mining landscape are classified and the concurrent impacts of mining on socio-environmental land uses were evaluated. This case study demonstrated how a range of recent and novel methods can be used to map socio-environmental mining landscapes. A time series of classified land use and land cover (LULC) maps was created using composites of multispectral Landsat images, vegetation indices and a Digital Elevation Model (DEM). Landsat historical imagery was used to successfully characterize coarse-scale high-level land covers via supervised Random Forest classification in Google Earth Engine (GEE). Web-based mapping by local experts was then used within selected zones of importance to characterise key fine thematic resolution land use categories; such fine resolution is beyond what is possible using only Landsat. Overall, the time series accurately estimated LULC change, and revealed significant temporal trends useful for studying socio-environmental indicators. The methods developed and their limitations were critically evaluated and potential ways to improve the workflow in terms of the quality and efficiency of data acquisition are proposed.

This thesis is concluded in Chapter 4, which synthesizes the contributions made in this study. Recommendations and challenges anticipated for future research towards the goal of a more spatially integrated assessment of socio-economic mining impacts are outlined.

Given the upcoming growth in demand, socioeconomic and environmental mining consequences must be handled in a multidimensional manner that involves interdisciplinary methods and coordinated efforts from all stakeholders. This research reinforces the potential that GIS and Remote Sensing holds to facilitate and optimise conventional socio-environmental impact assessments. The novel approach of stakeholder engagement via participatory GIS can be further enhanced to support successful socio-spatial data integration, inclusive analysis, and comprehensive planning throughout the mine life cycle to bring us a step closer in securing a sustainable future for mining.

Preface

I hereby declare that the material presented here was produced for this thesis and is primarily my own. The following publications and contributions are work conducted based on the contents in this thesis and in collaboration with other parties:

The content in **Chapter 2** is based on a paper in preparation:

Ang, M. L. E., Owen, J. R., Everingham, J., Kemp, D., Gibbins, C., & Lechner, A. M. (in preparation). Review of GIS and Remote Sensing Applications for Assessing the Socio-Economic and Environmental Mining Impacts. *The Extractive Industries and Society*.

The content in **Chapter 3** was published as:

Ang, M. L. E., Arts, D., Crawford, D., Labatos, B. V., Ngo, K. D., Owen, J. R., Gibbins, C., & Lechner, A. M. (2020). Socio-environmental land cover time series analysis of mining landscapes using Google Earth Engine and web-based mapping. *Remote Sensing Applications: Society and Environment.* https://doi.org/10.1016/j.rsase.2020.100458

Acknowledgements

First and foremost, I would like to express my deepest gratitude to the most dedicated and patient supervisors one could ever have, Professor Alex Lechner and Professor Chris Gibbins. The successful completion of this project is only possible with their skilful guidance, constructive feedback, and gracious encouragements. I am especially indebted to Professor Alex – thank you for not giving up on me and for all the wisdom and moral support you've enthusiastically shared. This work was generously funded by the Landscape, Ecology and Conservation (LEC) Laboratory and the Faculty of Science and Engineering (FOSE), University of Nottingham.

Sincerest thanks to members of the Didipio (OceanaGold) team, Bonifacio V. Labatos (Hero), Dirk Arts and Danielle Crawford, for supporting the Didipio mining project. Also, to newfound friends and associates made along the way, many thanks especially to John Owen, Deanna Kemp, Eleonore and Jo-Anne Everingham, from the University of Queensland's Mining and Resettlement Research and Practice Consortium hosted by the Centre for Social Responsibility in Mining (CSRM) at the Sustainable Minerals Institute.

I would also like to acknowledge and thank members from the Landscape, Ecology and Conservation (LEC) Lab, specifically Khanh, Karen, Abi, Zhi Hong and Steve who has directly contributed in part to this work. To Darrel, Khanh, Karen, Aliff, Celine, Zoe, Li Shuen, Leon, Aliyah, Shalini, Abi, Pouv, Sharun, Jeslyn, Sally and Jonas – I will fondly reminisce on our food hunts in Semenyih, game nights, mind-blowing conversations over meals, movie critiques and other things best left out here. Thank you for bringing life to the lab and filling my days with joy and laughter.

Last but not least, I thank my family, siblings and friends for their constant support, patience, and understanding throughout this process – Thank you for always reminding me that there is a life outside of work. Specially to those dearest to me – Thank you for believing in me and unconditionally seeing me through my most difficult times.

This would have been an impossible journey without every one of you. From the bottom of my heart, thank you all!

Table of Contents

Statement of Word Count ii

Abstract iii

Preface v

Acknowledgements vi

Table of Contents vii

List of Figures x

List of Tables: xii

Chapter 1. Introduction 1-1

1.1 Background 1-1

1.2 Research Aim and Objectives 1-3

1.3 Research Questions 1-4

1.4 Thesis Outline 1-4

Chapter 2. Systematic Review of GIS and Remote Sensing Applications for Assessing the Socio-Economic Mining Impacts 2-6

2.1 Introduction 2-6

2.2 Methods 2-8

2.2.1 Search Criteria 2-8

2.2.2 Data Compilation and Analysis 2-9

2.3 Results 2-15

2.3.1 Objective 1: Spatio-Temporal Distribution of Studies 2-15

2.3.2 Objective 2: Categories of Socio-Economic Mining Mining Impacts Spatially Studied 2-18

2.3.3 Objective 3: Social Science Methods and the Types of Stakeholders Engaged .. 2-21

2.3.4 Objective 4: GIS and Remote Sensing Approaches Utilized by Studies 2-23

2.4 Discussion 2-28

2.4.1 Overview of Current Research Development 2-28

2.4.2 Integrating Across Disciplines and Methods for Capturing Mining Impacts 2-29

2.4.3 Challenges and Recommendations for Moving Forward 2-35

2.5 Conclusion 2-37

Chapter 3. Socio-Environmental Land Cover Time Series Analysis of Mining Landscapes Using Google Earth Engine and Web-Based Mapping 3-38

3.1 Introduction 3-38

3.2 Materials and Methods 3-40

3.2.1 The Didipio Mine and Study Area 3-40

3.2.2 Land Use and Land Cover Classification Scheme and Environmental and Socioeconomic Indicators 3-42

3.2.3 Remote Sensing Data 3-46

3.2.4 Regional-Scale Mapping 3-48

3.2.5 Web-Based Participatory Mapping and Stakeholder Involvement 3-51

3.2.6 Change Assessments and Transition Matrix 3-53

3.3 Results and Discussion 3-53

3.3.1 Regional Classification Maps and Time Series 3-53

3.3.2 Zones of Importance: Participatory Mapping and Land Use Time Series 3-58

3.3.3 Land Use and Land Cover Transitions 3-63

3.3.4 Applications of Remote Sensing to Social Change Assessment 3-67

3.4 Conclusion 3-71

Chapter 4. Synthesis 4-72

4.1 Summary 4-72

4.2 Research questions and key findings 4-73

4.2.1 To what extent has the social, economic, and environmental mining impacts been studied in spatially explicit ways? 4-73

4.2.2 How can current limitations of GIS and Remote Sensing approaches be improved to spatially study socio-economic and environmental impacts? 4-73

4.2.3 How can the socio-environmental land use and land cover impacts in a mining region be best captured using spatially integrated social science approaches? 4-75

4.3 Closing Remarks 4-76

References 78

Appendix A – Chapter 2 104

Appendix B – Chapter 3 112

Appendix B1 112

Appendix B2 112

Appendix B3 113

List of Figures

Figure 2.1 A graphical illustration of the systematic literature review search query. 2-8

Figure 2.2 Spatio-temporal distribution of studies based on study area region. 2-15

Figure 2.3 The general characteristics of the studies. (A) the proportions of study area regions; (B) The various scales at which the studies were conducted; (C) stage of mining lifecycle; (D) types of commodity extraction method; and (E) the categories of commodities extracted. 2-17

Figure 2.4 Distribution of commodities and study area location. 2-17

Figure 2.5 The wheel of gaps in knowledge which demonstrates the capabilities of each of the following four method categories to capture the aspects of the Social Framework for Projects (Smyth & Vanclay, 2017). 2-19

Figure 2.6 The A) proportions of number of indicators per study and B) eight aspects of the Social Framework for Projects (Smyth & Vanclay, 2017) for each the overall literature and by each of the four method categories. 2-20

Figure 2.7 The alluvial shows the proportions and correlations between the variables for studies that implemented Social Science methods 2-22

Figure 2.8 Alluvial chart showing the proportions and correlations between the variables for studies that used Remote Sensing images and classification methods 2-25

Figure 2.9 A comparison of the spatial analysis method(s) applied by the A) overall literature review and each of the four method categories; B) GIS Only C) GIS and Remote Sensing, D) GIS and Social Science and E) GIS, Remote Sensing and Social Science 2-27

Figure 3.1. The 1,006.93 km^2 study area surrounding the Didipio gold-copper mine, in the Philippines. 3-42

Figure 3.2. Idealized land use and land cover classification scheme with the land use and land cover classes for regional remote sensing classification in red boxes and the web-based classification mapping in green. 3-44

Figure 3.3. A summary of the processing workflow for creating regional classification time series 3-50

Figure 3.4. Graphs indicating the changes in area (km2) of the regional land use and land cover classes from 1994 to 2018. The classes are split into 2 categories: a) Natural and b) Anthropogenic 3-56

Figure 3.5. The supervised classification maps of the a) 1994, b) 2005, c) 2010, d) 2015 and e) 2018 timesteps generated from Google Earth Engine (GEE) using the Random Forest Classifier. 3-57

Figure 3.6. Graphs indicating the changes in area (km^2) of the land use classes from 1994 to 2018. 3-59

Figure 3.7. A compilation of all the zones of importance land use mapped using Maptionnaire for 2018. 3-61

Figure 3.8. a) SE1 focuses on the land use and land cover changes in the Didipio Mining Site while b) SE2 focuses on the Agricultural and Built-up Area land use and land cover changes to the northwest of the Didipio Mine; these changes are marked by the black arrows. 3-62

Figure 3.9. An idealized flow chart to incorporate web-based mapping survey data more effectively into the classification time series formulation process. 3-70

Figure A 1 Distribution of author origin based on study area region (N=71). 105

Figure A 2 The temporal distribution of the types of extraction studied. 105

Figure A 3 Distribution of commodities based on year of study. 105

Figure A 4 Social Science methods applied, and the types of stakeholders engaged 106

Figure A 5 The list of Remote Sensing imageries (satellite imageries and basemap) and the types of classification methods used............106

Figure B 1 A demo of the Didipio Web-Based Mapping survey using Maptionnaire, an interactive, online, crowdsourcing, geospatial web mapping application to obtain feedback from the stakeholders at Didipio. 113

Figure B 2. A comparison of the original 2010 Google Earth Engine (GEE) classified image output (left) vs the processed Majority Filter output (right). 115

List of Tables:

Table A 1 List of study areas were grouped into regions based on the categories used in UN DESA (2018). 104

Table A 2 Full list of commodities as reported by the literature and categorized based on (McKenna et al., 2020)'s mine commodity categories.. 104

Table A 3 The list of Remote Sensing classification methods and keywords used by the original literature authors. 107

Table A 4 Summary of indices used by the literature for unsupervised imagery classification. 107

Table A 5 GIS methods used and categorized based (Longley et al., 2005)'s six types of spatial analysis 108

Table A 6 Summary of indices used by the literature for spatial analysis. 109

Table B 1 Level of Certainty of the web-based mapping land cover. 114

Table B 2 The list of composites for the 2010 timestep with different combinations of bands and their respective accuracy assessment scores. 114

Table B 3 The classifiers available in Google Earth Engine (GEE) and their respective accuracy assessment scores for the 2010 timestep. 114

Table B 4 The accuracy assessment results for the original Google Earth Engine (GEE) 2010 classified image and after applying the post-classification processing and the Majority Filter. 115

Table B 5 A compilation of the accuracy assessment results for all five timesteps after applying the post-classification processing. 116

Table B 6 A list of the Social Development and Management Program (SDMP), Community Development Program (CDP) and Corporate Social Responsibility (CSR) social investment projects that were identified by local experts via the Maptionnaire Web-Based Mapping Survey. 117

Table B 7 Land Use and Land Cover Transition Matrix for timestep 1994 to 2018 in km2. 118

Chapter 1. Introduction

1.1 Background

Minerals play an important role in modern civilization and affect the lives of millions of people globally (Githiria & Onifade, 2020). As the mining sector proliferates, due to pressures from the fields of economics and energy (Herrington, 2021; Svobodova et al., 2020; Xiao et al., 2021), there is a pressing need for a holistic understanding of the impact of mining on all stakeholders, so that informed decisions can be reached which maximise benefits while minimizing threats to a region and its population (Arts et al., 2019; Owen et al., 2022; Sonter et al., 2014; Y. Zhang et al., 2017). Addressing the conceptual, methodological, and practical limitations that currently impede this understanding is vital.

The impacts of mining on human experiences such as liveability, cultural well-being, social cohesion, quality of life and health (Petrov et al., 2018; Vanclay et al., 2015) are dynamic, multifaceted, and interwoven, with a range of favourable and unfavourable effects (Braimoh, 2006; Briones & Sepúlveda-Varas, 2016; Carmona et al., 2010; Shackleton, 2020). Although research on mining-related environmental transformations has gained considerable attention, uncertainties persist surrounding its socio-economic impacts on neighbouring populations (Goodchild et al., 2000). The extractive industries in resource-rich regions can promote economic activity, alleviate poverty through job creation and linkages, and improve life and well-being through better access to education, healthcare, and other essential utilities (D'Odorico et al., 2017; Hajkowicz et al., 2011; Yiran et al., 2012). On the other hand, mining regions are plagued with a myriad of social problems, which include increased social tension and conflict, increased inequality, and a loss of access to lands (Aragon & Rud, 2013a; Hook, 2019; Loayza & Rigolini, 2016a; Reeson et al., 2012a). Given these complex and diverse impacts, cross-disciplinary techniques have the ability to examine relationships across space, place, and time (Arts et al., 2019; Hook, 2019; Horsley et al., 2015; Lechner et al., 2017).

Mining impacts are typically region-specific because of highly localised variables, often disproportionately affect different socioeconomic levels, and frequently vary in their geographical extent, extending well beyond the initial location of the mine activity (Franks et al., 2010; Lechner, Owen, Ang, & Kemp, 2019; Lechner, Owen, Ang, Edraki, et al., 2019; Owen &

Kemp, 2013; Ticci & Escobal, 2015). Despite the existence of multiple case studies illustrating the effects of the mining industry on specific cities and communities, less is known about the characteristics of large-scale mining impacts from a geospatial perspective (Devenin & Bianchi, 2019), which encompasses an assessment of space and place (Goodchild et al., 2000). The assessment of social impacts frequently faces challenges due to a lack of data and costly data collection and processing across large areas. (Horsley et al., 2015; Uhlmann et al., 2014).

Numerous studies have indicated that including spatial centrality would offer a valuable dimension for capturing mining impacts at various scales and phases of the mine life cycle (Arts et al., 2019; Hentschel et al., 2000; Kivinen et al., 2018; Lechner, Owen, Ang, & Kemp, 2019; X. Y. Li et al., 2014; McIntyre et al., 2016; Rampellini & Veenendaal, 2016; Yiran et al., 2012). However, the utility of remote sensing and GIS for capturing the geospatial dimensions of social impacts remains under researched and underdeveloped (Werner et al., 2019). Despite their potential values, it is uncommon in a mining environment to apply interdisciplinary GIS and remote sensing technologies, notably land use and land cover (LULC) change analyses, to spatially monitor and characterise social changes (Lechner et al., 2019b; Werner et al., 2019). Generally, health impacts are more commonly studied geospatially using GIS as the main part of the analysis (DeLemos et al., 2007; Diringer et al., 2015; Shandro et al., 2011; Winkler et al., 2010) compared to economic and livelihood studies (Devenin and Bianchi, 2019; Hook, 2019; Rampellini and Veenendaal, 2016).

Techniques for satellite-based remote sensing are frequently used to assess and track the impacts of mining on the environment as well as to support activities for restoration and rehabilitation (Koruyan et al., 2012; Sonter et al., 2014; Xiao et al., 2020). Historical LULC change using remote sensing is an established method for understanding past and present physical properties of landscapes (Andersen et al., 1996; Briones and Seplveda-Varas, 2016; Pan et al., 1999). These studies provide details on the expansion, transformation, and abandonment of LULC as well as the environmental effects of these land conversions (Gyawali et al., 2004; Yiran et al., 2012). Freely available Landsat satellite imagery (whose historical archives date back to the 1970s) is frequently utilised to create time series visualisations due to its high temporal and moderate spatial resolution (Gómez et al., 2016; Huang et al., 2017;

Young et al., 2017). Time series analysis of land cover change can be used to characterise changes in mined land and its surrounding landscapes while keeping track of socioeconomic trends like poverty distribution and urbanisation (Hentschel et al., 2000; Mihai et al., 2015) and environmental degradation such as pollution and deforestation (Coppin et al., 2004; Yang et al., 2018). On the other hand, there is also a lot of untapped potential for using remote sensing and GIS to enhance social studies in mining environments, particularly historical satellite imagery and participatory mapping techniques to capture land use classes with greater thematic resolution, such as region-specific agriculture, which is challenging to detect using Landsat classification alone. Both coarse and fine thematic resolution land covers and land uses can be more successfully recorded by adopting a stakeholder-inclusive and integrated mapping perspective. These spatial approaches can support and improve stakeholder-inclusive social research on community livelihoods and well-being (Everingham et al., 2018; Kivinen et al., 2018; Yiran et al., 2012).

1.2 Research Aim and Objectives

The overarching goal of this research project is to explore the application of spatially explicit GIS and Remote Sensing approaches for evaluating the impacts of mining on society and the environment.

With this goal in mind, the objectives of this thesis are:

1) To provide a systematic and comprehensive compilation of all previous efforts that integrated GIS and remote sensing with social science approaches to capture the spatial aspects of mining's impacts on local communities.
2) To formulate recommendations for areas where further research can be done and how the integration of GIS, remote sensing and social science can be improved to better understand socio-economic mining impacts.
3) To characterize and evaluate the land cover changes in a mining landscape and its concurrent impacts on socio-environmental land uses.

1.3 Research Questions

1) To what extent has the social, economic, and environmental mining impacts been studied in spatially explicit ways?
2) How can current limitations of GIS and Remote Sensing approaches be improved to spatially study socio-economic and environmental impacts?
3) How can the socio-environmental land use and land cover impacts in a mining region (Didipio, Philippines) be best captured using spatially integrated social science approaches?

1.4 Thesis Outline

There are 4 chapters in this thesis. The literature review (Chapter 2) and the main empirical chapters (Chapter 3) are written so that they may be read independently as stand-alone research articles. Chapter 3 has been published while Chapter 2 is still in preparation for publication submission. Except for the formatting, which has been altered to preserve a consistent style throughout this thesis, the contents of the Chapter 3 remain the same as the published/to be submitted versions; the References for all chapters have been consolidated into a single list at the end of the thesis before the Appendix.

Chapter 2 reviews past empirical research that utilized GIS and remote sensing to geospatially study socio-economic and environmental mining impacts. It provides a systematic and comprehensive evaluation of all previous efforts that integrated GIS and remote sensing with social science approaches to spatially capture and assess mining impacts on local communities. This review guides the subsequent chapters by highlighting the limitations and advantages of the approaches utilized so far and recommendations for improving future research on spatially integrated evaluation of socio-economic mining impacts.

Chapter 3 investigates the land use and land cover changes of a mining region in Philippines to evaluate its the socio-environmental impacts. This case study utilized historical Landsat imagery with auxiliary data composites to classify coarse-scale land cover (ie: Vegetation, Water Body, Built-Up Area, Mining and Bareland) via a supervised Random Forest classification approach in Google Earth Engine. Stakeholder knowledge was integrated via a novel web-based participatory mapping to map key fine-scale land use (ie: Citrus, Rice Paddy, and Swidden Agriculture, and Small-Scale Mining) and provide critical local context to the time series trends obtained from the mapping process.

Finally, Chapter 4 summarizes this study's contributions with regard to the research questions: (1) the extent of how social-economic and environmental mining impacts have been spatially studied, (2) ways to improve current limitations of GIS and Remote Sensing approaches to spatially study socio-economic and environmental impacts, and (3) how socio-environmental mining impacts can be characterized using spatially integrated social science approaches. Recommendations and anticipated challenges for future research that aims at more spatially integrated assessment of socioeconomic impacts of mining are highlighted in the closing remarks section.

Chapter 2. Systematic Review of GIS and Remote Sensing Applications for Assessing the Socio-Economic Mining Impacts

Paper in preparation:

Ang, M. L. E., Owen, J. R., Everingham, J., Kemp, D., Gibbins, C., & Lechner, A. M. (in preparation). Review of GIS and Remote Sensing Applications for Assessing the Socio-Economic and Environmental Mining Impacts. *The Extractive Industries and Society*.

2.1 Introduction

Minerals are central to modern society affecting millions of people globally (Githiria & Onifade, 2020). As the mining industry continues to grow, there is a pressing need for a robust understanding of its impacts on all stakeholders, to enable informed decision-making that can maximize benefits and minimize risks associated with mineral extraction (Arts et al., 2019; Owen et al., 2022; Sonter et al., 2014; Y. Zhang et al., 2017). The first step is to address the practical, methodological, and conceptual constraints currently restricting this understanding.

Social impacts in mining landscapes are dynamic, complex, and interconnected, with variations of positive and negative consequences (Braimoh, 2006; Briones & Sepúlveda-Varas, 2016; Carmona et al., 2010; Shackleton, 2020) for liveability, cultural well-being, social cohesion, quality of life and health (Petrov et al., 2018; Vanclay et al., 2015). While the environmental transformations associated with mining have been the subject of much attention, questions remain on the socio-economic impact of mineral extraction on local communities (Goodchild et al., 2000). On the one hand, mining has great potential to contribute to increased economic activity, poverty alleviation through job creation and linkage creation, and to overall improved livelihoods and well-being through better access to education, healthcare and other basic amenities (D'Odorico et al., 2017; Hajkowicz et al., 2011; Yiran et al., 2012). On the other hand, social tension, conflicts, inequality, and loss of access to land are among the many social issues that arise in mining areas (Aragon & Rud, 2013a; Hook, 2019; Loayza & Rigolini, 2016a; Reeson et al., 2012a). Given these positive and negative dimensions, cross-disciplinary approaches hold potential to assess interactions across space, place and time, in order to provide fully integrated overall assessment (Arts et al., 2019; Hook, 2019; Horsley et al., 2015; Lechner et al., 2017).

Mining impacts are generally region specific due to effects of highly localized factors. These effects are unevenly felt at various societal levels and often vary in their geospatial extent, extending well beyond the mine operation's initial location (Franks et al., 2010; Lechner, Owen, Ang, & Kemp, 2019; Lechner, Owen, Ang, Edraki, et al., 2019; Owen & Kemp, 2013; Ticci & Escobal, 2015). Despite numerous case studies of the effects of the mining sector on individual towns and communities, little is known about large-scale mining impacts from a geospatial perspective (Devenin & Bianchi, 2019), which encompasses the analysis of space and place (Goodchild et al., 2000). Limited data availability and high data collection and analysis costs often pose challenges to the assessment of social impacts (Horsley et al., 2015; Uhlmann et al., 2014).

The utility of Remote Sensing and GIS for capturing the geospatial dimensions of social impacts remains under researched and underdeveloped (Werner et al., 2019). Generally, health impacts are more commonly studied geospatially using GIS as the main part of the analysis (DeLemos et al., 2007; Diringer et al., 2015; Shandro et al., 2011; Winkler et al., 2010) compared to economic and livelihood studies (Devenin and Bianchi, 2019; Hook, 2019; Rampellini and Veenendaal, 2016). It can be anticipated that with technical and conceptual advancement in GIS and Remote Sensing methods, the increase in frequency of their application is inevitable, and insights are likely to improve as a result of improvements in data (e.g. higher resolution). Accordingly, a review of the past GIS and Remote Sensing applications to better understand the socio-economic impacts is timely.

This chapter reviews past empirical research that utilized GIS and Remote Sensing to geospatially study socio-economic and environmental aspects of mining impacts. The review has a particular focus on assessing the extent to which multidisciplinary approaches have been applied within the Social Framework for Projects, to further knowledge of mining's impacts on people's well-being and the social sustainability of projects (Smyth & Vanclay, 2017). The chapter has four objectives: (1) To determine the spatio-temporal distribution of studies looking at socio-economic and environmental impacts and types of mining commodities studied. (2) To identify the categories of socio-economic mining impacts that have been studied in spatially explicit ways (3) To identify the social science approaches used by these studies and the types of stakeholders engaged. (4) To determine the Remote Sensing and GIS approaches used by the studies. Upon reviewing the existing state of research efforts, we present an overview of the current research developments and spatially integrated approaches for capturing mining impacts. We conclude by making recommendations for areas where further research can be done and how the integration of GIS, Remote Sensing and Social Science can be improved to better understand socio-economic mining impacts.

2.2 Methods

2.2.1 Search Criteria

A systematic approach was applied via an online search in the SCOPUS database conducted from the 1st September to 31st of October 2021 using a specified search query (Figure 2.1). This rigorous and explicit methodology was applied to ensure a comprehensive overview of existing literature and research gaps (Meerpohl et al., 2012). Only peer-reviewed journal articles published in English were queried (Figure 2.1); conference proceedings, books and non-peer reviewed articles were not included.

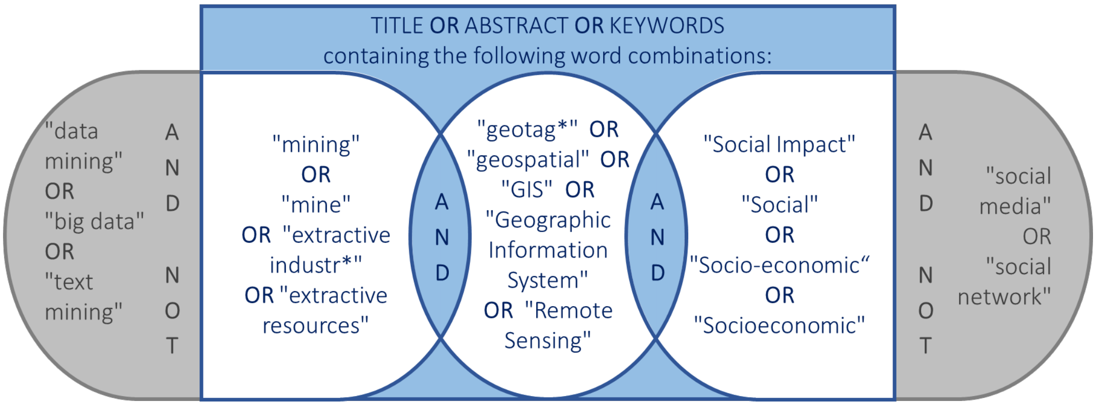


Figure 2.1 A graphical illustration of the systematic literature review search query: TITLE-ABS-KEY (("Social Impact" OR "Social" OR "Socio-economic" OR "Socioeconomic") AND NOT ("social media" OR "social network")) AND (TITLE-ABS-KEY ("geotag" OR "geospatial" OR "GIS" OR "Geographic Information System" OR "Remote Sensing")) AND TITLE-ABS-KEY (("mining" OR "mine" OR "extractive industr*" OR "extractive resources") AND NOT ("data mining" OR "big data" OR "text mining")). The coloured areas in light blue indicate the focus of the literature search query for further filtering.*

The abstracts of the literature captured by the search query (Figure 2.1) were then manually screened. Only studies that meet the following criteria were included in the full analysis:

a) Studies conducted on mining sites, regions, or countries dependent on resource extraction.
b) Studies that specifically examined social and economic mining impacts. Papers that studied environmental impacts as well were included if they also analysed socioeconomic impacts.
c) Studies that utilized GIS and/or Remote Sensing methods, either as a major or minor component of their methods, to spatially capture these impacts

The terms 'spatial' and 'geospatial' were sometimes used interchangeably in the papers, and some papers had clear geospatial elements despite not using either term. Therefore, we were careful to include all peer-reviewed work that included geospatial elements, irrespective of how they defined or used these terms. Papers that simply used GIS or Remote Sensing to map or illustrate mining areas or mineral distributions (e.g. (Erb-Satullo, 2021), which represented purely technological or methodological advancements (e.g. (Balaniuk et al., 2020; Kamali et al., 2015; Zhu & Yu, 2016), or which focused on purely ecological mining impacts but did not undertake any social-related impact analysis, (e.g. (Cosimo et al., 2021; Kiere et al., 2021; Y. feng Li et al., 2009; Peng et al., 2016; Wedding et al., 2013) were not included.

2.2.2 Data Compilation and Analysis

An archive was compiled to summarize the literature based on the following key variables; 'General Information', 'Mine-Related' information, 'Geospatially-Assessed Mine Impacts', 'Social Science' method and 'GIS and Remote Sensing' applications applied (Table 2.1).

Table 2.1. Literature review metadata list for summarizing and categorising the studies.

	General Information		Mining Related			Geospatially-Assessed Mine Impacts	Social Science		
	Scale of assessment	Research Approach	Commodity	Stages of Mine Life Cycle	Type of Extraction		Stakeholders	Participation Method	Social Science Data collected
Categories/Class	•Global •Continental •Country •Regional •Mine Sites (>1) •Mine Site (n=1)	•GIS only •GIS and Remote Sensing •GIS and Social Science •GIS, Remote Sensing and Social Science	•Coal •Metalliferous* (ie: zinc, gold, diamond, iron, tin, and mercury mines) •Quarry (ie: ironsand, hard rock, and limestone) •Oil and Gas * Green energy minerals will be highlighted	•Pre-Mining (ie: exploration, design and planning, construction) •During Mining (ie: production) •Post-Mining (ie: closure and reclamation/ rehabilitation, abandoned) •Multiple (across several life cycle) •NA (unspecified or not applicable)	•Surface Mining (ie: quarry/ open cut/ pit/ cast) •Underground •Small Scale Artisanal Mining •Unspecified	•Environment •Land •People •Community •Culture •Livelihoods •Infrastructure •Housing	•Vulnerable (ie: elderly/ women/ children) •Indigenous Community •Local Community and Visitors •Academics and Experts •NGO •Businesses and Industry •Mining •Government	•PGIS and Geovisualization •Survey/ Questionnaire •Interview •Meeting •Focus Group •Workshop	•Environment •Land •People •Community •Culture •Livelihoods •Infrastructure •Housing
Notes and References			Based on (McKenna et al., 2020)'s mine commodity categories and *(Herrington, 2021)'s list of anticipated essential green energy commodities			Based on (Smyth & Vanclay, 2017)'s Social Framework for Projects			Based on (Smyth & Vanclay, 2017)'s Social Framework for Projects

Continue from Table 2.1.

	GIS and Remote Sensing						
	Satellite Imagery or Sensors used	Remote Sensing and Geospatial Data collected	Spatial Resolution	Temporal Scale	Classification Method	Accuracy	Spatial Analysis Method
Categories/Class	•Satellite (ie: Landsat, SPOT, MODIS) •Sensor (ie: ASTER) •Basemap (ie: Google basemap)	•Environment •Land •People •Community •Culture •Livelihoods •Infrastructure •Housing	•Low (>30m) •Medium (5-30m) •High (<5m)	•Uni-temporal •Bi-temporal •Multi-temporal	•Supervised (ie: Decision Tree, Random Forest, GEOBIA, Manual interpretation) •Unsupervised (ie: Index)	•>80 •70 to 80 •<70 •Not Reported	•Queries and Reasoning •Measurements •Transformations •Descriptive Summaries •Optimization •Hypothesis Testing
Notes and References		Based on (Smyth & Vanclay, 2017)'s Social Framework for Projects					Based on (Longley et al., 2005)'s six types of spatial analysis

2.2.2.1 Objective 1: To determine the spatio-temporal distribution of studies looking at socio-economic and environmental impacts and types of mining commodities studied.

The 'General Information' on the selected papers (title, year of publication, keywords, country or region of study and scale of assessment) was used to create a basic data base. We present the study areas by geographic regions (Table A 1) instead of individual countries. This is especially useful for distinguishing studies in Asia which has around 60% of the world's population (UN DESA, 2018) and is made up of many culturally unique regions, with contrasting levels of endemism and biodiversity values (Myers et al., 2000). To summarize the 'Research Approach', the studies were grouped into four sub-categories: 'GIS only', 'GIS and Remote Sensing', 'GIS and Social Science' or 'GIS, Remote Sensing and Social Science' (Table 2.2).

*Table 2.2 The definition of the four method categories used to group the literature. * The definition of data extraction method for each study method category is italicised and bold.*

Study Method Category	**Methods used**			**Definition**
	Data Generation*		**Data Analysis**	
	Remote Sensing	**Social Science**	**GIS**	
GIS only	No	No	Yes	Combinations of geospatial and geoprocessing methods were used to analyse geospatial data.
GIS and Remote Sensing	Yes	No	Yes	***Remote sensing products (ie: climate data, DEM, satellite imagery and basemap) were used either directly or subsequent image processing techniques were applied (ie: land cover classification).*** **AND** Geospatial and geoprocessing methods, with or without additional geospatial data, were used to analyse the datasets.
GIS and Social Science	No	Yes	Yes	***Data were qualitatively and/or quantitatively collected from stakeholders using social science methods such as PGIS, survey, questionnaire, interview, meeting, focus group sessions and/or workshops***. **AND** Geospatial and and geoprocessing methods were used to analyse the social data with or without additional geospatial data.
GIS only	Yes	Yes	Yes	***Remote sensing products (ie: climate data, DEM, satellite imagery and basemap) were used either directly or subsequent image processing techniques were applied (ie: land cover classification).*** **AND** ***Data were also qualitatively and/or quantitatively collected from stakeholders using social science methods such as PGIS, survey, questionnaire, interview, meeting, focus group sessions and/or workshops***. **AND** Geospatial and geoprocessing methods were used to analyse the social and Remote Sensing data with or without additional geospatial data.

‘Commodity’ (type of mineral)’, ‘Stage of Mine Life Cycle’ and ‘Type of Extraction’ were determined from papers to assess trends and patterns in the type of mines being studied. The sub-categories of the ‘Commodity’ were ‘Coal’, ‘Metalliferous’, ‘Quarry’ and ‘Oil and Gas’ (McKenna et al., 2020). Commodities that may be associated with the increasing demand of raw materials critical for the green energy revolution (Herrington, 2021) were highlighted as part of this categorisation. The ‘Stages of Mine Life Cycle’ studied is divided into the ‘Pre-mining’, ‘During’ and ‘Post-mining’ phases. Those that studied more than one stage were classified as ‘Multiple’ and studies with unspecified life cycle stage are marked as ‘NA’. The ‘Type of Extraction’ is based on McKenna et al. (2020)’s list, and includes ‘Surface Mining’, ‘Underground’, and ‘Small-Scale Artisanal Mining’; unreported types are classified as ‘Unspecified’.

2.2.2.2 Objective 2: To identify the categories of socio-economic mining impacts that have been studied in spatially explicit ways.

We adopted a framework to help with analysis of the content of the papers. The Social Framework for Projects (Smyth & Vanclay, 2017) was built upon existing models and frameworks and is applied in this study due to its comprehensive coverage of various socio-environmental factors making it highly applicable for large projects to understand, assess, plan, and manage the diverse social sustainability and well-being issues (Smyth & Vanclay, 2017). Additionally, the thoroughly constructed categories within the framework provide a fitting summary of the various dynamics of socio-economic and environmental impacts, without which would be difficult to discern. Using this framework, we classified the ‘Geospatially-Assessed Mine Impacts’ studied using the eight categories in the Social Framework for Projects (Smyth & Vanclay, 2017): ‘Environment’, ‘Land’, ‘People’, ‘Community’, ‘Culture’, ‘Livelihoods’, ‘Infrastructure’ and ‘Housing’.

2.2.2.3 Objective 3: To identify the social science approaches used by these studies and the types of stakeholders engaged.

As social mining impacts most severely affect local and vulnerable groups (Owen et al., 2022), we were interested to know the proportion of studies that include stakeholders in their assessment, in particular, the local and indigenous communities. The types of ‘Stakeholders’ involved, and the ‘Participation Method’ was recorded to determine the extent of public engagement and social science approaches used. The categories of ‘Stakeholders’, are divided into ‘Vulnerable’ which includes the elderly, women and children, ‘Indigenous Community’ which would include natives that are heavily dependent on the land and natural resources, ‘Local Community and Visitors’ which includes people living and working in the area, ‘Experts and Academics’ which includes researchers and field experts, non-governmental organization (‘NGO’), ‘Businesses and Industries’ owners such as those in the agricultural sectors, ‘Mining’ authorities and employees, and ‘Government’ officials. The ‘Participation Method’ was divided into participatory geographic information system ‘(PGIS) and Citizen Science’, ‘Survey/Questionnaire’, ‘Interview’, ‘Meeting’, ‘Focus Group’ and ‘Workshop’.

2.2.2.4 Objective 4: To determine the Remote Sensing and GIS approaches used by the studies

To determine the range and nature of the GIS and Remote Sensing approaches applied and to compare the variety of geospatial products used to study various socio-economic and environmental impact categories, we extracted information on the ‘Satellite Imagery’ or ‘Sensors’ used, ‘Remote Sensing and Geospatial Data’ collected, ‘Spatial resolution’, ‘Temporal scale’, LULC ‘Classification’ or ‘Spatial’ methods, spectral indices (‘Index’), and reported ‘Data Accuracy’.

‘Sensors’ were grouped into ‘Satellites’ (ie: Landsat, SPOT and MODIS), ‘Sensor’ (ie: ASTER), and ‘Basemap’ (ie: Google Earth). For studies that do not utilize sensors and instead obtained pre-processed, remotely sensed or geospatial data, the types of data used were categorized based on the Smyth & Vanclay (2017) Social Framework for Projects. The ‘Spatial Resolution’ was ‘High’ for resolution less than 5 m, ‘Medium’ for resolution between 5 to 30 m and ‘Low’ for resolution above 30 m. The ‘Temporal scale’ of the studies indicates the measurement period(s) which are grouped into ‘Uni-temporal’ for single timestep studied, ‘Bi-temporal’ for studies using two timesteps and ‘Multi-temporal’ for studies with three or more timesteps.

‘Classification method’ was divided into supervised and unsupervised. ‘Supervised’ classification includes Geographic Object-Based Image Analysis (‘GEOBIA’) for studies which utilized segmentation and image-objects instead of pixels for classification. Methods using training samples and machine learning algorithms such as Random Forests, Support Vector Machines (SVM), Classification and Regression Trees (CART), Maximum Likelihood and Convolutional Neural Network (CNN) were also classified under 'Supervised' classification, as were those that digitized polygons to manually create classes. On the other hand, 'Unsupervised' classification includes studies which classified pixels based on indices such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Build-up Index (NDBI) or other unsupervised methods such as ISOSEG (using k-Means), self-organization cluster analysis (ISOCLUST—from IDRISI), and Iterative Self-Organizing Data Analysis (ISODATA).

'Accuracy' assessment is important for assessing the reliability of LULC classification. An accuracy of 80% and above is considered high while 70% is the more commonly applied threshold (Anderson et al., 1976; Foody, 2002; Lunetta et al., 1991). We assessed reported accuracy in papers and used the 'Not reported' class for studies which carried out classification but did not perform or report the accuracy assessment results. Finally, the 'Spatial' methods used in papers was classified according to (Longley et al., 2005)'s six types of spatial analyses to help summarize the variety of GIS approaches used (Table 2.3).

Table 2.3 Longley et al. (2005)'s six types of spatial analyses and the respective definitions.

Type of Spatial Analysis	Definition
Queries and reasoning	Basic data queries are carried out such as overlay analysis and comparing the location or spatial distribution of an object
Measurements	Numerical values used to describe the geographical aspects of data through methods such as calculating area, proximity analysis, area intersect and buffer analysis
Transformations	Data is altered through spatial interpolation such as Kriging and Inverse distance weight (IDW).
Descriptive summaries	Spatial descriptive statistics methods to summarize datasets
Optimization	Techniques are implemented to determine ideal locations based on a set of user-defined criteria such as weighted overlay for site-location analysis and value compatibility analysis (VCA)
Hypothesis testing	Involves a more complex reasoning process and inferential statistics to determine the likelihood of an observed spatial pattern being reflected by the broader population. Examples of this category includes studies which utilizes modelling such as Spatial Regression model, conflict potential modelling and environmental impact classification model, and indices such as preference and value index (PVS) and weighted preference index (WPS).

2.3 Results

The initial search yielded 448 studies published between 1989 and 2021. Of these, only 210 English language articles were published in peer-reviewed journals. The abstract screening and then final checking of the 210 articles to determine if papers undertook GIS/Remote Sensing analysis of socio-economic impacts (rather than simply mapping of mineral distributions or focusing solely on ecological impacts) returned a total of 71 studies that were included in the final review.

2.3.1 Objective 1: Spatio-Temporal Distribution of Studies

From this set of 71 studies, the earliest was a study in India, South Asia, published in 1996 (Figure 2.2) that used Remote Sensing to determine land use and land cover (LULC) changes associated with an increase in mining activity over a 20-year period (Jhanwar, 1996). There were no other studies captured until 2005 and after 2014, there was a steady increase in publications per year. More than three-quarters of the studies were published post 2014, with the highest number of 11 papers published per year both in 2020 and 2021. In terms of the geographical distribution, the studies are relatively well distributed across the east and the west with the highest number of studies carried out in Europe and China (Figure 2.3A). The distribution of the first authors' primary research institutions have been compiled in Figure A 1 where a higher proportion of authors being based in the western regions compared to the east.

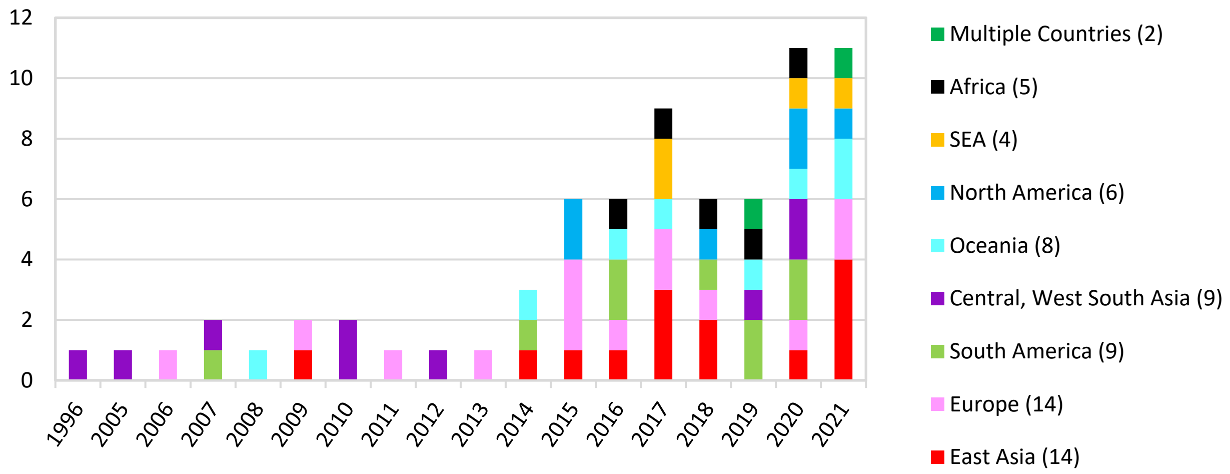


Figure 2.2 Spatio-temporal distribution of studies based on study area region (N=71). The total number of studies carried out in each region is indicated in brackets, ie: East Asia (n=14)

Three quarters of the studies were carried out at the 'Regional' scale while the remaining covered areas at the 'Mine Site', 'Mine Sites', 'Country' and 'Multiple Countries and Continental' scale (Figure 2.3B).

The bulk of the studies focused on impacts during the active mining (ie: production) stage (61%), with only 18% of studies analysing impacts across multiple stages of the mine life cycle (Figure 2.3C). Only two studies were carried out during the pre-mining stage, both of which used the spatial analytical hierarchy process (AHP) to locate the most ideal location either for pit development (Risk et al., 2020) or a gilsonite processing plant (Kazemi et al., 2020). On the other hand, three studies were carried out on post-mining landscapes. These three were (a) an assessment of ecological rehabilitation efforts via community participatory methods (Rich et al., 2015), (b) the development of Mining Incidence Documentation & Assessment Scheme (MIDAS) which is a geospatial database for effective, widespread and systematic spatial analysis (Werner et al., 2020), and (c) Remote Sensing image classification-based, multi-dimensional index system to evaluate the spatio-temporal evolution of Production-Living-Ecological Space (PLES) (Tao & Wang, 2021).

Forty papers (56%) reported on the type of mineral extraction studied which included either or a combination of underground, artisanal small-scale mining (ASM) and surface mining (Figure 2.3D). The remaining 31 papers did not specify any extraction type. Seven of the studies on ASM were linked to gold extraction and were published within the last 4 years (Figure A 2). Four out of the six underground mining studies were coal related. The coal mining studies make up a large proportion of the literature (Figure 2.3E) and are concentrated within the last seven years (81%), peaking in 2021 (n=7) (Figure A 3). The majority of the coal mining studies were carried out in China (42%) (Figure 2.4), in line with the increasing amount of coal mined from this country (e.g. 50% of the global coal production in 2012 came from China (Xiao et al., 2017).

The number of studies capturing metalliferous commodities associated with securing a green energy future (Herrington, 2021) (Table A 2) were more frequent within the last decade than prior to this (Figure A 3), even if the intention of studying these minerals is not related with Herrington's (2021) narrative.

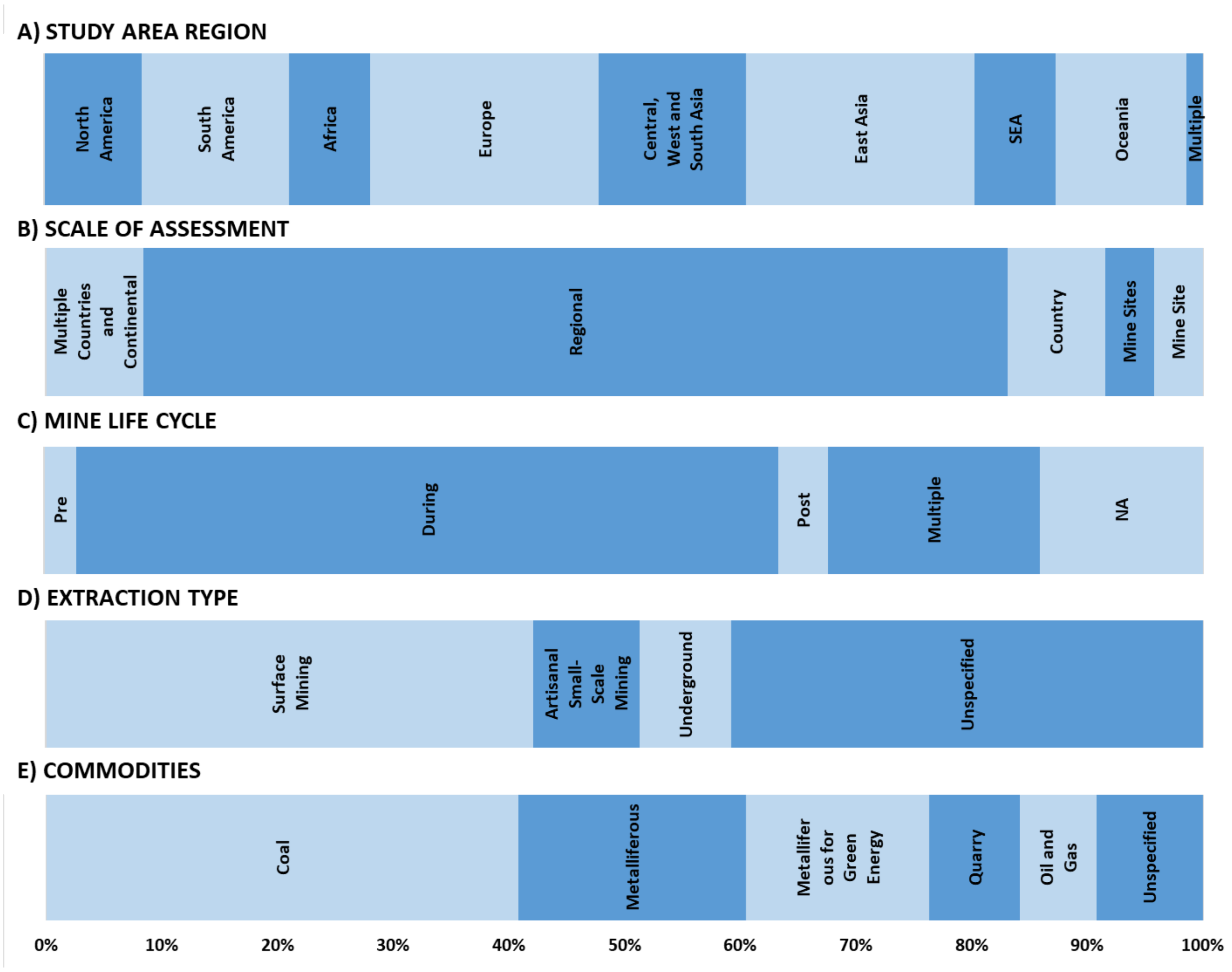


Figure 2.3 The general characteristics of the studies (N=71). (A) the proportions of study area regions; (B) The various scales at which the studies were conducted; (C) stage of mining lifecycle; (D) types of commodity extraction method; and (E) the categories of commodities extracted.

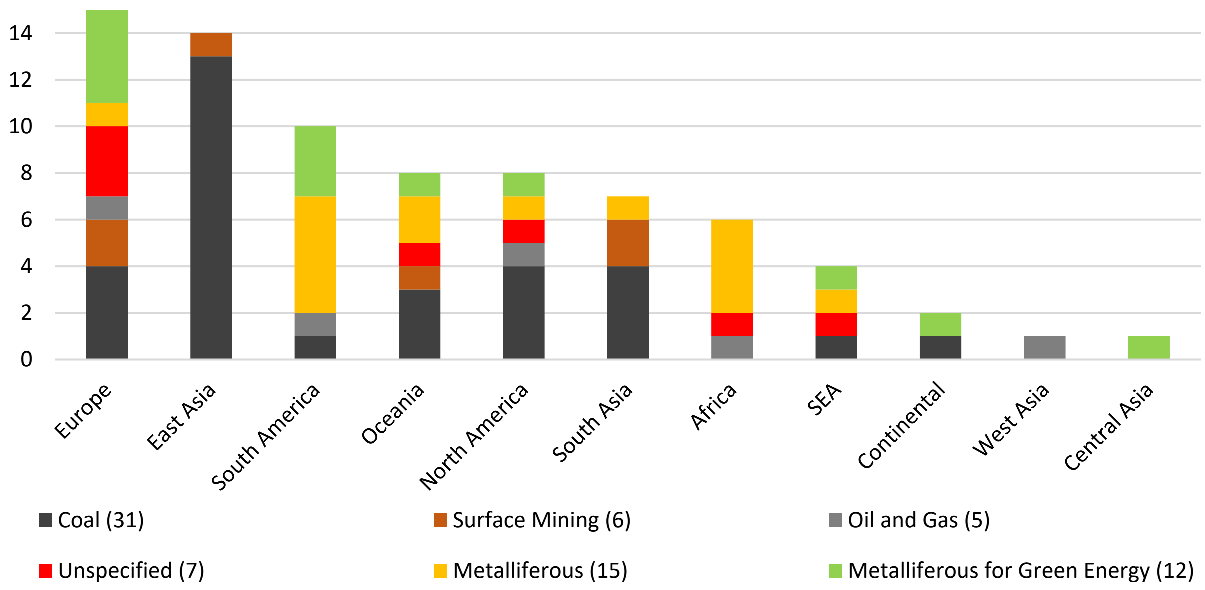


Figure 2.4 Distribution of commodities and study area location.

2.3.2 Objective 2: Categories of Socio-Economic Mining Mining Impacts Spatially Studied

Overall, all eight categories of the socio-economic and environmental impacts identified by the Social Framework for Projects (Smyth & Vanclay, 2017) were successfully captured by the literature (Figure 2.5) with the integration of GIS, Remote Sensing and Social Science approaches. However, it is observed that the intangible aspects (ie: 'Culture') were notably unable to be captured, especially using Remote Sensing approaches alone, and as demonstrated by the low percentages in Figure 2.6 to be the most difficult category to capture even with other approaches.

A fair portion of the socio-economic and environmental impacts identified by the Social Framework for Projects (Smyth & Vanclay, 2017) were successfully captured by the literature (Figure 2.5) with the integration of GIS, Remote Sensing and Social Science approaches. It is observed that the intangible aspects were notably unable to be captured. Most of the studies captured between two and four categories of the Social Framework for Projects (Smyth & Vanclay, 2017), with three categories being the modal value (Figure 2.6A). 'GIS only' and 'GIS and Remote Sensing' mostly captured three indicators (light yellow bar) per study (Figure 2.6A). For 'GIS and Social Science' and 'GIS, Remote Sensing and Social Science' method categories, the studies captured mostly two indicators (orange bar) per study (Figure 2.6A). From Figure 2.6A, the highest number of indicators captured per study was six, with only one paper in the 'GIS and Social Science' category (Pattanayak et al., 2010) successfully captured 7 indicators (Figure 2.6E).

The most studied indicator was 'Land' followed by 'Livelihoods'. For the 'GIS and Remote Sensing' method category, 'Infrastructure' was the third most captured indicator while for 'GIS only', the number of studies that captured 'People' were higher than 'Land'. The environmental ('Environment' and 'Land'), social ('People', 'Community', 'Infrastructure', 'Housing') and economic ('Livelihoods') indicators were well covered by all four Study Method Category. 'Culture' indicator was lacking in most studies, particularly in the 'GIS and Remote Sensing' group, likely due to the intangible properties of this social impact which requires the integration of social science approaches to extract.

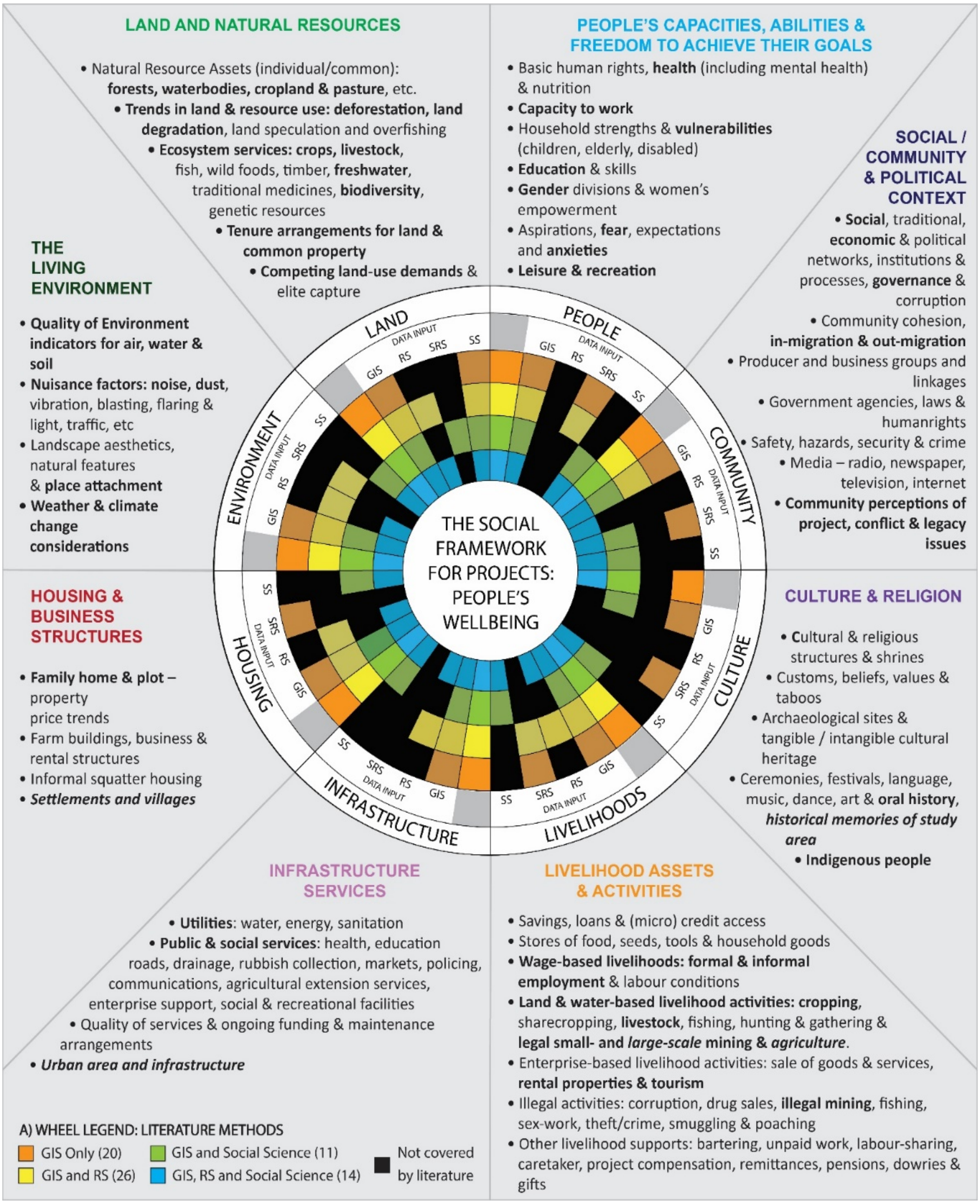


Figure 2.5 A) [At the centre of the figure] the wheel of gaps in knowledge which demonstrates the capabilities of each of the following four method categories to capture the aspects of the Social Framework for Projects (Smyth & Vanclay, 2017). Literature coverage is represented by the coloured cells within the four circular layers in the wheel: (1) GIS Only (outermost in orange), (2) GIS and Remote Sensing (second outermost in yellow), (3) GIS and Social Science (second innermost in green) and (4) GIS, Remote Sensing and Social Science (innermost in blue). The black cells are knowledge gaps that were not covered by the literature. The five subsegments within each of the eight aspects of the Social Framework for Projects (Smyth & Vanclay, 2017) represent (A) the summary coverage for

each major segments, (B) GIS – geospatial data input, (C) SRS – spatially referenced social data input (ie: PGIS data and census data that was collated into grids or non-political boundaries or regions of interest), (D) RS – Remote Sensing data input both collected and/or pre-processed (ie: climatic products and classified LULC), and (E) SS – non-spatial Social Science data input (ie: quantitative or qualitative data collected from surveys and interviews with local stakeholders). B) [The grey area surrounding the wheel (A)] is the Social Framework for Projects (Smyth & Vanclay, 2017) updated with the socio-economic and environmental impacts that were spatially studied by the literature (in bold). Additional impacts that were not in the original list but found in this literature review are italicised.

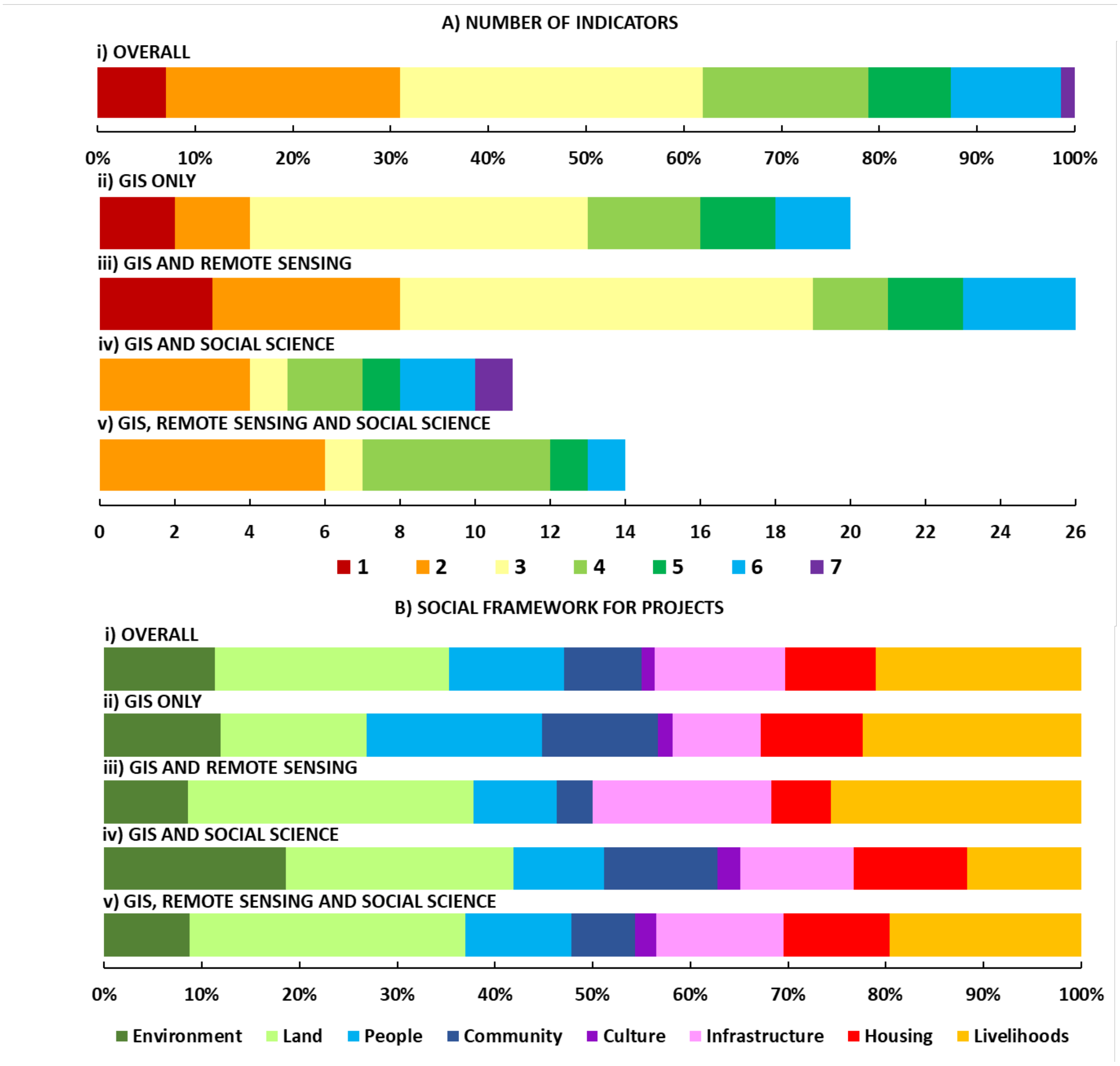


Figure 2.6 A) The proportions of number of indicators per study for each the overall literature (N=71) and by each of the four method categories. B) The proportions of the eight aspects of the Social Framework for Projects (Smyth & Vanclay, 2017) being studied by the overall literature (N=71) and by each of the four method categories.

2.3.3 Objective 3: Social Science Methods and the Types of Stakeholders Engaged

Social science methods were implemented to capture quantitative and qualitative data from stakeholders in 25 out of the 71 studies (Figure 2.7). Majority of the studies were carried out at the 'Regional' scale with areas mining for 'Coal' and 'Metalliferous' commodities. The most common methods used were 'Survey/Questionnaire' and 'Interview'. Other methods include Participatory GIS ('PGIS') and Citizen Science, 'Workshops', 'Meetings' and only one study organized a 'Focus Group' session (Figure A 4).

The top four stakeholder groups engaged were the 'Local Community and visitors', people in the 'Mining industry' and 'Government' as well as 'Academics and Experts', in that order. Other stakeholders engaged were 'Businesses and Industry' members, non-governmental organizations ('NGOs'), 'Indigenous Community' and 'Vulnerable Community', which includes the elderly, women, and children. Although only four studies specifically mentioned involving vulnerable community members, the remaining studies that engaged the 'Indigenous Community' and 'Local Community and Visitors' most likely also captured the elderly and females. Overall, a variety of stakeholders were represented by the studies that implemented social science methods. All eight social framework categories (Smyth & Vanclay, 2017) were captured across all these studies.

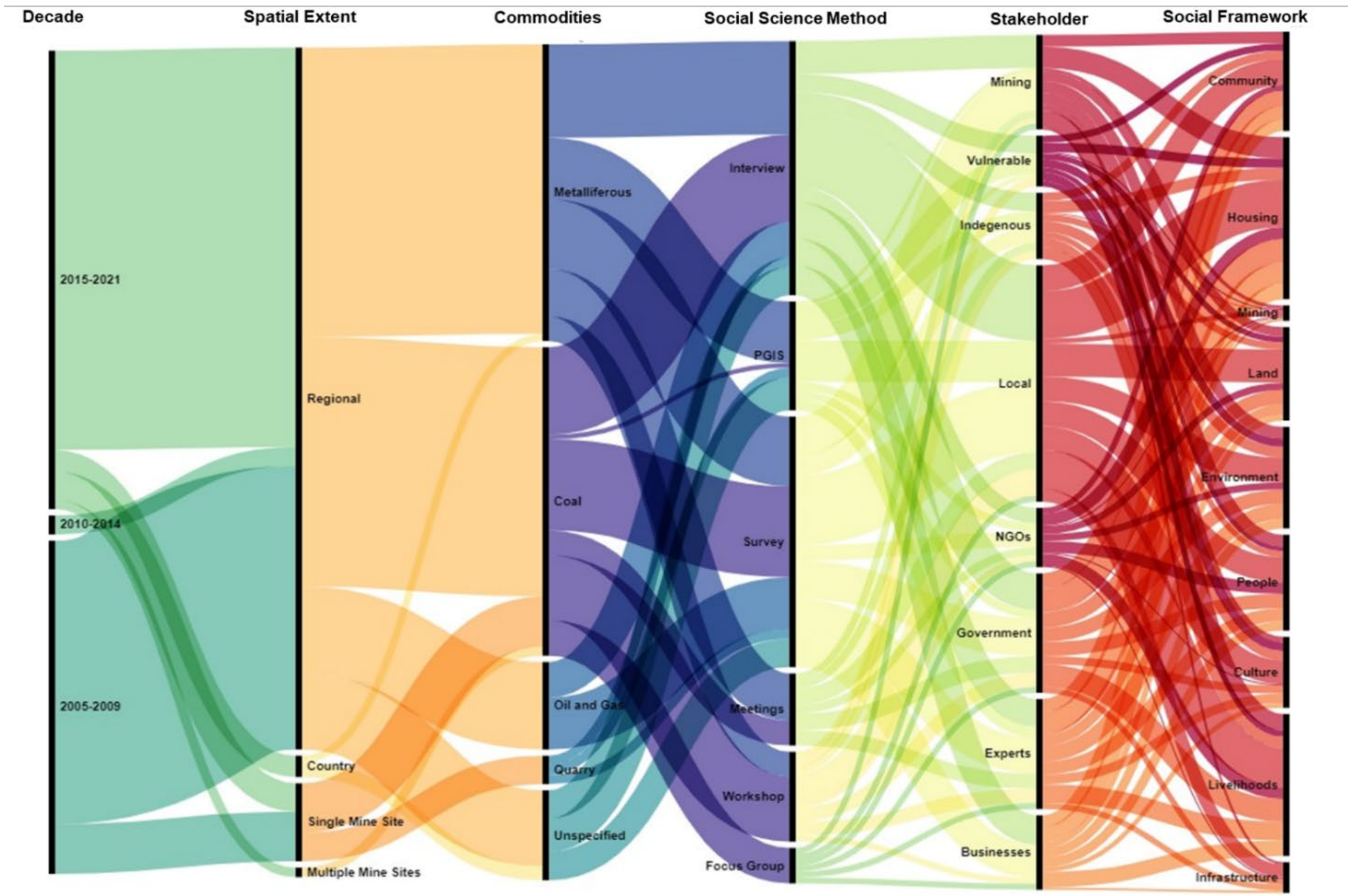


Figure 2.7 The alluvial shows the proportions and correlations between the variables for studies that implemented Social Science methods (n=25). Note: some studies may apply one or more combinations of stakeholders and social science methods.

2.3.4 Objective 4: GIS and Remote Sensing Approaches Utilized by Studies

2.3.4.1 Remote Sensing

A total of 40 of the 71 papers implemented Remote Sensing via either one of four applications; (1) utilized Remote Sensing data in the form of only pre-processed and readily available Remote Sensing products (n=4), (2) only used satellite imagery processed with classification methods (n=24) or (3) used a combination of both pre-processed Remote Sensing data and processed satellite images (n=12). Based on the alluvial chart (Figure 2.8), the majority of the studies were conducted at the regional scale, with only a handful conducted at the 'country', 'multiple countries' and 'continental' level. Generally studies were conducted across multiple timescales, and included 'decadal', 'bi-temporal', 'tri-temporal' and 'multi-temporal' year assessments. Studies that applied change-detection and time-series analysis especially for land use and land cover (LULC) assessment usually employ imageries spanning multiple timesteps across decades.

High resolution satellite image (resolution <5m) that were used included 'Google' basemaps, 'SPOT', 'WorldView' and 'IKONOS'. Medium resolution satellite image (resolution 5 to 30m) used were 'ALOS', 'Corona' satellite, 'Huanjing' satellite and 'Landsat'. 'Landsat' products were used by 70% of the studies that carried out image processing (n=26) (Figure A 5). The Indian Remote Sensing ('IRS') satellites and 'MODIS' were among the lowest resolution satellites that were used (resolutions above 30m).

The classification methods applied included 'Supervised Classification' using Object-Based Image Analysis (OBIA), manual visual interpretation and digitization, decision tree, random forest and other supervised methods such as Neural Net Interpretation (X. Zhang et al., 2016), Convolutional Neural Networks (CNN) (Tao & Wang, 2021), Spectral Angle Mapping (SAM) algorithm (Boakye et al., 2020) and Supervised Support Vector Machine (SVM) algorithm (Schmid et al., 2013). 'Unsupervised Classification' included use of the CLASlite software, and clustering algorithms (full list and references in Table A 3). Indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Enhanced Vegetation Index (EVI), Normalized Difference Build-up Index (NDBI), Built-up Area Index

(BAI) and Normalized Difference Coal Index (NDCI) were classiffied in our analysis as part of the 'Unsupervised Miscellaneous' category (Table A 4).

Only 22 out of 37 papers that classified satellite imagery conducted and reported accuracy assessment scores. These scores were grouped into 3 categories; '60% to 70%' (n=1), '70% to 80%' (n=4) and 'above 80%' (n=17). Overall, a higher proportion of studies that utilized 'Unsupervised', 'Supervised', 'GEOBIA' and 'Manual' classification methods reported accuracies above 80%. Almost half of the studies that conducted 'Supervised – Manual' classification using visual interpretation of satellite imagery did not conduct or report on the accuracy assessment scores. Due to the nature of the human, visual-based interpretation, manual classification is assumed to be fairly accurate when compared to machine learning algorithms.

Remote sensing methods only characterized six out of eight of the categories in Smyth & Vanclay's (2017) Social Framework for Projects (Figure 2.8). The gaps in the indicators that were spatially captured and studied by Remote Sensing alone highlights the difficulties in translating intangible properties of people's well-being into spatial ananlysis, as we can see in the People and Culture categories. Only one study managed to extract Community indicators in the form of social investment project sites (Ang et al., 2020); this was done with the aid of local knowledge and PGIS methods.

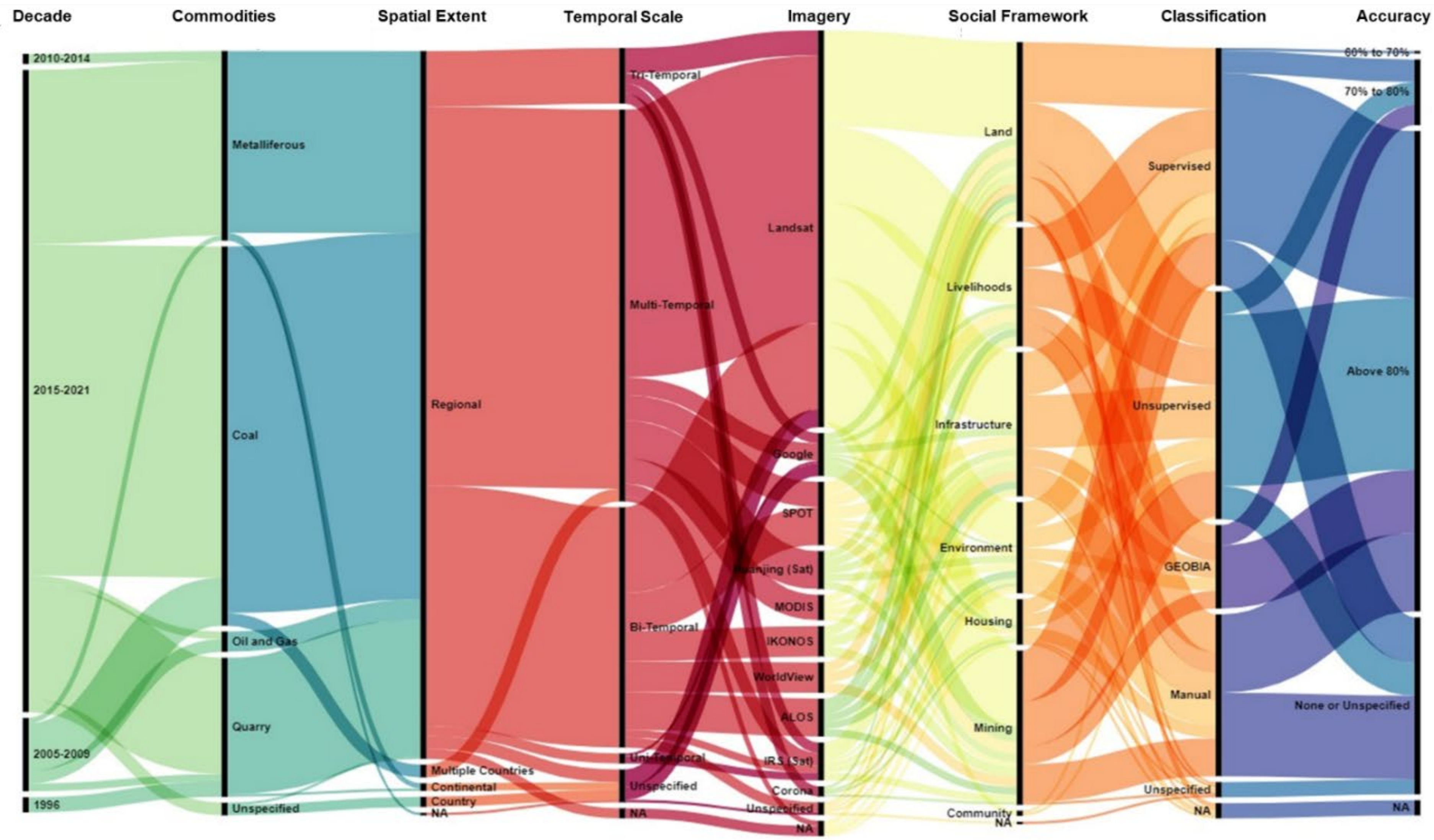


Figure 2.8 Alluvial chart showing the proportions and correlations between the variables for studies that used Remote Sensing images and classification methods (n=40)

2.3.4.2 GIS

All studies in this literature review included some form of spatial analysis (definition of the categories can be found in Table 2.3 and the full list of the analyses are compiled in Table A 5). The majority of the reviewed studies combined spatial analysis with Remote Sensing (n=26), while some analysed GIS data only (n=20), others used a combination of GIS, Remote Sensing and Social Science data (n=14), and finally, the smallest group only integrated GIS and Social Science methods (n=11) (Figure 2.9 and Figure 2.5). Overall, 'Measurements' is the most implemented spatial analysis while 'Optimization' is the least (Figure 2.9A).

Of the 20 studies using only 'GIS' (Figure 2.9B), the most frequent spatial analyses used were 'Measurements', 'Transformation' and 'Statistical Analysis'. Based on the cells highlighted in orange in the outermost circular layer (Figure 2.5), this literature category successfully studied all eight Social Framework for Projects categories (Smyth & Vanclay, 2017). It is also clear from Figure 2.5 that there are GIS data for all eight categories, while spatially referenced social (SRS) data used in this literature category only covered the 'People', 'Community', 'Culture', 'Livelihoods', and 'Housing' aspect of peoples' wellbeing.

26 papers combined GIS data and spatial analysis together with Remote Sensing (Figure 2.5). A large portion of these studies used 'Measurements' (Figure 2.9C). The single study that had spatial analysis related to 'PGIS and Geovisualisation' did not explicitly engaged stakeholders but provided recommendations that geospatial data and imagery be used to visualize impact, an in turn use these visualisations to for presentation and engagement with stakeholders (Krieger et al., 2012). Overall, the integration of Remote Sensing and GIS analysis managed to spatially capture seven of the eight Social Framework for Projects categories (Smyth & Vanclay, 2017) as shown by the yellow cells within the second, outermost circle (Figure 2.5).

15% of the literature (n=11) integrated GIS with social science methods (Figure 2.5). 'PGIS and Geovisualisation' and 'Process Model' were the most implemented spatial analyses (Figure 2.9D). All five studies that carried out 'PGIS and Geovisualisation' spatial analysis used PGIS approaches and citizen science to engage with stakeholders. The green cells in Figure 2.5 (second innermost circle) demonstrated that this literature category successfully extracted data and produced spatial outputs of indicators related to all eight Social Framework for Projects categories (Smyth & Vanclay, 2017). This is expected as the incorporation of social science is key to fully integrate intrinsic and intangible social aspects, especially in the 'People', 'Community' and 'Culture' categories. Studies in this group mostly combined GIS and social science data, with SRS data only available in the 'Land', and 'Community' category.

Finally, a total of 14 papers (20%) combined spatial analysis with Remote Sensing and social science methods (Figure 2.5). 'Measurements' were by far the most common spatial analysis used in this group (Figure 2.9D). The second most utilized spatial analysis was 'PGIS and Geovisualisation' implemented by three studies. All eight Social Framework for Projects categories (Smyth & Vanclay, 2017) were captured using this method category as shown in Figure 2.5's blue cells within the innermost, circle. Where GIS, SRS and Remote Sensing data were unavailable, Social Science approaches were used instead, as seen in the 'Culture' category. With the integration of "tacit knowledge embodied in life experiences and reproduced in everyday behaviour and speech" (Babidge et al., 2019), cultural indicators, such as historical events are more readily discerned. These studies highlight the potential of multidisciplinary and integrated approaches, with authors stressing the critical role of stakeholder engagement in validating and complementing mapped environmental observations and impact assessment outputs via inimitable endemic local knowledge.

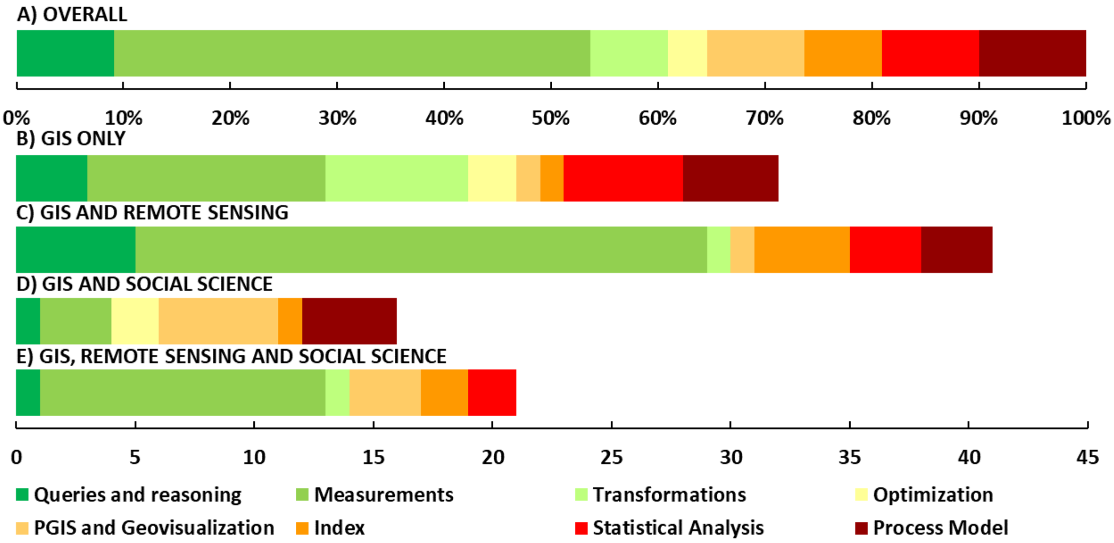


Figure 2.9 A comparison of the spatial analysis method(s) applied by the A) overall literature review (N=71) and each of the four method categories (full list in Table 2.2); B) GIS Only C) GIS and Remote Sensing, D) GIS and Social Science and E) GIS, Remote Sensing and Social Science.

2.4 Discussion

2.4.1 Overview of Current Research Development

The increase in mining-related studies using some type of spatial analysis (Figure 2.2 and Figure A 1) reflects the recently expanding growth in Remote Sensing literature over the last decade (Goodchild et al., 2000; McKenna et al., 2020). It can also be potentially linked to the increasing relevance of sustainability in the mineral industry as both technological advancement and supply and demand have progressively increased (Segura-Salazar & Tavares, 2018). Recently, research has become focused on the future of coal and other non-renewables, as encouraged by the rise of competitive green energy and cheaper renewables (Herrington, 2021) as well as new commitments being made to phase-out coal (UNFCCC, 2021). Recent developments in the mature coal industry may also be a source of motivation, such as the decline in productivity due to technological change and decrease in technical efficiency (De Valck et al., 2021).

Despite coal-mining existing for millennia, it is only recently that studies started focusing on the social aspects of both underground and surface coal-mining (Figure A 2 and Figure A 3) likely due to international pressures and sustainability and human right movements. The focus on understanding social aspects of mining impacts is not confined to coal; e.g. the Third World Conference on Disaster Risk Reduction (DRR) recognized and advocated the participation of local stakeholders in DRR management, which in turned motivated the participatory GIS risk mapping study in underground salt mines in Solotvyno, Ukraine (Onencan et al., 2018). Interdisciplinary approaches such as the hybrid cost-benefit analysis (CBA) supported such work, with researchers using a combination of holistic, primary data (socio-economical, environmental, land use and ecosystem services data) – combined with weightings from social impact risk matrices (De Valck et al., 2021).

Research on how the mining sector affects towns and communities is common, but relatively little is known about the characteristics of large-scale (ie: country, regional and global) mining impacts from a geospatial perspective (Devenin & Bianchi, 2019; Goodchild et al., 2000). The majority of the studies that included geospatial data collection and analysis at the regional scale (Figure 2.3) were enabled by GIS and Remote Sensing approaches. Studies at the regional scale often offer the best compromise between the amount of effort and time needed for the analysis versus the extent of captured impacts. Often the co-location of other industries (Kotey & Rolfe, 2014) affects socio-economic and environmental impacts of mining, so regional studies are important to provide the big picture trends and options, e.g. how different mining companies can come together to resolve social conflicts that may arise as a result of their combined or interactive effects. Additionally, the importance of capturing mining effects across the surrounding system components such as natural environment, geology, economy, and community in tandem instead of in isolation (Lechner et al., 2017) may be part of the motivating force in encouraging more studies to use an integrated, overall system-thinking approach. However, a potential cost of large-scale work is level of detail and resolution. Small scale studies can sometimes be more cost-effective and are critical for shedding light on ground-level social conflicts that affect individual and communities. Thus, although adopting a single case-study design may not be easily replicated in other regions or generalized for a wider scale (ie: global), it remains essential for understanding and addressing location-specific issues.

2.4.2 Integrating Across Disciplines and Methods for Capturing Mining Impacts

A mining operation has a variety of positive and negative effects on receiving environments during its lifetime, including nearby biodiversity, water and communities (Lechner et al., 2017; Xiao et al., 2021). The most frequently cited hypotheses related to the root causes of community conflict centre on the idea that the extractive industries are in competition with settlements, agricultural and other forms of alternative livelihood practices (Haslam & Tanimoune, 2016; Lechner, Owen, Ang, Edraki, et al., 2019). Seen in these terms, social conflict can be seen to have a territorial basis and usually arise when the peoples' livelihoods and/or well-being are threatened or incompatible with mining (Haslam & Tanimoune, 2016; Lechner, Owen, Ang, Edraki, et al., 2019) or unrecognised land ownership and indigenous land rights (Haslam & Tanimoune, 2016). Geospatially-integrated social science approaches provide possible means and evidence to characterize these land conflict and incorporating spatial centrality would provide an additional dimension useful for capturing mining impacts at various scales and stages of the mine life cycle (Arts et al., 2019; Hentschel et al., 2000; Kivinen et al., 2018;

Lechner, Owen, Ang, & Kemp, 2019; X. Y. Li et al., 2014; McIntyre et al., 2016; Rampellini & Veenendaal, 2016; Yiran et al., 2012).

2.4.2.1 Social Approaches

Local knowledge via stakeholder engagement remains vital to provide meaningful context to quantitative spatial evidence. Direct interaction with the impacted communities is required to shed light on the underlying complexities surrounding the socio-economic and environmental mining consequences. And the bottom-up approach with spatial integration is often more effective at identifying and resolving the fundamental causes of impacts (Pearce et al., 2021; Virgone et al., 2018). The significant negative response from the local community is easily prompted by the slightest inaction or action by the mining management (Brereton et al., 2008; Prno & Slocombe, 2014). Although a significant number of community participants acknowledged the economic and safety benefits of coal mining, the term "cumulative consequences" is more often perceived as adverse than favourable (Bebbington et al., 2008; Brereton et al., 2008; Prno & Slocombe, 2014). The main concerns brought up by communities are often related but not limited to degradation of ecologically vulnerable territories, water consumption, pollution, and environmental hazards such as landslides (Bebbington et al., 2008; Werner et al., 2019; Xiao et al., 2021). Although mine rehabilitation is considered a major legal requirement, its success is often not guaranteed and subject to many socio-economic and environmental variables (Mudd, 2010). The silver lining is that social pressures are often key to influence mining rehabilitation directly or indirectly by demanding changes in social structures such as through industrial transformation, economic development, and policy formulation, (Xiao et al., 2021). Geospatial approaches are critical for measuring and mapping such degradation and rehabilitation progress (Cocheci et al., 2015; Lechner, Owen, Ang, Edraki, et al., 2019; Rich et al., 2015; Schmid et al., 2013).

Limitations: The main disadvantages of traditional social science approaches (ie: via surveys and interviews) reported is that human memory may often be inaccurate. In the absence of the maps or scientific explanations of complex ecological systems, discussions amongst the participants tend to be speculative (Babidge et al., 2019). In addition, research participants faced difficulties relating ongoing or potential impacts with proposed mining landscape changes because they could not "see" the relationship or understand how their livelihoods areas would be compromised (Pearce et al., 2021). Furthermore, qualitative socio-economic data without geospatial properties (ie: not mapped out) presents a challenge to be integrated and analysed with GIS or Remote Sensing data. Hence, quantitative socio-economic data (ie: mapped and logged experience) are important to validate and where necessary, guide discussions with visual prompts. The development of a more spatially oriented perspective in future social scientific research would require coordinated effort to progress and disperse geographic technologies and concepts, such as geodatabases and spatial analysis, as central theme cutting across the conventional disciplinary boundaries of the social sciences (Goodchild et al., 2000).

Advantages: Public involvement and stakeholder engagement (Figure 2.7 and Figure A 4) in Environmental Impact Assessments (EIAs) is seen as a crucial component of the process in order to supplement technical expertise with local knowledge, context and environmental awareness (Pearce et al., 2021) while also encouraging social acceptance and local empowerment (Campbell, 2012; Marais, 2013; Marais & Verna, 2019). Hence, it is encouraging that all the studies that implemented social science approaches had included participations from one or more stakeholder groups (Figure A 4). The bottom-up approach, a strength of the PGIS approach regarding information gathering (Pearce et al., 2021), is more effective at targeting root causes of impacts and direct engagement with the affected communities is necessary to shed light on underlying intricacies surrounding socio-economic and environmental mining impacts. Additionally, integrating spatial approaches would enable the visualisation of these impacts. For example, Brereton et al. (2008) mapped the spatial distribution of complaints received by the mines over time which enabled the cross analysis of the location of complaints and its corresponding period to determine the root cause. Also, Pearce et al. (2021) helped the research participants visualize the areas where proposed mining activities would overlap with their social values and livelihoods. In one study, maps of landcover change were used as an ethnographic tool to elicit and identify people's perceptions of landscape change processes and the ways in which landscape change may be connected to local socio-cultural processes and political or economic institutions (Babidge et al., 2019).

2.4.2.2 Remote Sensing and GIS Approaches

The multifaceted dimensions of the socio-ecological changes brought on by industrial extraction can be uncovered by the spatial integration of environmental indicators such as climate data, satellite remote sensing analysis, with local perspective, historical observations, and explanations of these changes in the region (Babidge et al., 2019). Remote Sensing applications for climate, pollution and LULC change monitoring are well established, with relatively high accuracy and access to unaltered historical data (McKenna et al., 2020). Aside from capturing natural LULC (ie: vegetation and water body), Remote Sensing applications have successfully incorporated socio-economic elements observed in LULC impact studies is via urban, settlements, and agriculture land mapping (Figure 2.8 and Figure 2.5). Technological advancements such as the availability of high-resolution (<5m) satellite imagery – Ikonos and WorldView-2 (Ferring & Hausermann, 2019; Hausermann et al., 2018) – enabled the capture of intricate ASM-related LULC changes using Remote Sensing. Additionally, the recent popularity of ASM and underground mining studies is likely encouraged by efforts focused on establishing mining-related databases. For example, the inventories of mineral sites prepared by the National Service of Geology and Mining (Servicio Nacional de Geología y Minería - SERNAGEOMIN) (Rivera, 2020) and the Guyana Geology and Mines Commission (GGMC) Annual Reports (Hook, 2019) which were used to map ASM locations. Also, the Integrated WebGIS in the Republic of Kosovo (Meha et al., 2011) was used for implementing resettlement strategies in underground mining areas.

GIS successfully facilitated the consolidation of various socio-economic and environmental indicators such as the case of poverty mapping via socioeconomic outcome indicators (Hentschel et al., 2000; Loayza & Rigolini, 2016a; Londono Castaneda et al., 2018), risk mapping (Chen et al., 2015; Onencan et al., 2018; Risk et al., 2020; Saedpanah & Amanollahi, 2019) and landscape ratings in landscape quality assessment (Molina et al., 2016). Multi-parameter analysis is critical in decision-making for land use planning and natural resource management. Incorporating spatio-temporal analyses of different resources (ie: mineral values, water resources, and community infrastructure) enables the identification of potential areas of conflict between these factors (Craynon et al., 2015) and the interdependencies, causes and trends in both conflict and social acceptance in mining landscapes (Haslam & Tanimoune, 2016; W. Liu & Agusdinata, 2020; Pactwa & Górniak-Zimroz, 2021). Other examples of such approaches include hybrid cost-benefit analysis (De Valck et al., 2021) and multi-dimensional index system to provide a detailed examination of the Production-Living-Ecological Space (PLES) Evolution of resource-based urbans cities at different stages of ecological restoration (Tao & Wang, 2021). Additionally, mixed methodological techniques are essential to addressing the intricate connections between environmental change and infectious disease dynamics (Ferring & Hausermann, 2019).

Incorporating spatial outputs via GIS also enhances the visualization capability and increases the assessment efficiency especially where factors are diverse and complex. Such as the case of the spatial variability of climate, hydrology, terrain, vegetation, soil and other geographic parameters, GIS enables the delineation of areas of various risk ratings for a detailed assessment (Chen et al., 2015). GIS also provides the means to spatially visually characterize and analyse the unequal spatial distribution of such impacts and values, providing the evidence for policy implications, such as wealth concentration, poverty, and environmental inequality (Greenberg, 2018). That said in terms of socio-economic impacts, it is often infeasible and non-functional to present geospatial land use changes in the absence of key local knowledge for context. To accommodate this limitation, participatory GIS is a key approach used by several studies. For example, for mapping fine-scale LULC and identifying the cause of citrus agriculture decline in Didipio through feedback from on-the-ground experts with strong local knowledge (Ang et al., 2020), and to discuss landuse changes in a mining landscape and its impact on the indigenous community (Babidge et al., 2019). GIS also enabled the mapping of locations of complaints received by the mining companies (Brereton et al., 2008). This was achieved through workshop, surveys, interviews, and carrying out focus group sessions with a variety of stakeholders from welfare organizations, locals, and representatives from mining and other industries (Brereton et al., 2008).

Both participatory GIS and geovisualisation combined allow for the rapid and effective communication of data patterns and so are useful for assisting decision making processes to evaluate where, how, and why changes have occurred. Krieger et al. (2012) suggested the use of Remote Sensing for visualisation purposes and object-based imagery analysis to synthesise and integrate social, health, and environmental information, including potential resettlement strategies. Rampellini & Veenendaal (2016) explicitly describe the use of geospatial analysis and geovisualisation to complement other analysis (ie: economic and demographic modelling). In addition, incorporating high-resolution satellite imagery into a visual narrative would also be helpful to geo-code and rectify field photos, ensuring accurate local knowledge integration into satellite-based maps. Overall, spatio-temporal analysis and geovisualisation of socio-economic and environmental impact factors at appropriate scales can facilitate planning, decision making and policy-making processes to better understand “where, how and why” these system changes have occurred (Rampellini & Veenendaal, 2016).

Limitations: Spatial approaches come with their set of disadvantages such as limited freely available or paywall-restricted, high-resolution imagery and datasets. Werner et al. (2020) pointed out that the creation of national databases for monitoring inactive or abandoned mines for restoration and/or rehabilitation has received comparably less scientific attention. A variety of prospective GIS and Remote Sensing applications to evaluate mine impacts have shown that such databases that include data on mine location and nature can supply essential preliminary data needed (Pavloudakis et al., 2009a; Schmid et al., 2013; Werner et al., 2020). Researchers with financial limitations are often compelled to work within the means of open access datasets (ie: Landsat and Google) at the cost of lower resolution and generalization (Figure A 5). The availability of quality datasets at large spatial scales is also often a challenge. Also, studies showed that intangible properties of social well-being, especially ‘People’ and ‘Culture’ are difficult to capture using Remote Sensing alone; there is a need for supplementary spatially-reference social (SRS) or GIS data (Ang et al., 2020; Babidge et al., 2019; Onencan et al., 2018; Pearce et al., 2021; Rich et al., 2015). The integration of local perspective and knowledge is imperative to provide meaningful context and data interpretation.

Advantages: The above challenges often result in the innovation of creative, mixed-methods and analytical approaches. For example, the classification of freely available and temporally extensive Landsat imagery is used to overcome the lack of official land utilization investigation data (Tao & Wang, 2021) (Table A 3 to Table A 6) and satellite imagery is combined with land function evaluation technology to analyse long term production-living-ecological space (PLES) (Tao & Wang, 2021). This method overcomes data unavailability and enables operation convenience, unfortunately, at the cost of data precision especially between coarse (ie: vegetation) and fine scale (ie: natural vs artificial pastures) landuse. In another study, using remotely sensed data from the Landsat series, nighttime light, and precipitation data gathered through Google Earth Engine, Kimijima et al. (2021) evaluated the change in ASM operations in Gorontalo, Indonesia, between 2014 and 2020. The handful of studies that managed to produce spatial outputs of indicators for 'People' and 'Community' were successful only due to the integration of available census and demographic GIS or SRS data such as population and migration patterns (Fohringer et al., 2021; Valle & Tucker Lima, 2014). In the absence of SRS or GIS data, innovative links with LULC data are required. For example, (Boakye et al., 2020) manged to extract people's response to changing economic opportunities through LULC change, specifically the conversion of forest and farmland to the more economically lucrative mining compared to agriculture, while (Xiao et al., 2017) were able to link immigration and village movement with environmental hazards due to flooding and land degradation.

2.4.3 Challenges and Recommendations for Moving Forward

A multifaceted issue such as mining and its impacts requires analysis from various perspectives. Focused, interdisciplinary studies that employ communitarian, behavioural, or development economics to assess cost to community is rarely deployed in mining-related research but critical (Owen et al., 2021). Geospatial approaches alone are not sufficient to bring to light the intricacies of the complex social, cultural, and economic interconnection in a mining landscape. Similarly, traditional ethnographic approaches may not be able to accurately capture the environmental and geographical changes especially historical changes. The integration of both methods is considered key by multiple studies to completely understand the complex system. This, however, is a considerable challenge (Lechner et al., 2017).

For the successful integration of geospatial approaches, the socio-economic variables of interest need to be georeferenced to enable effective national or regionally aggregated analysis (Haslam & Tanimoune, 2016), such as spatially referenced social (SRS) data that are derived from elicited social survey methods and then mapped (Lechner et al., 2014). Geospatially explicit studies which utilizes geographically accurate data are more capable of producing location-specific targets for mitigation effects and tracking the movement and spatial patterns of socio-economic indicators (ie: poverty and migration) or LULC change. These observations can then be related to other spatially fluid data (e.g climate). Geospatial analysis is often more cost effective compared to field work and provide reasonably accurate data especially when studying areas in remote regions. PGIS can contribute to this immensely to collect both spatial and social data without having to deploy scientists on the field.

Census data can be represented at various spatial scales. However, due to changing administrative boundaries or updates in population development, it makes it hard to analyse and make comparisons between data. Although potentially requiring a higher cost of data collection and long-term planning, high-resolution geospatial data would help lessen this effect if the precise location of the data is recorded instead of basing it on the administrative boundaries. This is important especially for mobility studies or studies on landscape changes. Werner et al. (2020) stresses the importance of systemic, widespread, and formalized consistency to effectively document abandoned mines, rehabilitation and/or remediation efforts at a national level and worldwide. Commensurability - assessed using the same units of measure – is also key. Drawing on (Lechner et al., 2014)'s stance on spatial uncertainty within both SRS data and biophysical data, it is vital that uncertainties are addressed or adequately reported when conducting analysis.

Additionally, more efforts are needed to make data easily accessible for scientific progress. Xiao et al. (2021) pointed out that data on the distribution and physical characteristics of mining locations in China are not open to the public while De Valck et al. (2021) pointed out that limited data on ecosystem services are available in the regional areas in Central Queensland. Fewer studies have therefore been able to quantify the linked relationship between coal resource growth and the state of the social-ecological system at higher spatial resolutions. An example of attempts being made in this direction is the National Spatial Data Infrastructure (NSDI) as an organisational strategy being implemented in Kosovo to increase the number of applications and availability of spatial data via institutional structures, regulations, and standards necessary to disseminate spatial information from a variety of sources to prospective users (Meha et al., 2011).

2.5 Conclusion

Interdisciplinary data capture and analysis is a functional step in this direction and the only way to spatially capture and coherently analyse the various key aspects of socio-environmental well-being. It is promising that more research has recently focused on socio-economic mining impacts while fully or partially utilizing the capabilities that GIS and Remote Sensing has to offer to advance traditional social science approaches. The key approaches that can improve the integration of GIS, Remote Sensing and Social Science are participatory GIS and geovisualization for stakeholder engagement, LULC analysis for extracting socio-economic and environmental indicators, and multi-parameter analysis. Concerted efforts would be required to address the challenges of data availability, transparency and quality, geographic characterisation, commensurability, and validation towards the goal of a more spatially integrated assessment of socio-economic mining impacts. More possible approaches to include interdisciplinary data capture and analysis, particularly to research intangible socio-economic impacts, might be explored in future research as GIS and remote sensing technology and applications continue to advance. These are all important for successful data integration, inclusive analysis, and comprehensive planning throughout the mine life cycle to bring us a step closer in securing a sustainable future for mining.

Chapter 3. Socio-Environmental Land Cover Time Series Analysis of Mining Landscapes Using Google Earth Engine and Web-Based Mapping

Published as:

Ang, M. L. E., Arts, D., Crawford, D., Labatos, B. V., Ngo, K. D., Owen, J. R., Gibbins, C., & Lechner, A. M. (2020). Socio-environmental land cover time series analysis of mining landscapes using Google Earth Engine and web-based mapping. *Remote Sensing Applications: Society and Environment.* https://doi.org/10.1016/j.rsase.2020.100458

3.1 Introduction

Mining directly and indirectly influences both land cover and land use, leading to socio-environmental transformations at a range of spatial and temporal scales (Briassoulis, 2019; Mudd, 2010; Werner et al., 2019). The operational footprint of mining projects is dynamic, and operations can trigger socio-economic progression affecting economic flows, social inequality, and an intensification of certain types of land use and land cover change, such as land clearance for infrastructure development (Aragon & Rud, 2013b; Loayza & Rigolini, 2016b; Reeson et al., 2012b). Additionally, the poor management of waste can result in long-term physical alteration of the landscape, pollution, and disrupted ecosystem processes (Rockström et al., 2009; Sonter et al., 2014; Werner et al., 2019). Consequently, local residents are affected by socio-environmental changes, with land-dependent or low-income populations most at risk (Schueler et al., 2011; Shackleton, 2020), if not properly addressed.

Recent studies have highlighted a clear gap in the availability of data that can be used to identify local mining effects, or to monitor mining-inflicted changes over time (Arts et al., 2019; McIntyre et al., 2016; Pavloudakis et al., 2009a). Robust sourcing and reporting of data on social and environmental changes are considered essential for companies if they are to meet basic impact management obligations (Sonter et al., 2014). Furthermore, it is crucial to quantify the spatial patterns in these changes, to more effectively understand and predict future trends (Y. Zhang et al., 2017). The absence of data greatly limits the development of targeted strategies to mitigate site-specific socio-environmental impacts (Lechner et al., 2016; Virgone et al., 2018). However, given the complex nature of the dynamic mining landscape, it remains a challenge to effectively and comprehensively describe these patterns of change (Everingham et al., 2018; Y. Zhang et al., 2017). Integrating quantitative biophysical data (e.g. land cover changes and distribution of settlements) using GIS and remote sensing with qualitative region-specific social data (e.g. health and demography) has potential to characterise and manage these landscapes for addressing multidisciplinary issues (Everingham et al., 2018; Lechner, Owen, Ang, & Kemp, 2019) associated with the socio-ecological systems perspective (Polhill et al., 2016; O. R. Young et al., 2006).

Satellite-based remote sensing techniques are widely applied for evaluating and monitoring mining impacts on the environment and to support remediation and rehabilitation initiatives (Koruyan et al., 2012a; Sonter et al., 2014; Xiao et al., 2020). Historical studies of land use and land cover change using remote sensing is an established method for understanding past and present physical properties of landscapes (Andersen et al., 1996; Briones & Sepúlveda-Varas, 2016; Pan et al., 1999), providing details, for example, of intensification, conversion and abandonment of specific regions, and the environmental impacts of these transformations (Gyawali et al., 2004; Yiran et al., 2012). Landsat satellite imagery, with its historical archives dating back to the 1970s, is often used for creating time series depictions due to its high temporal and moderate spatial resolution (Gómez et al., 2016; Huang et al., 2017; N. E. Young et al., 2017). Characterising changes in mined land and surrounding landscapes can be accomplished with time series analysis of land cover change ((Lechner et al., 2019a; Li et al., 2015) to monitor socio-economic patterns such as urban growth and poverty distribution (Hentschel et al., 2000; Mihai et al., 2015), and environmental disturbances, such as vegetation clearance and pollution (Coppin et al., 2004; Yang et al., 2018).

Utilising GIS and remote sensing to complement stakeholder-inclusive social studies, such as on community well-being and livelihoods, has often been emphasized (Everingham et al., 2018; Kivinen et al., 2018; Yiran et al., 2012). However, the interdisciplinary application of GIS and remote sensing tools, specifically land use and land cover change analysis to spatially monitor and characterise social changes, is not common in a mining context (Lechner, Owen, Ang, & Kemp, 2019; Werner et al., 2019). Published studies concern only assessment of cropland and agricultural land use changes on local communities and food security (Matejicek

& Kopackova, 2010), deforestation from the expansion of farmlands and livelihood consequences (Schueler et al., 2011), influence of coal resource exhaustion on land use change (Wen et al., 2018) and potential conflicts from the growing proximity of mining sites to settlements and increasing land scarcity (Lechner et al., 2019a). Hence, there is a great unexplored potential for utilising remote sensing, especially historical Landsat data, to support social studies in mining landscapes. Additionally, participatory mapping approaches can be incorporated to capture land use classes with finer thematic resolution, such as region-specific agriculture, that are difficult to pick up using Landsat classification alone. Thematic resolution describes the level of classification detail within a hierarchy of land cover classes; with finer scale classes often more difficult to distinguish (Lechner & Rhodes, 2016). By taking on a unique mapping perspective, both coarse and fine thematic resolution land covers and land uses can be more effectively captured.

With all this in mind, the aim of this study was to characterize and evaluate the land cover changes in a mining landscape and its concurrent impacts on socio-environmental land uses. Historical imagery from Landsat 5 and 8 were used to create a time series of regional-scale land cover over the period between 1994 through to 2018 for the Didipio gold-copper mine in the Philippines and its environs. The two approaches implemented in this study were (1) a supervised classification in GEE to characterise high-level coarse thematic resolution land covers for the whole region that can be derived using the moderate Landsat pixel resolution; and (2) a web-based mapping survey to capture key, fine thematic resolution land cover categories within zones of importance identified by the local experts. We conclude by discussing the effectiveness of our approaches for assessing socio-environmental changes and its limitations. Refinements of the workflow to improve the quality of data acquired were also presented.

3.2 Materials and Methods

3.2.1 The Didipio Mine and Study Area

Didipio is a gold-copper mine located 270 km northeast of Manila on the north of Luzon Island, Philippines (Figure 3.1). The Philippine Government granted the Didipio Operation a Financial or Technical Assistance Agreement (“FTAA”) in 1994. The FTAA covers an area of approximately 158 km^2, located between the Nueva Viscaya and Quirino provinces. Construction activities began onsite in 2008 but was put on hold for a few years to allow for project re-scoping. Construction was completed in 2012 with commercial production commencing in 2013. Mining operation transitioned from open pit to underground in 2016. Surrounding the mine are two significant towns, Cabarroguis and Kasibu. An area of 1,006.93 km^2 was selected for the present assessment (Figure 3.1); this area includes these two towns, to integrate the key communities within the mine's social catchment. Social catchments exist beyond the mine site and are not necessarily situated within the municipal boundaries. They also represent the territories occupied by communities of interest that have important implications in the administrative, policy and planning network in the region (Macgregor & Hugo, 2001).

The community in this area is mostly comprised of indigenous people practicing rural highland farming cultures and lifestyle (Botengan et al., 2019). Agriculture is an important livelihood in this region (Holden, 2015; Schneider, 2017), producing fruits such as citrus, mango and banana, vegetables, root crops, rice and corn. Large areas were dedicated to rainfed and irrigated rice production. The presence of mining has brought about linear infrastructure development, promoting mobility within and outside of the community. This has also led to increased access to tertiary education and communication facilities, improving interactions between the residents and the wider community (Botengan et al., 2019). The influx of migrants and flow of goods and commodities have been observed with economic growth, an increase in job availability and business opportunities in the region (Domingo, 2020). A rapid increase in population was due to the increase in immigration into Didipio, just before the commencement of the mining operation (Resources Environment and Economics Center for Studies (REECS), 2019).

The owners of the Didipio mine have put in place various social development management programmes such as scholarship grants, electricity, livelihood projects and health programs to support communities in close proximity to the mine (Griffiths et al., 2014; Schneider, 2017). However, water loss or river quality deterioration and pollution from mining waste, damage or loss of lands and consequently the loss of livelihood in the agricultural, small-scale mining, fisheries and farming industries, remain as negative mining impacts (Botengan et al., 2019; Griffiths et al., 2014; Schneider, 2017). While these are perceived by the communities, the link between mining and these changes has yet to be studied and confirmed.

With the current underlying uncertainties surrounding the project (Chavez, 2020), clarity regarding both environmental and socio-economic impacts is key in determining the best next steps and a reasonable course of action. An overarching goal of the current work was to ensure that quality data depicting the changes in the region is obtained to benefit current and future assessments. The methods outlined below were designed in an attempt to achieve this goal.

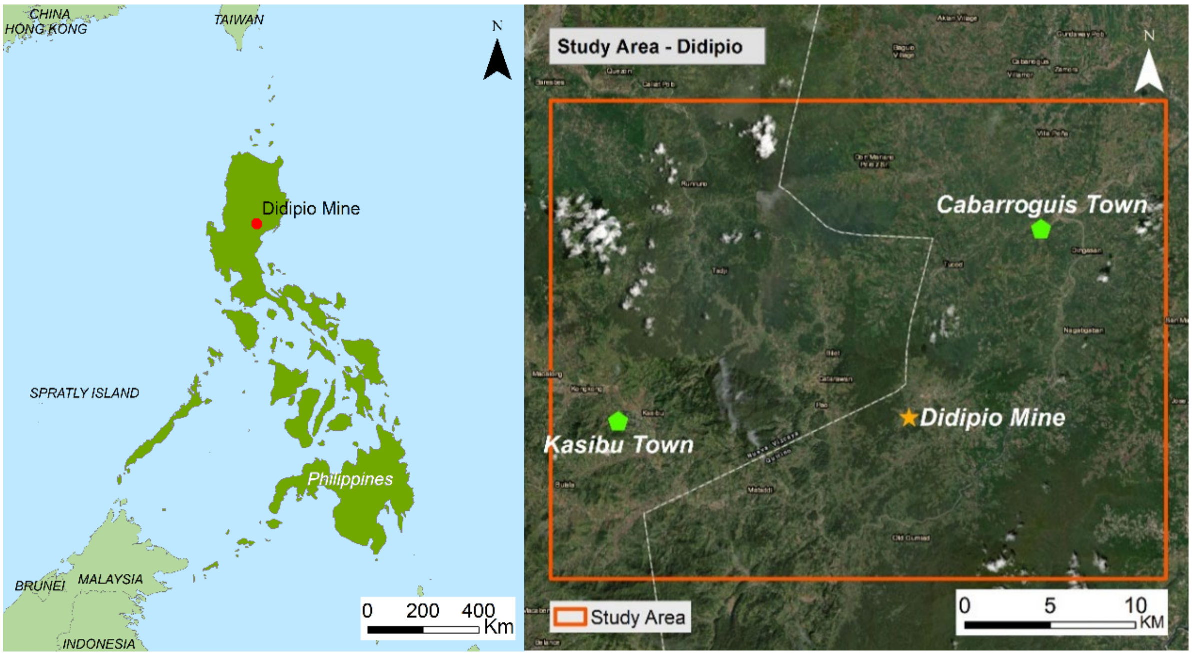


Figure 3.1. The 1,006.93 km² study area surrounding the Didipio gold-copper mine, in the Philippines.

3.2.2 Land Use and Land Cover Classification Scheme and Environmental and Socioeconomic Indicators

Before carrying out the analysis, a hierarchical land use and land cover classification scheme was developed to outline the various spatial characteristics of the study area (Figure 2). This was based on the coal mining schema developed by Lechner and colleagues (2016) and later updated by Lechner and colleagues (2019), for gold copper mines. While previous applications have focused on the mine site (Lechner et al., 2016), and the direct surrounding land covers (Lechner, Owen, Ang, Edraki, et al., 2019), this chapter focuses on regional-scale change. The idealised schema represents a multi-level hierarchy of land use and cover surface features that is formulated from finer thematic resolution land use classes, such as specific agricultural crops and social investment projects, to coarser thematic resolution land cover, such as vegetation, bareland and water body (refer to (Lechner and Rhodes, 2016) for discussion on thematic resolution). In this study, the high-level (Briassoulis, 2019; Fisher et al., 2005), coarse-thematic resolution land cover classes were mapped using supervised classification and the key fine thematic resolution land use categories within zones of importance were characterized using a participatory web-based mapping.

Positive and negative environmental and socioeconomic impacts are linked to transitions within and between several land uses and land covers (Table 3.1). A thorough discussion of Table 3.1 and the associations between the land use and land cover with the socioeconomic impact indicators are presented in Section 3.3.3. The coarser thematic resolution of land covers such as vegetation, water and bareland are essential for capturing environmental impacts, while mining and built-up areas are linked to socio-economic indicators such as population growth and infrastructure development. The land use classes with finer thematic resolution, such as specific agriculture and small-scale mining classes linked to economic impacts and livelihoods, cannot be captured using Landsat imagery alone; this is due to the difficulties in differentiating the spectral signatures that are homogeneous with other land use and land covers. Additionally, the land use classes associated with the Didipio Mine's Corporate Social Responsibility (CSR) impact can only be captured using PPGIS as they do not have the unique spectral properties required for remote sensing classification.

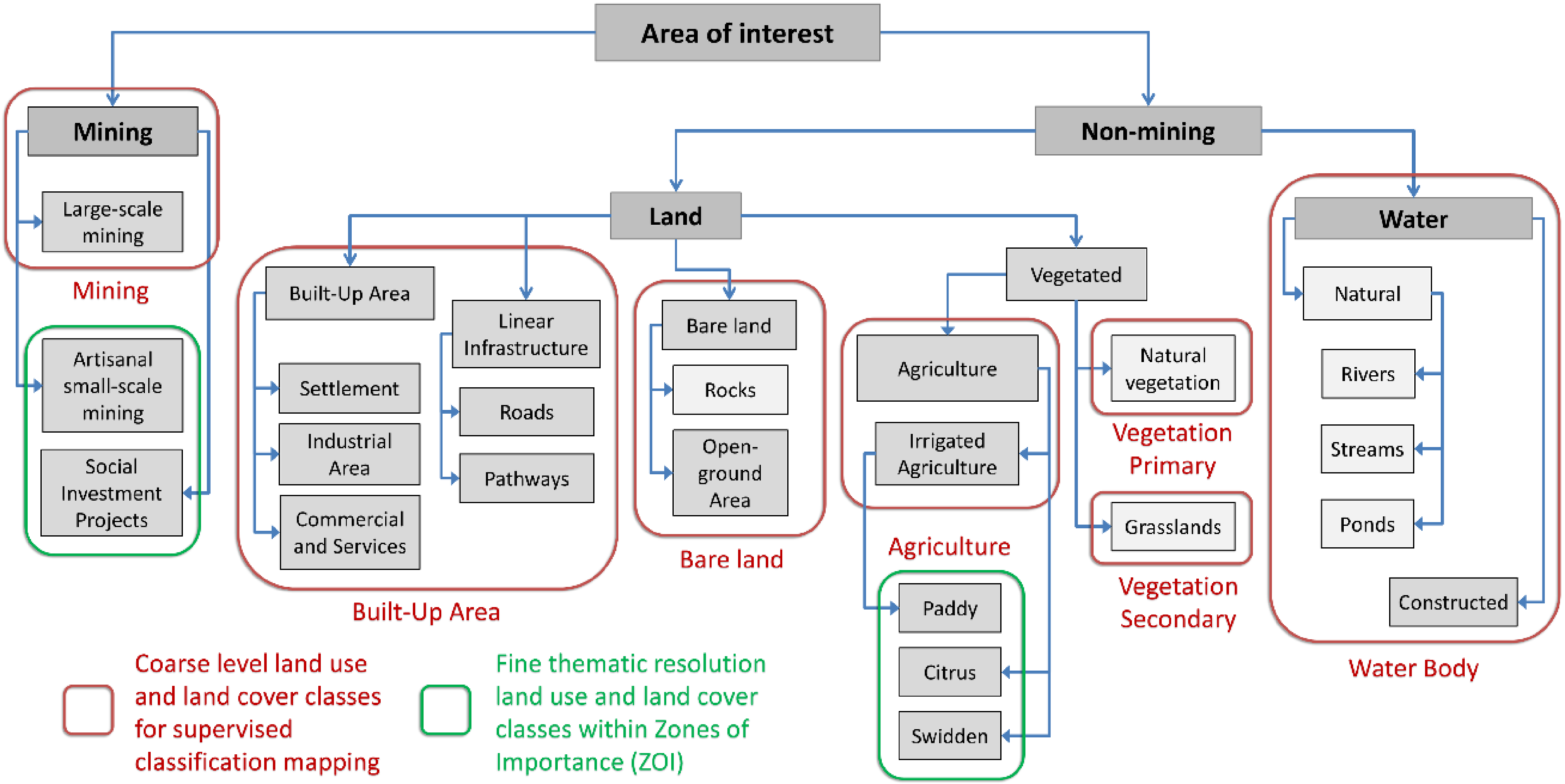


Figure 3.2. Idealized land use and land cover classification scheme with the land use and land cover classes for regional remote sensing classification in red boxes and the web-based classification mapping in green.

Table 3.1. The environmental and socioeconomic indicators linked to the land use and land cover.

Method	Land Cover	Environmental Indicators: Biodiversity, Habitat and Ecosystem Services	Environmental Indicators: Environmental Quality and Climate Change	Socio-Economic Indicators: Human Footprint	Socio-Economic Indicators: Economy and Livelihood	Socio-Economic Indicators: Population Distribution	Socio-Economic Indicators: Urban areas, Settlements and Associated Infrastructure Development	Socio-Economic Indicators: Didipio Mine Corporate Social Responsibility (CSR)
Remote Sensing	Primary Vegetation	x	x					
	Secondary Vegetation	x	x	x				
	Water Body	x	x					
	Bareland		x	x				
	Agriculture		x	x	x			
	Mining			x	x	x	x	
	Built-up Area			x		x	x	
PPGIS	Small Scale Mining			x	x	x		
	Agriculture - Citrus		x	x	x			
	Agriculture - Paddy		x	x	x			
	Agriculture - Swidden		x	x	x			
	Social Development and Management Program (SDMP)			x		x	x	x
	Community Development Program (CDP)			x		x	x	x

3.2.3 Remote Sensing Data

Atmospherically corrected, high-level, 30m by 30m Landsat Surface Reflectance data, accessed through GEE, were used. The timeframe of the imagery selected for true colour mapping was from 1988 to 2018 (Table 3.2a). Two datasets were compiled (Table 3.2a): (1) True colour time series dates and (2) Classification time series dates. Dataset 1, with a higher temporal resolution made up of 15 images from 1988 to 2018, was used to construct a true colour time series video to provide a general assessment of land cover changes for engaging with the local experts (Table 3.2a). The video can be accessed via this link: https://youtu.be/DYxEdwZ7Vkw.

From Dataset 1, five time-steps were selected and compiled as Dataset 2 for the classification time series (Table 3.2a). These five time-steps were chosen to provide an even coverage of the life of the mine, include key land change events in the study area and filtered for the least cloudy imagery available within the time-step range for a more efficient change analysis. Another essential criterion for the selection of these dates was the availability of high-resolution auxiliary remote sensing data, which could be used to ground truth (Table 3.2b). Without field data, higher spatial resolution field data is required to validate the lower resolution Landsat imagery and identify finer resolution features such as the footprint of houses and crops which is important for distinguishing the land use and land cover classes. Dataset 2 was processed next as described in Section 3.2.4.

Table 3.2. Landsat sensor and bands used and image dates (day/month) for the true colour time series, classification mapping time series, and the auxiliary reference data used as ground truth.

a) Landsat Satellite Data

Landsat	Bands		Wavelength range (µm)	Dataset 1: True colour Time Series Dates	Comments	Dataset 2: Classification Time Series Dates
LS 8	Multispectral	Coastal	0.43–0.45	2018 (17/11)	cloudy	2018 (17/11)
OLI/TIRS		Blue	0.45–0.51	2016 (13/02)		
		Green	0.53–0.59	2015 (27/12)	cloudy	2015 (27/12)
		Red	0.64–0.67			
		NIR	0.85–0.88			
		SWIR1	1.57–1.65			
		SWIR2	2.11–2.29			
	Panchromatic	Panchromatic	0.50–0.68			
LS 5	Multispectral	Green	0.5-0.6	2010 (12/02)		2010 (12/02)
TM		Red	0.6-0.7	2008 (29/05)	cloudy	
		NIR 1	0.7-0.8	2006 (06/09)	cloudy	
				2005 (05/05)		2005 (05/05)
				2004 (05/07)	cloudy	
				2001 (23/03)	cloudy	
				1998 (03/06)	cloudy	
		NIR	0.8-1.1	1997 (22/10)	cloudy	
				1996 (25/03) 1994 (12/08)	cloudy	
				1990 (10/04)	cloudy	1994 (12/08)
				1988 (31/01)		

b) Auxiliary Reference Data

Site	Sensor	Data type	Pixel Size	Source	Date	Comments
Didipio	Landsat 8	Pansharpened	15 m	USGS	2018 (17/11), 2015 (27/12)	
	World view 2	True Colour	0.5 m	ArcGIS base map	2010 (18/09)	High Cloud Cover
	World view 2	True Colour	0.5 m	Google Earth	2015 (31/12)	
	SRTM	Digital Elevation Model (DEM)	90 m	USGS	2001 (Feb)	Low Cloud Cover High Cloud Cover
	Sentinel	Optical Imagery	10 m	USGS	2018 (02/07) 2016 (09/03)	Covers only the Didipio Mine

3.2.4 Regional-Scale Mapping

Google Earth Engine (GEE) is an open source, cloud-based platform and is particularly well-suited for time series analysis because of its access to a virtually unlimited processing and storage capacity, and extensive library of multi-temporal remote sensing data (Gorelick et al., 2017; Mutanga & Kumar, 2019). Although the GEE platform has only been recently developed, there is a growing literature on its application (Kumar & Mutanga, 2018); however, very few of these studies relate to mining assessments. A Scopus keywords search for "Google Earth Engine" AND "Mining" (21st May 2020) identified 10 related papers after filtering for commission errors. Only five studies (Dlamini & Xulu, 2019; He et al., 2020; Pericak et al., 2018; Xiao et al., 2020; Yang et al., 2018) applied GEE in mining landscapes over a significantly long period and all these studies focused on remote sensing of biophysical phenomenon such as mining rehabilitation. The links to the codes used in this study are listed in Appendix B2. Three processing stages were undertaken to create a time series of classified maps (Figure 3.3). In the first step (1a), imagery from the Landsat archive in GEE were filtered to determine the least cloudy scenes (less than 5% cloud cover). The availability of cloud-free, single scene Landsat images was constrained by the region's climate, which is prone to high rainfall frequency and typhoons (Holden, 2015). Hence, cloudy years were pre-processed to remove cloudy pixels using a cloud masking and mosaicking algorithm in GEE (Shelestov et al., 2017; Tsai et al., 2018) to compose cloud-free pixels from images throughout the year. Landsat 8 imagery for the year 2015 and 2018 underwent an additional pan-sharpening step in ArcGIS Pro to be used as auxiliary reference data. In addition to the multi-spectral composites, three vegetation indices were derived: the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Enhanced Vegetation Index (EVI).

In the final step of 1a, a composite was created for the next processing step by combining three types of data sets: (1) the pre-processed Bands 2 to 7 for Landsat 8 or Bands 1 to 5 for Landsat 5, (2) the Global SRTM Landforms slope data layer, and (3) NDVI, EVI and NDWI indices layers. This method of compositing stacks of ancillary data such as indices and a digital elevation model (DEM) layer has been found to improve overall classification accuracy (Table B 2) in previous studies (Domaç & Süzen, 2006; Dorren et al., 2003; Sluiter & Pebesma, 2010; Tsai et al., 2018; Xie et al., 2008).

In step 1b, a supervised classification was performed first by testing several classification algorithms compiled in Table B 3. The Random Forest classifier yielded the highest classification accuracy (Table B 3) when tested against the other classifiers (CART, GmoMaxEnt, SVM, Minimum Distance and Naïve Bayes). Other studies have also demonstrated that random forest performs better than other classifiers (Baltzer & Davies, 2012; Balzter et al., 2015; Belgiu & Drăgu, 2016; Breiman, 2001; Dlamini & Xulu, 2019; Kulkarni & Lowe, 2016; Pal, 2005) and are robust against potential collinearity and overfitting issues (Belgiu & Drăgu, 2016; Breiman, 2001; Matsuki et al., 2016; Teluguntla et al., 2018) that may arise from integrating the spectrally similar NDVI and EVI layers. The Random Forest method reduces redundancy by effectively selecting relevant spectral properties from a composite when classifying features of interest (Abdel-Rahman et al., 2013; Matsuki et al., 2016; Rodriguez-Galiano et al., 2012).

A total of 180 training points was used in the supervised classification. Seventy percent (70%) of the training points were used for the classification, while 30% were reserved for the accuracy assessment, with both steps carried out in GEE. The classified images were exported from GEE to ArcGIS Pro for correction of the line work via digitization and reclassification of any misclassified areas, with the aid of the auxiliary reference data in Table 3.2b and the land use and land cover classes guidelines in Table 3.3a. To remove the single, isolated pixels and clean the salt-and-pepper pixel effects (Figure B 2), contiguous land use or land cover made up of three pixels or less were identified and replaced with neighbouring pixel values using the Majority Filter tool; the before-and-after comparison is shown in Figure B 2. Open Street Map (OSM) data were used for checking the river and streams which were included under the Water Body land cover class after verification in Google Earth Pro. Mining areas were also extracted from the classified images at this stage.

In Step 2, the same classification methods in Step 1 were repeated with the rest of the time series imagery, with the addition of the previously classified images used as reference points. This procedure was important to ensure cohesion between the classification of each time-step. Linework alteration and attribution were carried out for time-steps that showed discrepancies in the classification such as the overestimation or underestimation of land use and land cover. This was done by either repeating the classifications in Step 1 or via digitization.

In Step 3, the accuracy assessment for each time-step was carried out using the remaining 30% of the training points in Step 1. The auxiliary data in Table 3.2b and the original Landsat data were used as ground truths for this analysis. This method of validation is commonly practiced (Foody, 2002; X. H. Liu et al., 2002; Plourde & Congalton, 2003), especially in studies that involve data spanning lengthy historical timeframes, although field or high-resolution data is preferred if feasible (Cohen et al., 2010; Gómez et al., 2016; Tilahun & Teferie, 2015). An error matrix, user and producer accuracy and Kappa accuracy values were generated at the end of this assessment. Local experts were consulted for a final review to validate the classified time series.

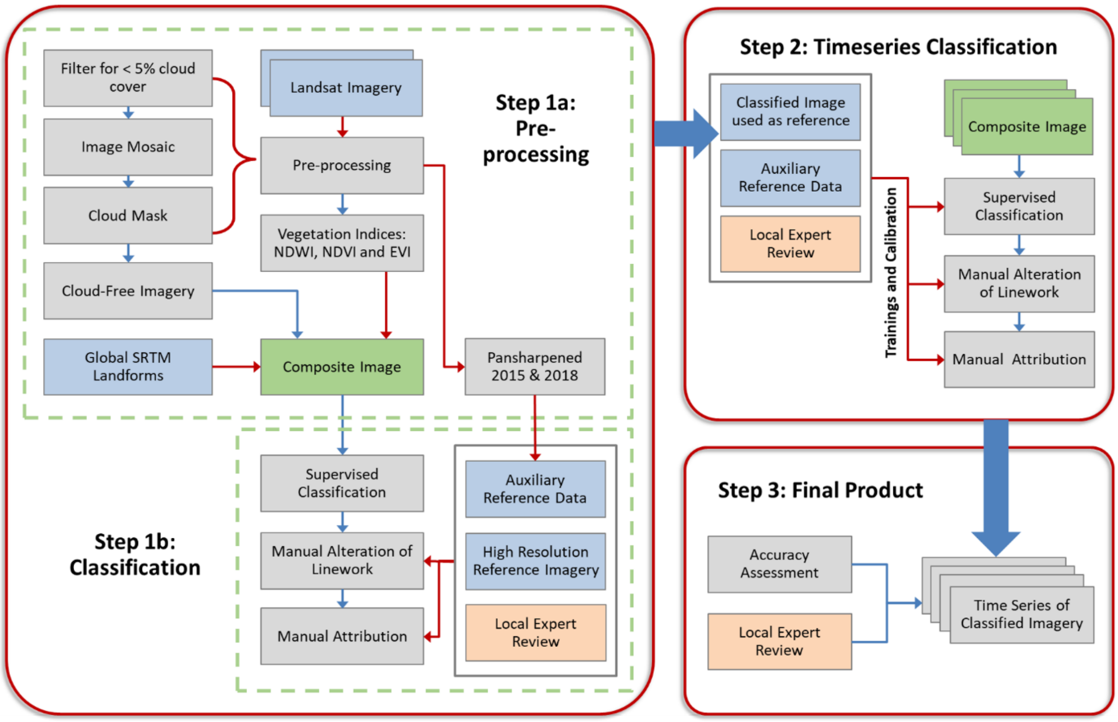


Figure 3.3. A summary of the processing workflow for creating regional classification time series.

Table 3.3. Land use and land cover classes classified in this study and specific information used for guiding the classification (see Appendix A for detailed description of the SDMP and CDP land use classes).

a) Regional Classification	**Specific classification rules and definitions**
Water Body	Rivers, lakes and reservoirs (both natural and artificial water bodies and aquaculture).
Vegetation Primary	Primary forests and dense, secondary forests and/or abandoned plantations.
Vegetation Secondary	Areas of regrowth, short shrubs and permanent or temporary grasslands.
Agriculture	Irrigated agriculture.
Mining	Large-scale mining.
Bare land	Rocks and natural or artificial open-ground areas of land that have no vegetation cover, not including mining surfaces.
Built-up Area	Residential/settlements, industrial, commercial, urban and related infrastructure.
b) Zones of Importance Classification	**Specific classification rules and definitions**
Demography	Areas with important demographic growth.
Agriculture - Citrus	Citrus plantations.
Agriculture - Paddy	Rice plantations.
Agriculture - Swidden	Areas of swidden agriculture or shifting cultivation or rotational farming activities.
Small Scale Mining	Artisanal and illegal small-scale mining.
SDMP	Social Development and Management Program (SDMP) - mandatory projects
CDP	Community Development Program (CDP) - voluntary projects

3.2.5 Web-Based Participatory Mapping and Stakeholder Involvement

Web-based and participatory mapping, including Public Participatory Geographic Information System (PPGIS), was used to support mapping of land cover and land use changes in the study area. Web-based platforms can support collection of PPGIS data from various stakeholder groups and over large areas (Brown & Raymond, 2014; Kivinen et al., 2018). In mining landscapes, PPGIS has been used for characterising land use preferences, experiences, and values to a landscape and/or specific locations (Brown & Kyttä, 2014; Kingston et al., 2000; Sieber, 2006). This allows for specific placed-based knowledge to be collected from local stakeholders and experts (Kivinen et al., 2018). In this study, a web-based mapping survey was carried out using Maptionnaire (Figure B 1), an interactive, online, crowdsourcing, geospatial web mapping application, to characterise specific land uses of interest within the zones of importance. This survey was carried out for three months from August to October 2019.

The purpose of the participatory mapping was to engage local experts to characterise land uses of interest and zones of importance. These fine thematic resolution land uses (refer to (Lechner and Rhodes, 2016) for discussion on thematic resolution) such as specific forms of agriculture like citrus, land uses such as small-scale mining and land features such as infrastructure projects are challenging to extract from 30 m moderate resolution Landsat imagery (Gómez et al., 2016). Local experts were therefore sourced for the participatory mapping as they provide specific in-situ knowledge that greatly exceeds the spatial and temporal resolution of even the most advanced remote sensing data. The land uses of interest (listed in Table 3.3b) were first compiled and then mapped by Didipio staff members who lived and worked in the region. The social investment projects that the respondents identified (Table B 6) were split into two categories: Social Development and Management Program (SDMP) and Community Development Program (CDP). A more detailed explanation of these two classes is compiled in Table B 6.

The web-based survey mapping responses were digitized by local experts with reference to the high-resolution, true colour 2018 satellite basemap in Maptionnaire, which matched the latest classification time-step. The mapping was conducted by four employees of the Didipio mine in coordination with the Barangay (smallest administrative unit in the Philippines) officials of the host and adjacent communities. This includes the two provinces neighbouring the Didipio Mine; Alimit, Belet, Binogawan, Capisaan, Camamasi, Wangal and Tukod in the Municipality of Kasibu, Nueva Viscaya Province and Dibibi, Dingasan and Tucod in the Municipality Cabarroguis, Quirino Province. The survey data was validated by cross referencing with available high-resolution ground truth and the respective classified timesteps. By working in reverse from 2015 to 1994, land use and land cover changes were then manually digitized within all 416 polygons; the corresponding levels of certainty (Table B 1) across all five timesteps were recorded based on available high-resolution ground truth imagery (Table 3.2b) and referring to Table 3.3. The output of this process was a time series maps showing the classified land use within the zones of importance.

3.2.6 Change Assessments and Transition Matrix

The time series maps were used to determine spatial land use and land cover changes over time. To quantitatively analyse this, the area of each class (Table 3.3) at all five timesteps was calculated from the classification time series maps and tabulated. Graphs indicating the trends of temporal changes in area (km^2) were compiled and analysed. In order to provide functional interpretations of the temporal variations observed in the time series, land use and land cover transition matrixes (Braimoh, 2006; B. Zhang et al., 2017) were tabulated. The five classification time-steps (Table 3.2) were divided into two critical timeframes: timeframe 1 was the first 17 years where moderate changes were observed before the first visible mining activity started (1994 to 2010), while timeframe 2 was the 9 recent years within which prominent land cover and land use transformations took place (2010 to 2018). An additional table was tabulated for the total 1994 to 2018 timeframe as a reference. The transition matrixes tabulated were cross-referenced with Table 3.1 to link the trends observed with the relevant environmental and socio-economic indicators.

3.3 Results and Discussion

3.3.1 Regional Classification Maps and Time Series

The supervised classification maps are shown in Figure 3.5. A time series video of the classification maps was created to provide a visual representation of the land use and land cover changes from 1994 to 2018. The video can be accessed via this link: https://youtu.be/rYRI1a9YZdY. The supervised classification without the web-based mapping provided an accurate estimate of the regional changes that have occurred in Didipio and demonstrated significant trends. These changes would have been impossible to capture without the capacity of remotely sensed Landsat satellite imagery to go back in time.

The accuracy assessment results of all the timesteps (1994, 2005, 2010, 2015 and 2018) after the post-classification processing were compiled in Table B 5. This table indicates that the supervised classification accurately mapped a significant percentage of the six classes that was trained from the Landsat image (water body (Water Body), primary vegetation (Vege Primary), secondary vegetation (Vege Secondary), bare land (Bareland), built-up area (Built-up Area) and irrigated agriculture (Agriculture)). Although using the Majority Filter tool in ArcGIS Pro to rectify the salt-and-pepper issue across the classification (Figure B 2) decreased the classification accuracy by approximately 1% (Table B 4), it provided a visually improved output and the classification accuracies remain relatively high for both the Kappa and Overall Accuracy and ranged between 91% and 95% (Table B 5). These values indicate that 9 to 5% of the pixels are classified incorrectly; however, accuracies greater than 85% are commonly regarded as high (Anderson et al., 1976; Foody, 2008; Lunetta et al., 1991). As a comparison, a systematic review by (McKenna et al., 2020) calculated an average overall mapping accuracy of 84% for studies on remote sensing of mine site rehabilitation for ecological outcomes. The individual land cover classes which were inaccurately mapped, as well as the magnitude of the mapping errors, both varied between years; this variation is unavoidable in such time series analysis. In some cases, accuracies for a single class were as low as 77% (for Built-up Area in 2015) but overall, still achieved a high accuracy.

The analyses indicate that the changes in the Didipio region vary substantially by land use and land cover type, with prominent changes observed in the primary and secondary vegetation classes. Other changes are less pronounced, (e.g., irrigated agriculture), which may be the result of classification inaccuracies from the complex land use at fine scales and the comparatively coarse imagery. It is important to note that areas classified as belonging to a given class may contain other land use or land cover classes that share similar spectral properties. For example, some of the primary vegetation class may include abandoned, overgrown plantations and some of the secondary vegetation may include agriculture such as individual fruit trees planted on grasslands. Additionally, houses or buildings that are sparsely distributed and smaller than Landsat's 30m-by-30m resolution may not be detected as a built-up area and may be misclassified as other land cover classes, depending on their surroundings. Only the irrigated agriculture could be distinguished using the classification methods applied because the spectral properties of irrigated agriculture differ significantly enough from their non-irrigated counterparts which have very similar spectral properties. For example, dry, harvested paddy fields are easily confused with bare soil while dryland agriculture and plantation appear similar to the non-agriculture grasslands and forest, respectively. Additionally, when using only the classification methods and the moderate Landsat pixel resolution, small-scale mining could not be automatically distinguished alone as their fine scale and spectral properties resembles that of built-up area or bare land.

Overall, there was a 41% decrease in the Vegetation Primary class, compared to increasing trends in all other land cover classes (Figure 3.4 and Table 3.4). This is discussed further in Section 3.3. By 2018, only 59% of primary vegetation was left intact while there was an increase of 23% of water body and 52% of secondary vegetation. For the Built-up Area, there was a steady increase over time with the highest rate of increase from 1994 to 2005 followed by a slower rate of increase in the most recent years. Evidence of a consistent trend in the Bareland class is limited, but it is assumed that fluctuations in this land cover class are related to temporary disturbance due to transitioning or brief changes from one land cover class to another. The changes in the Mining class is in accordance with the Didipio Mine development: mine construction began in 2008, with the first appearance of mining activity in the 2010 timestep and an exponential increase in 2015. When mining activities went underground in 2016, the rate of increase in surface expression of the mining area slowed down.

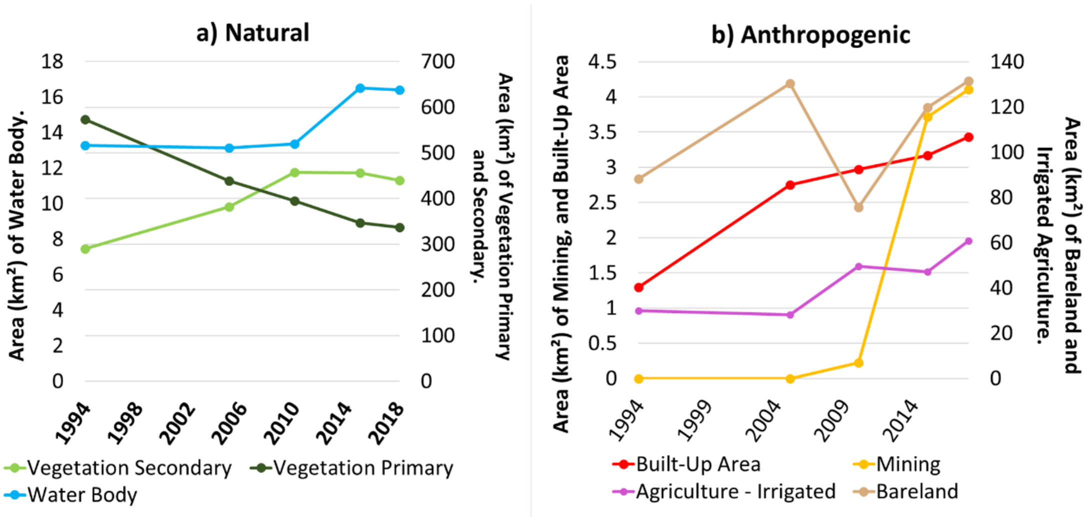


Figure 3.4. Graphs indicating the changes in area (km2) of the regional land use and land cover classes from 1994 to 2018. The classes are split into 2 categories: a) Natural and b) Anthropogenic. Note that Dual y-axis has been used for both a) and b) due to significant differences in the scales of area (km2).

Table 3.4. The numeric compilation of the area (km²) of all the land cover and land use classes from 1994 to 2018. For the Social Development and Management Program (SDMP) and Community Development Program (CDP) Class, the numbers in brackets indicate the number of project sites identified using auxiliary data (in some cases, these projects were smaller than the pixel size of the Landsat sensor so therefore did not contribute to the area estimates as shown in the 1994 and 2005 timesteps).

Regional Classification	**1994**	**2005**	**2010**	**2015**	**2018**
Water Body	13.28	13.15	13.36	16.50	16.40
Vegetation Primary	573.54	438.57	395.40	346.50	337.22
Vegetation Secondary	290.02	381.81	456.83	455.73	439.43
Bareland	88.33	130.34	75.66	119.84	131.43
Mining	0.00	0.00	0.23	3.71	4.11
Built-Up Area	1.29	2.75	2.97	3.17	3.43
Agriculture - Irrigated	29.87	28.10	49.55	47.10	60.83
Zones of Importance Classification	**1994**	**2005**	**2010**	**2015**	**2018**
Agriculture - Citrus	3.51	4.24	4.43	4.13	3.96
Agriculture - Rice Paddy	6.20	6.50	6.44	7.25	7.55
Agriculture – Swidden	2.24	2.71	3.09	2.84	3.45
Small-Scale Mining	0.00	0.00	0.00	0.0945	0.1098
SDMP	0.0000 (3)	0.0000 (4)	0.0018 (4)	0.0027 (5)	0.0036 (5)
CDP	0.11 (4)	0.28 (5)	0.61 (5)	0.72 (8)	0.73 (9)

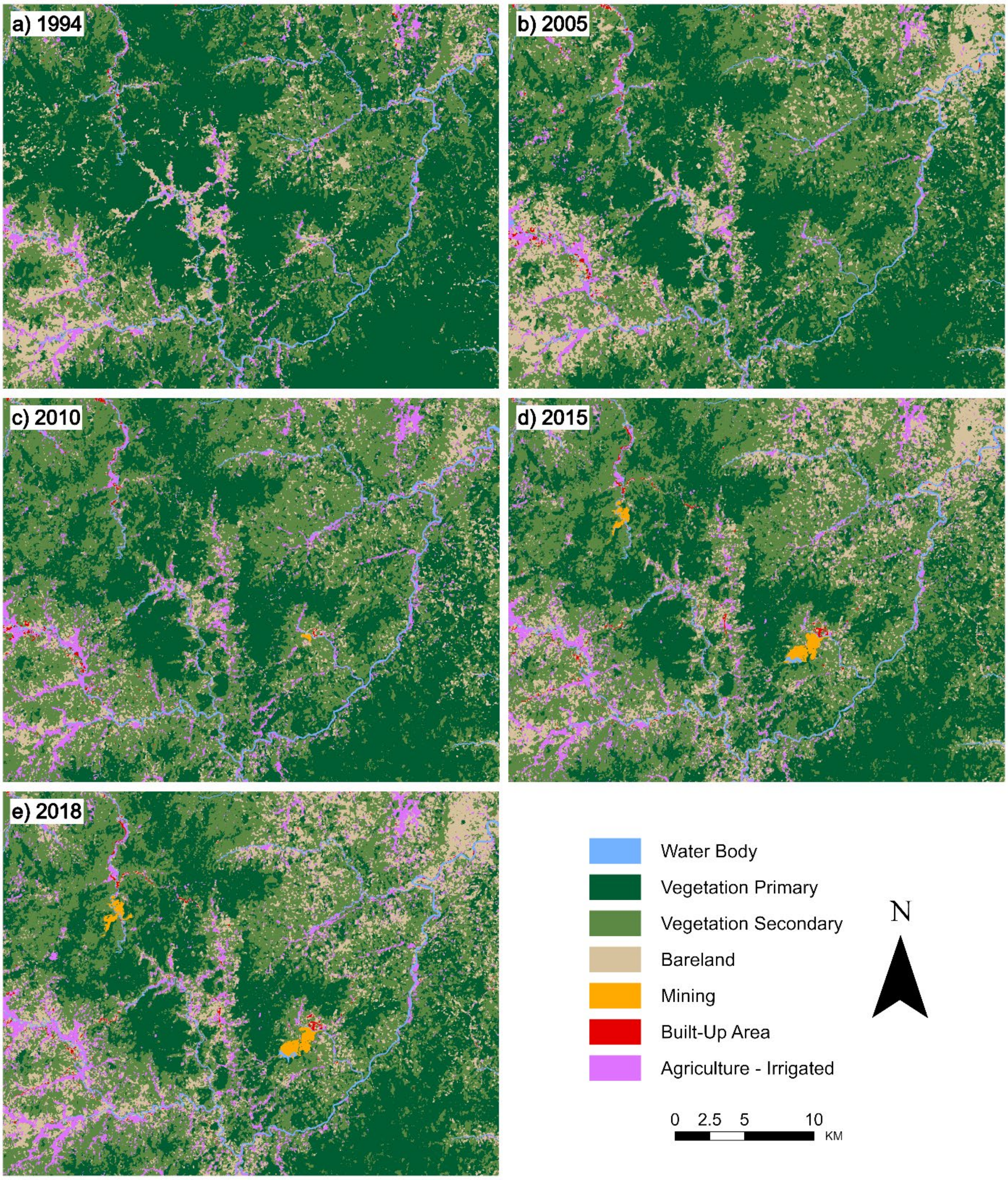


Figure 3.5. The supervised classification maps of the a) 1994, b) 2005, c) 2010, d) 2015 and e) 2018 timesteps generated from Google Earth Engine (GEE) using the Random Forest Classifier.

3.3.2 Zones of Importance: Participatory Mapping and Land Use Time Series

A total of 416 polygons and 8 polylines made up the zones of importance that were mapped by the local experts via the web-based survey (Figure 3.7). From the classified zones of importance land use maps that were generated, the areas of each land use class were analysed and plotted in Figure 3.6 to illustrate the changes that occurred from 1994 to 2018.

Based on Figure 3.6a, the swidden and irrigated rice paddy agriculture showed a relatively constant increase over time while citrus only followed the same trend up until 2010, after which it declined in 2015 and 2018. These are important trends that highlight how the livelihoods of farmers have changed over time. We speculate that the underlying cause of the decline in citrus agriculture post 2010 is closely linked to an infestation of huang long bing or citrus greening disease and citrus tristeza virus (CTV), that was dispersed by the black citrus virus (Capuna, 2007; Lagasca, 2007, 2014). The spread of these diseases severely affected citrus production in the region which then deterred further expansion of citrus plantations. Additionally, droughts exacerbated by climate change are likely to have affected agricultural production (Resources Environment and Economics Center for Studies (REECS), 2019). These hypotheses could be assessed in future social change assessments. The agricultural production and climate data such as rainfall in the region could be cross-examined with these trends and spatially mapped for identifying vulnerable regions to efficiently target mitigation efforts and prevention strategies.

Figure 3.6b shows changes in small-scale mining, which includes both artisanal and illegal counterparts. Small-scale mining was only evident in 2015. This seems to indicate that these mines begun after the construction completion of the Didipio Mine in 2012 and the commencement of commercial production in 2013 (OceanaGold, 2019). The Social Development and Management Program (SDMP) and Community Development Program (CDP) social investment project (in terms of infrastructure development) extents and locations were identified as individual polygons in Figure 3.7 and the details of these projects are listed in Table B 6. It is important to note that apart from infrastructure development, the Didipio Mine contributes funding to education, health and sanitation. The changes in the area and number of project sites are highlighted in Table 3.4. Figure 3.6b and Table 3.4 show that the SDMP area was small compared to area occupied by other classes from 1994 to 2010 and slowly increased from 2015 to 2018. The CDP land cover class had a slow rate of area increase from 1994 to 2010, then slowed down in 2015 and was almost stagnant until 2018, amounting to an area of 0.73 km^2. Overall, the social investment projects that are categorized under SDMP and CDP did not have a large impact on the total study area due to the extent of the project sites.

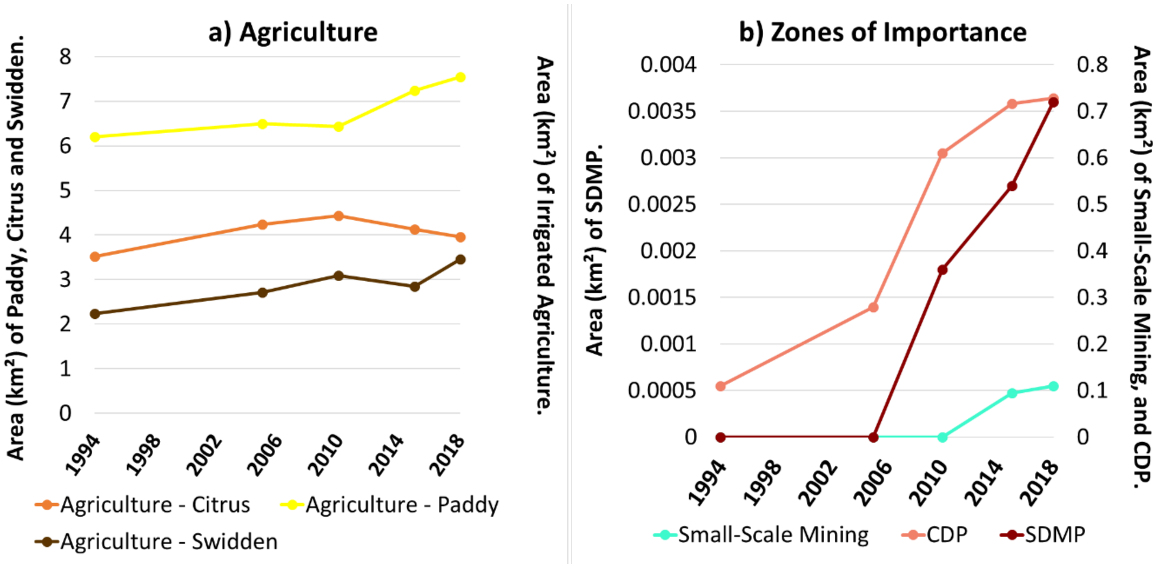


Figure 3.6. Graphs indicating the changes in area (km^2) of the land use classes from 1994 to 2018. The land use classes are split into two categories; a) Agriculture and b) Zones of Importance. Dual y-axis has been used for both a) and b) due to significant differences in the scales of area (km^2).

The zones of importance land cover classes were acquired at very high resolution compared to the study area extent of 1,006.93 km^2 (Figure 3.7) so zoom-ins have been used to provide a clearer representation. Figure 3.8 demonstrates the land cover and land use changes of the specific extent at each of the five time-steps (1994, 2005, 2010, 2015 and 2018). It is important to note that in some cases, the fine-scale land use, such as small-scale mining, were too small to be captured by the moderate 30m2 Landsat pixel resolution and are extremely difficult to classify even with auxiliary data as they were often obscured by other land cover, such as vegetation and bare land. Hence, this does not confirm an absence of these land use classes in those timesteps.

Figure 3.8a highlights the changes that occurred in the Didipio Mine site. In 1994, there were some built-up areas present, indicating possible settlements, and a variety of agricultural activities (mainly paddy and swidden agriculture). In 2005, the SMDP and CDP social investment projects were initiated in this area, but the previous built-up areas have been converted to bare land, irrigated agriculture and vegetation. There also seemed to be regrowth of natural vegetation in the area and less irrigated agriculture. Over the next ten years, until 2015, the mining land cover developments continued at a significant rate, promoting an increase in built-up areas, swidden agriculture and small-scale mining in its surrounding area. From 2015 to 2018, the rate of development in all the land use and land cover classes appeared to have eased, as evident in Figure 3.4 and Figure 3.6. The agricultural patterns of change were highlighted in Specific Extent (SE) 2 (Figure 3.8b) which is located to the northwest of the Didipio mine site. Citrus and Paddy were popularly grown in this area from 1994. The subtle transitions between these two agricultural land use classes and to other land uses are evident throughout the time series, from 1994 to 2018.

The exact locations of these land use changes are clearly presented in the time series and can be conveniently compared side-by-side, making it easier for locating important areas of change. Having visual representations of landscape changes and impacts are useful for engaging with stakeholder groups. Additionally, zooming into these specific extents makes it more effective at capturing subtle but possibly important changes that would be obscured when analysing changes only at a regional scale. The option to select specific extents to focus the time series analysis on is useful for mining companies to support specific narratives around social change. Such narratives can be identified through a participatory process and/or through the application of qualitative GIS (Lechner et al., 2019b) during the company's social change assessments. However, it is crucial that these changes are validated by people on the ground, as the level of certainty of the time series decreases the further back in time we go (Table B 1).

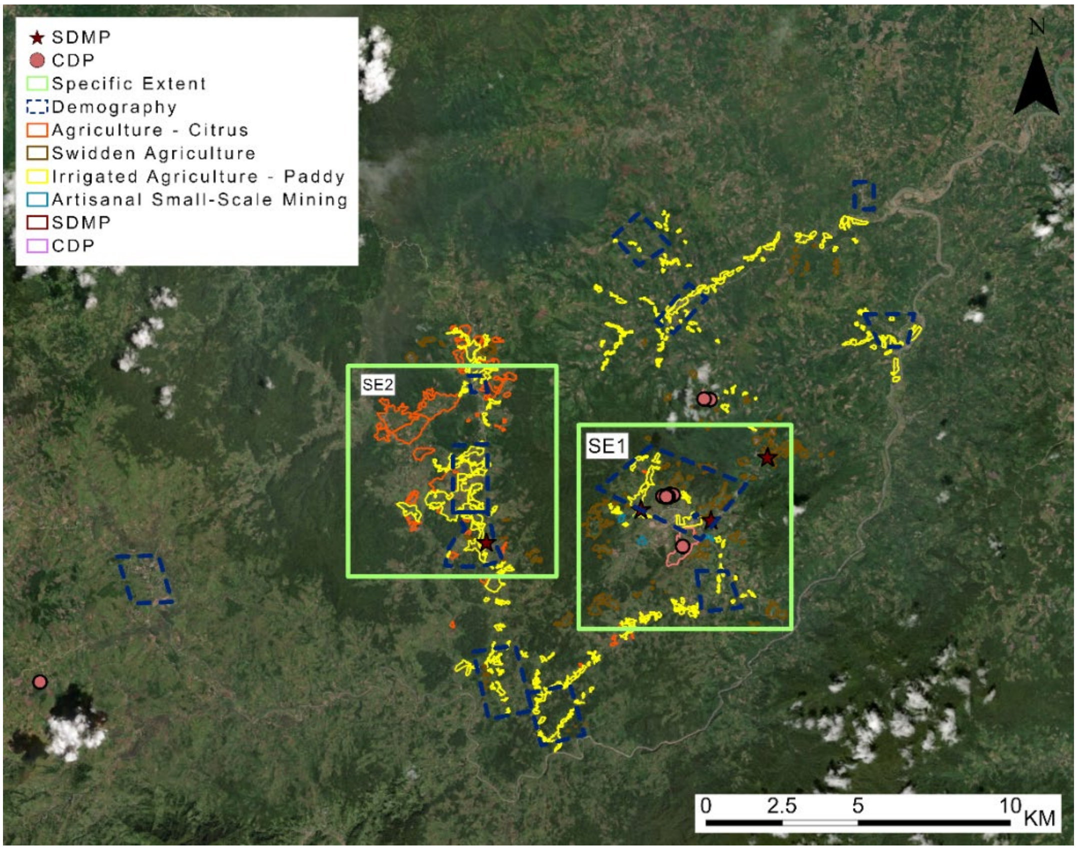


Figure 3.7. A compilation of all the zones of importance land use mapped using Maptionnaire for 2018. The green boxes indicate the Specific Extents (SE) chosen to highlight the zoom ins of significant regions of interest. Points have been used in addition to polygons to mark the Social Development and Management Program (SDMP) and Community Development Program (CDP) project areas that are too small to be visualized

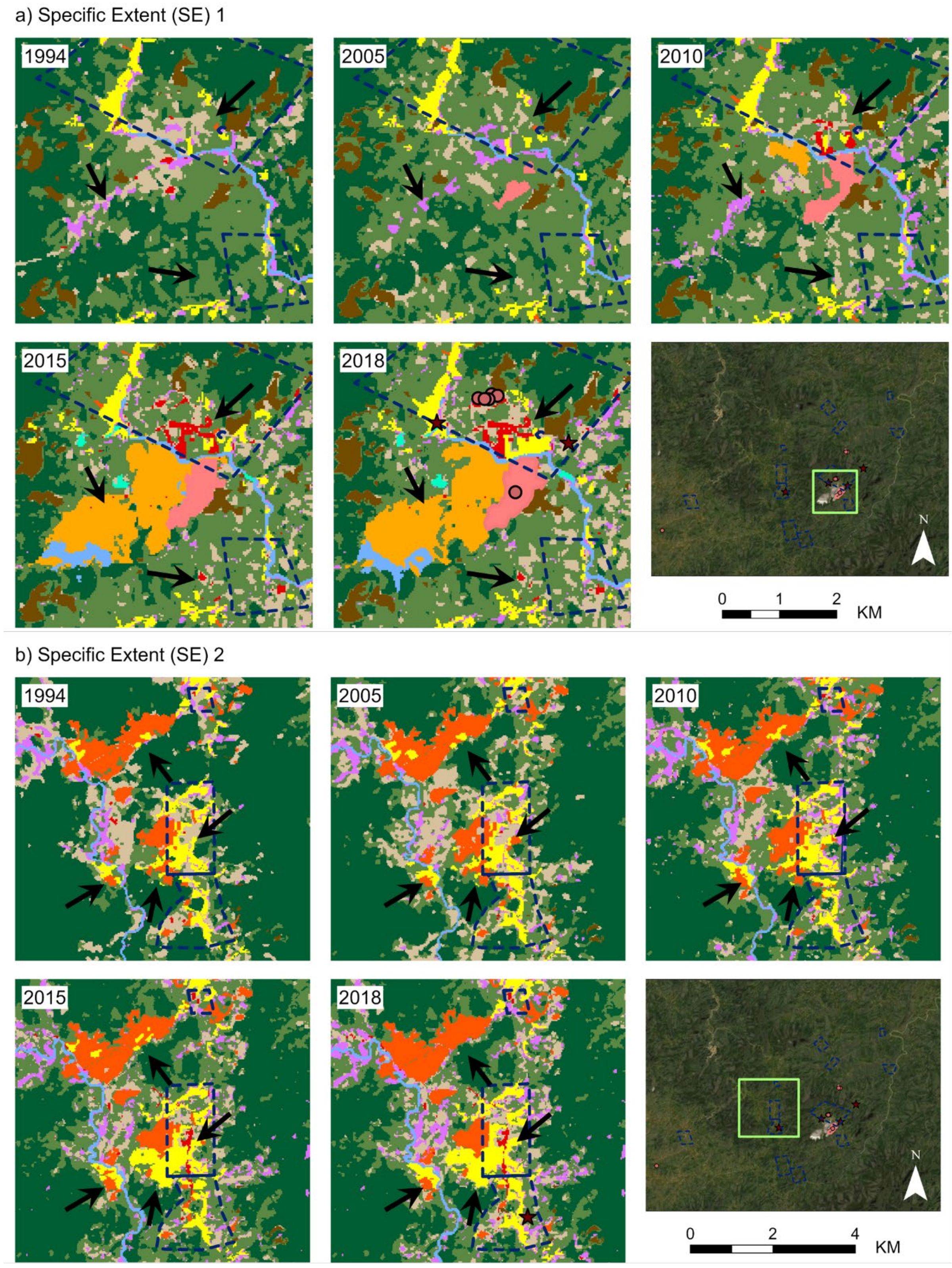


Figure 3.8. a) SE1 focuses on the land use and land cover changes in the Didipio Mining Site while b) SE2 focuses on the Agricultural and Built-up Area land use and land cover changes to the northwest of the Didipio Mine; these changes are marked by the black arrows.

3.3.3 Land Use and Land Cover Transitions

The time series maps captured information on the spatio-temporal variations in land use and land cover change over time. The details of the land use and land cover transitions between the 1994 and 2010 timesteps (timeframe 1) were compiled in Table 3.5 and Table 3.6 for timeframe 2 (2010 and 2018). The 24 years of land cover changes that occurred from 1994 to 2018 were compiled in Table B 7.

Based on evidence in Table 3.5 and 6, the largest land cover transition was from primary vegetation to secondary vegetation; this was a change of 145.51 km^2 for timeframe 1 and 43.33 km^2 for timeframe 2. Changes in the water body class were subtle compared to the primary and secondary vegetation classes. The greatest transition from water body were to secondary vegetation, followed closely by irrigated agriculture and bare land. Between 1994 to 2010, and 2010 to 2018 consecutively, 20.84 km^2 and 9.40 km^2 of primary vegetation, and 30.30 km^2 and 81.21 km^2 of secondary vegetation, were converted to bare land; this shows a significantly higher proportion of vegetated land cover being cleared in the more recent years post 2010, potentially for agriculture or infrastructure development. In fact, a total of 35.01 km^2 (timeframe 1) and 36.09 km^2 (timeframe 2) of waterbody, primary and secondary vegetation and bare land were converted to agricultural land uses. Transitions between the different agricultural land uses were also observed. The conversion was initially balanced between citrus and paddy in timeframe 1 but in timeframe 2, the transition leaned towards paddy cultivation instead; the highest conversion was 0.53 km^2 from citrus to paddy, compared to 0.19 km^2 of paddy to citrus.

A total of 0.20 km^2 (timeframe 1) and 3.55 km^2 (timeframe 2) of primary and secondary vegetation, bare land and water body, as well as 0.03 km^2 (timeframe 1) and 0.35 km^2 (timeframe 2) of built-up area, social development projects and agricultural land uses, were converted to mining. The transition to small scale mining was one of the most minimal, amounting to 0.10 $km^2$and only occurred from 2010 onwards; the affected land cover classes were water body, primary and secondary vegetation and the agricultural land uses. Finally, the land cover transitions to the SDMP and CDP social development projects were too subtle to be detected, accumulating up to 0.60 km^2 and 0 .73 km^2; mostly these were from the secondary vegetation class and some bare land areas. Overall, these changes seemed more prominent in the 2010 to 2018 timeframe compared to the 1994 to 2010 one, concurring to the trends reported in Section 3.1 and 3.2 (Figure 3.4, Figure 3.6 and Table 3.4).

Based on Table 3.1, the water body, primary vegetation and secondary vegetation classes directly correlate to the bio-physical characteristics of the natural environment. The degradation and transformation of these classes into other land cover or land use provide the means of assessing environmental quality. Hence, the decrease in primary vegetation indicates habitat and biodiversity loss in the area which are likely to have negative impacts on ecosystem services such as climate regulation and natural water quality management (Braimoh, 2006; W. Liu & Agusdinata, 2020). Changes in the locations of built-up areas, social development projects and large or small-scale mining is a good indicator of population distribution (Table 3.1). This can be subsequently linked to data on population density, income, loss of land, migration and education, to discern socio-economic impacts such as poverty and well-being (Fan et al., 2016; Nuissl et al., 2009). Most land converted to mining consisted of natural land covers, but a portion of irrigated agriculture land use were also affected in this transition; this may have produced a displacement of agricultural lands.

Trends in agriculture are a useful proxy for climate change, human footprint, economy and livelihood (Table 3.1). For example, the patterns of conversions between citrus and paddy occurred synchronously with the spread of the citrus greening disease and the black citrus virus in the region post 2010 (Capuna, 2007; Lagasca, 2007). This shift was likely triggered by the significant decline in productivity and a higher and more costly risk of crop failure (as discussed in Section 3.2) despite the existing overseas market demand (Lagasca, 2014). These shifts effects can, also be explained by natural disasters such as typhoons which are common in this region (Holden, 2015). It is highly likely that natural and anthropogenic factors operate in tandem to cause changes in agriculture (Chanthorn et al., 2016). The rural population is largely dependent on agriculture, requiring access to natural resources such as a constant supply of clean water and fertile lands. Hence, climate change and environmental degradation can have detrimental effects on these vulnerable populations, notably an increase in poverty.

Table 3.5. Land Use and Land Cover Transition Matrix for timestep 1994 to 2010 in km². Note that the diagonal line (highlighted in grey) does not track across the table because some land use and land cover classes (e.g. SDMP) were not detected in the former timestep but present in the latter timestep. Additionally, the variables labelled with 0.00 km² indicated areas of land use and land cover classes detected that were less than 0.01 km².

		Land Use and Land Cover 2010 (km²)												
		Water Body	**Vegetation Primary**	**Vegetation Secondary**	**Bareland**	**Mining**	**Built-Up Area**	**SDMP**	**CDP**	**Agriculture - Irrigated**	**Agriculture - Citrus**	**Agriculture - Paddy**	**Agriculture - Swidden**	**Grand Total (km²)**
Land Use and Land Cover 1994 (km²)	**Water Body**	9.86		1.55	0.30		0.11			1.41	0.00	0.05	0.00	13.28
	Vegetation Primary	0.91	395.40	145.51	20.84	0.00	0.15		0.00	9.85	0.18	0.16	0.22	573.22
	Vegetation Secondary	0.98		241.57	30.30	0.08	1.43		0.49	12.53	0.85	0.74	0.88	289.85
	Bareland	0.47		57.48	21.14	0.12	0.91	0.00	0.01	7.76	0.12	0.21	0.05	88.27
	Built-Up Area	0.11		0.48	0.32	0.02	0.22			0.15		0.00		1.30
	CDP			0.01	0.00				0.10					0.11
	Agriculture - Irrigated	0.99		8.62	2.47	0.01	0.14		0.00	17.37	0.03	0.22	0.01	29.86
	Agriculture - Citrus	0.00		0.21	0.08					0.01	3.04	0.15	0.00	3.49
	Agriculture - Paddy	0.05		0.50	0.06		0.01		0.00	0.41	0.20	4.89	0.08	6.20
	Agriculture - Swidden	0.00		0.31	0.05		0.00	0.00	0.00	0.01	0.00	0.01	1.85	2.23
	Grand Total	13.37	395.40	456.24	75.56	0.23	2.97	0.00	0.60	49.50	4.42	6.43	3.09	1007.81

Table 3.6. Land Use and Land Cover Transition Matrix for timestep 2010 to 2018 in km^2. Note that the diagonal line (highlighted in grey) does not track across the table because some land use and land cover classes (e.g. Small-Scale Mining) were not detected in the former timestep but present in the latter timestep. Additionally, the variables labelled with 0.00 km^2 indicated areas of land use and land cover classes detected that were less than 0.01 km^2.

		Land Use and Land Cover 2018 (km2)													
		Water Body	Vegetation Primary	Vegetation Secondary	Bareland	Mining	Small-Scale Mining	Built-Up Area	SDMP	CDP	Agriculture - Irrigated	Agriculture - Citrus	Agriculture - Paddy	Agriculture - Swidden	Grand Total (km2)
Land Use and Land Cover 2010 (km2)	Water Body	11.76		0.79	0.29	0.02	0.02	0.03	0.00		0.39	0.00	0.06		13.36
	Vegetation Primary	0.32	337.22	43.33	9.40	0.82		0.03		0.00	4.20	0.01	0.02	0.05	395.40
	Vegetation Secondary	2.00		345.05	81.21	2.27	0.01	1.24	0.00	0.13	22.86	0.19	0.99	0.66	456.61
	Bareland	0.45		34.84	32.07	0.44	0.00	1.15	0.00	0.01	6.43	0.08	0.08	0.07	75.62
	Mining	0.00		0.02		0.21									0.23
	Built-Up Area	0.11		0.71	1.04	0.04		0.67	0.00		0.34	0.00	0.05		2.96
	SDMP				0.00		0.00	0.00	0.00		0.00		0.00		0.00
	CDP			0.01	0.01	0.00		0.00		0.58	0.00			0.00	0.60
	Agriculture - Irrigated	1.67		13.59	7.04	0.31	0.00	0.29			26.20	0.02	0.39	0.01	49.52
	Agriculture - Citrus	0.01		0.18	0.11			0.00			0.03	3.47	0.53	0.10	4.43
	Agriculture - Paddy	0.07		0.36	0.15		0.00	0.02	0.00		0.32	0.19	5.31	0.02	6.44
	Agriculture - Swidden	0.00		0.27	0.07		0.07	0.00	0.00	0.01	0.02	0.00	0.11	2.54	3.09
	Grand Total	16.39	337.22	439.15	131.39	4.11	0.10	3.43	0.00	0.73	60.79	3.96	7.54	3.45	1008.26

3.3.4 Applications of Remote Sensing to Social Change Assessment

Mining can have intensive and extensive positive and negative impacts on communities as a consequence of land use and land change, and these impacts can be effectively mapped and quantified with remote sensing technology (Antwi et al., 2008; Koruyan et al., 2012b; Lima et al., 2016; Pavloudakis et al., 2009a) to support the characterisation of the various elements associated with a mining socio-ecological system. Remote sensing with GIS can be used to support and develop complex workflows via data management, analysis and visual presentations of land cover change and its consequences (Radulescu & Radulescu, 2011). Hence, GIS and remote sensing applications are increasingly playing a vital role in mining land management (Antwi et al., 2008; Koruyan et al., 2012b; Pavloudakis et al., 2009b; Radulescu & Radulescu, 2011). However, their application for supporting community development is still in its infancy.

Social changes do not occur in isolation but influence each other in a dynamic and systemic manner within a socio-ecological system. These changes can often be hard to access solely via ethnographic approaches (the dominant approach used by mining companies). Hence, this study could assist by providing an additional element to social change assessment by allowing stakeholders to visualize past changes in the mining landscape. Additionally, the trends observed from this study can be used to triangulate qualitative and quantitative social data using spatially integrated GIS approaches (Lechner et al., 2019b). Furthermore, the social data can be used to validate remote sensing data and ensure that it is accurate; this is especially important for the older time periods when high resolution ground validation data are unavailable. Remote sensing data can help stakeholders understand the changes that have occurred, notably through the provision of quantitative estimates of land use and land cover change; this facilitates collaboration, effective planning and allocation of resources for future projects. For example, local experts can identify zones where agriculture threats such as market fluctuations, inadequate irrigation supply and extreme weather events are prevalent, which can be cross-referenced with the types of land cover maps produced in this study so that spatially explicit programmes to improve the agriculture sector can designed and implemented.

Current and future remote sensing sensors, such as Sentinel, with high spatial, temporal, spectral and radiometric resolution, can enable the classification of the land covers and land use that we found problematic to identify with Landsat. However, for looking into the past, only Landsat and SPOT have the time series data needed to characterise historical land cover changes stretching back decades. In our study, we were able to classify coarse thematic resolution land cover classes but were unable to automate the classification of site-specific land use classes such as the various agriculture types and SDMP which are also critical for understanding social change trajectories. Due to the high-level and complex nature of these land cover classes, over-generalization is inevitable when using moderate-resolution sensors such as Landsat (Briassoulis, 2019; Comber et al., 2005; Fisher et al., 2005). Further refinement of fine thematic resolution land use variations within these high-level land covers was attempted but was ultimately constrained by the data resolution. Nonetheless, we believe that the benefits of using Landsat data greatly outweighs this limitation due to the extent of its historical archives.

We demonstrated that web-based mapping using current high-resolution true colour imagery and historic Landsat can potentially address this issue, although, the further we go back in time the less certain we are of the accuracy of the mapped outputs. This is one area where local experts are a valuable resource. In the future, technological and methodological advances such as computer vision techniques including deep learning with super resolution mapping (Ghaffar et al., 2019; Lechner et al., 2020) may address these limitations. However, local knowledge from on the ground experts will ultimately still play a significant role in identifying high-resolution, site-specific and historical land use changes that are important to support social change assessment. Nonetheless, memories can fade, hence, it is important to digitally capture useful local knowledge to prevent permanent loss.

The use of web-based mapping in the present study was in response to the inability of Landsat to characterise critical land cover components, especially in older images. It was developed through an iterative process that came from discussions with collaborators and local experts. This study represents one of the first such documented efforts to map regional scale land cover using remote sensing and web-based mapping to assess socio-environmental change. With the knowledge and experience gathered, an idealised workflow (Figure 3.9) is proposed for future studies. In Step 1a and 1b of the workflow, we suggest that the web-based mapping survey would be executed first to obtain critical high-resolution ground truth data and for experts to consider whether any important land use or land cover classes are missing. Next, supervised classification approaches would be carried out (Step 1c) using the ground-truth data identified in Step 1a and 1b as training data to map land cover in all the chosen time-steps. This is followed by Steps 2a and 2b which involves running a second web-based mapping activity to assess the fitness of the classification and to map any missing elements for specific locations in the land cover maps. Additionally, land use and land covers that are challenging to map using a supervised classification and moderate to coarse resolution remote sensing data can be refined using this method. The outputs from the web-based mapping and the remote sensing supervised classification will be harmonized in Step 2c. The final harmonized outputs represent a regional scale map consisting of the coarse thematic resolution land use and land cover classified using supervised classification of remote sensing imagery and fine thematic resolution mapping using a web-based participatory approach.

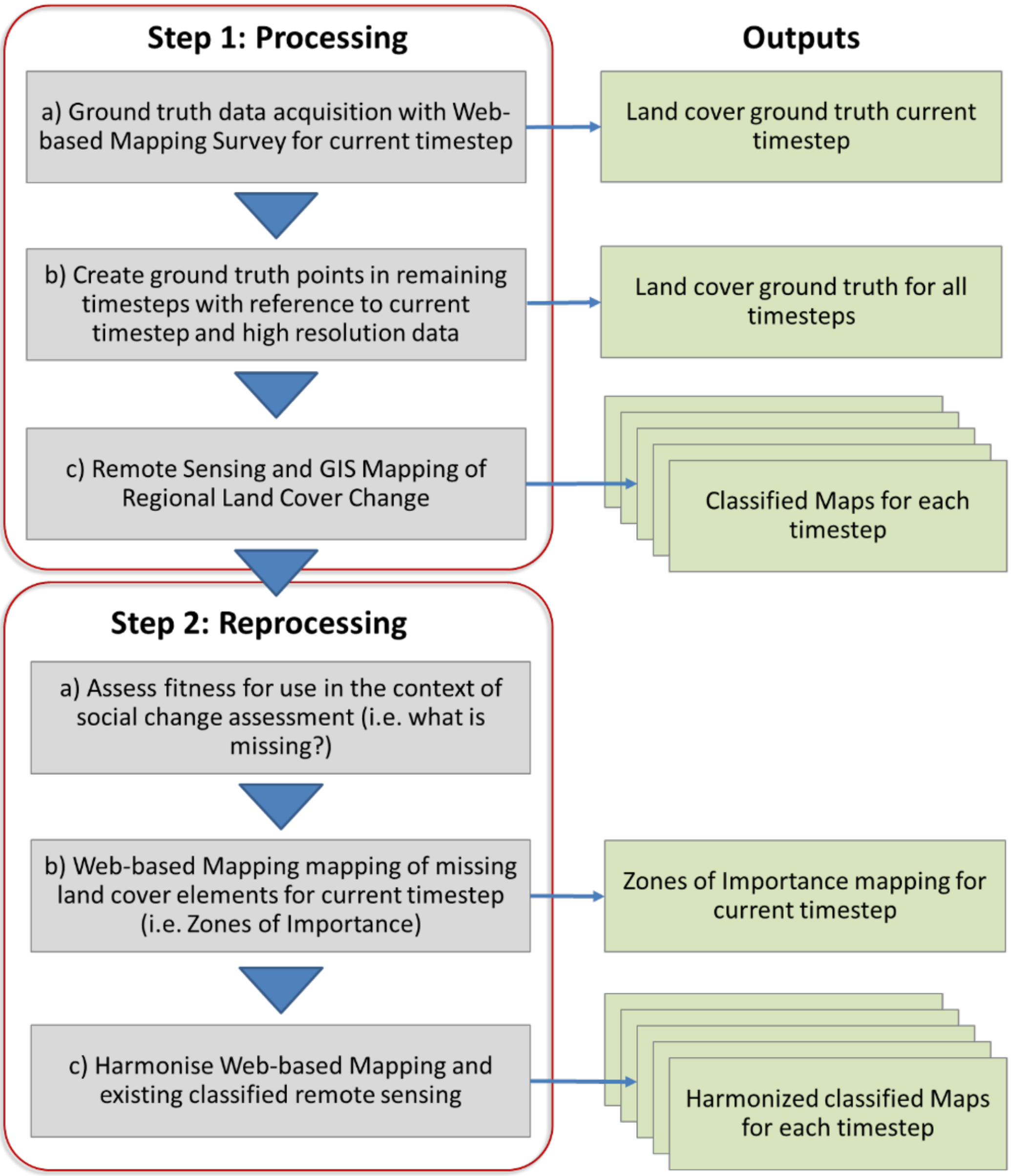


Figure 3.9. An idealized flow chart to incorporate web-based mapping survey data more effectively into the classification time series formulation process.

3.4 Conclusion

This study represents one of the few examples of regional mapping of land use and land cover changes using remote sensing and web-based mapping to assess and quantify socio-environmental impacts for supporting mine planning and social change assessments. A high-accuracy time series of the region surrounding the Didipio Mine in Philippines between 1994 and 2018 was successfully created using a combination of supervised classification in Google Earth Engine and web-based mapping. High-level, coarse thematic resolution land cover classes were successfully characterized using a supervised Random Forest classification approach and by compositing stacks of ancillary data consisting of multispectral and multitemporal Landsat images, vegetation indices and a Digital Elevation Model (DEM). This study also highlighted that the application of web-based mapping by local experts is necessary to identify key fine thematic resolution land uses in the zones of importance.

The final time series produced using Landsat, accurately identified critical temporal trends in the study area. These land use and land cover transitions provide important insights for studying socio-environmental indicators. The remote sensing mapping can be triangulated with social data (e.g. ethnographic data) for characterising ongoing social-environmental impacts, to assist subsequent social change assessments. Land cover time series mapping expands the range of possibilities for further analyses, to promote a deeper understanding of the dynamic relationship between extractive resources and the surrounding landscape through a socio-ecological systems approach.

Chapter 4. Synthesis

4.1 Summary

This thesis investigated spatially explicit GIS and remote sensing approaches for assessing the effects of mining on society and the environment. The pressing need for robust analyses and reliable reporting of data on the local and regional changes that result from mining is deemed crucial for mining companies to successfully identify, monitor, sustainably mitigate, and manage these socio-economic and environmental impacts given the impending increase in supply and demand (Chapter 1). Remote sensing and GIS methods have the potential to facilitate and optimise conventional social science approaches for understanding historical and existing socio-environmental impacts, by enabling spatial data collection and triangulation (Chapter 2). Local knowledge acquired through stakeholder participation is emphasised as essential for providing meaningful context to quantitative geographical evidence (Chapter 2 and Chapter 3). Further research in spatially integrated social science approaches can be improved to establish innovative transdisciplinary data collection and analysis critical for assessing less tangible socio-economic implications (Chapter 2 and Chapter 3).

This final chapter reiterates the thesis's contributions and makes recommendations for areas where further research can be done and how future work on the integration of GIS, remote sensing and social science can be improved to advance the field for a comprehensive understanding of socio-economic mining impacts. Section 4.2 summarises key findings with respect to the research questions posed in Chapter 1. This thesis is concluded in Section 4.3.

4.2 Research questions and key findings

4.2.1 To what extent has the social, economic, and environmental mining impacts been studied in spatially explicit ways?

Mine implications for society, the economy, and the environment are multifaceted, necessitating transdisciplinary methods and coordinated efforts from all specialists and stakeholders to be addressed efficiently and sustainably. This need is made pressing by the imminent increase in demand for mineral resources. It is promising that more recent research has focused on socioeconomic mining impacts while completely or in part utilising GIS and remote sensing technologies to complement traditional social science methods.

Overall, Chapter 2 demonstrated that the integration of GIS, Remote Sensing and Social Science approaches successfully captured all aspects of the socio-economic and environmental impacts identified by the Social Framework for Projects (Smyth & Vanclay, 2017); 'Environment', 'Land', 'People', 'Community', 'Culture', 'Livelihood', 'Infrastructure' and 'Housing'. However, it is only through a collaborative spatially integrated social science approach that the intangible aspects of social impacts (ie: Culture – including historical memories and indigenous knowledge) can be effectively captured to understand the underlying intricacies surrounding the socio-economic and environmental effects of mining. Additionally, direct interaction with the affected communities is imperative and stakeholder participation to acquire local knowledge is recognized as vital for providing contextual relevance to quantitative spatial evidence.

4.2.2 How can current limitations of GIS and Remote Sensing approaches be improved to spatially study socio-economic and environmental impacts?

The socio-economic variables of interest must be geospatially recorded to enable effective nationally or regionally aggregated analysis (Haslam & Tanimoune, 2016), for example, spatially referenced social (SRS) data that are derived from elicited social survey methods and then mapped (Lechner et al., 2014). Spatially explicit studies employing geographically precise data are particularly capable of establishing location-specific targets for mitigation plans and are effective at tracking the movement and spatial patterns of impacts, which can be triangulated with other spatially fluid variables (i.e. climate). Compared to fieldwork, remote sensing technology is more cost-effective and provides reasonably accurate data, particularly when investigating remote locations. On the other hand, PGIS can collect both spatial and social data to a great extent, without relying on the need to deploy scientists into the field.

Werner et al. (2020) stresses the importance of systemic, widespread, and formalized consistency to effectively document abandoned mines, rehabilitation and/or remediation efforts at a national level and worldwide. Commensurability - assessed using the same units of measure – is also key. Additionally, it is vital that uncertainties are addressed or adequately reported when conducting analysis (Lechner et al., 2014). Census data may be represented at a variety of spatial resolutions; however, it is challenging to conduct analysis and comparisons between data due to differences in political and geographic borders. Even though it might cost more to collect data and plan for the long term, high-resolution geospatial data would help lessen this effect if the precise location of the data is recorded instead of basing it on the administrative boundaries.

Additionally, more efforts are needed to make data easily accessible for scientific progress. Xiao et al. (2021) pointed out that data on the distribution and physical characteristics of mining locations in China are not open to the public while De Valck et al. (2021) pointed out that limited data on ecosystem services are available in the regional areas in Central Queensland. Fewer studies have therefore been able to quantify the relationship between coal resource growth and the state of the social-ecological system at higher spatial resolutions. An example of an attempt being made in this direction is the National Spatial Data Infrastructure (NSDI) as an organisational strategy being implemented in Kosovo to increase the number of applications and availability of spatial data via institutional structures, regulations, and standards necessary to disseminate spatial information from a variety of sources to prospective users (Meha et al., 2011).

4.2.3 How can the socio-environmental land use and land cover impacts in a mining region be best captured using spatially integrated social science approaches?

Remote sensing and participatory mapping approaches were integrated in Chapter 3 to map the regional land use and land cover changes for quantifying socio-environmental impacts in the mining region of Didipio, Philippines. A high-accuracy time series of the area surrounding the Didipio Mine between 1994 and 2018 was produced using the successful combination of web-based mapping and supervised Random Forest classification in Google Earth Engine. Auxiliary data composites made up of multispectral and multitemporal Landsat images, vegetation indices, and Digital Elevation Model (DEM) was integrated into the supervised classification approach, and high-level, coarse thematic resolution land cover classes (ie: Vegetation, Water Body, Built-Up Area, Mining and Bareland) were effectively identified. The work in Chapter 3 also underlined the significance of validation and mapping inputs by on the ground experts to identify essential, fine thematic resolution land uses (ie: Small-Scale Mining, Citrus, Rice Paddy, and Swidden Agriculture) in critical zones.

Critical temporal trends in the study area were accurately identified in the final time series generated using Landsat data. These changes in LULC offer crucial insights for researching socio-environmental indicators. To facilitate future assessments of social change, social data (ie: demographic data) can be triangulated with remote sensing mapping to spatially characterise social-environmental impacts. Through a socio-ecological systems perspective, LULC time series mapping opens up the possibility of additional analyses, fostering a deeper insight of the dynamic relationship between mining and the surrounding landscape.

4.3 Closing Remarks

Socio-economic and environmental impacts of mining are multifaceted, and so require multidisciplinary approaches and collaborative efforts from all different experts and stakeholders in order to be addressed effectively and sustainably, especially. To fully understand the intricate socio-economic and environmental connections in a mining landscape, geospatial techniques alone are insufficient. Traditional qualitative methods similarly are unable to fully capture geographical and environmental changes, particularly historical impacts. Numerous authors have concluded that the key to fully comprehend this complex system is to combine these multiple approaches, qualitive and quantitative, social and environmental, which nonetheless, presents a significant challenge (Lechner et al., 2017).

Overall, it is promising that more research has recently focused on socio-economic mining impacts, and either fully or partially utilized GIS and remote sensing to do this. These tools represent an advancement of traditional social science approaches. Integration of GIS and remote sensing applications with social science methods is a step in the right direction and the only way to spatially capture and analyse complex linkages between the various socio-economic and environmental indicators. Remote sensing has enabled both spatio-temporal analysis at medium-resolution for regional scale and high-resolution site-scale studies to quantify significant LULC changes connected to socio-economic indices. Additionally, Participatory GIS has also been shown to be the best socio-spatial tool for geospatially documenting and mapping community perceptions for a holistic understanding of the changes and impacts occurring within the complex mining landscape.

It is emphasized that local knowledge via stakeholder engagement remains vital to provide meaningful context to quantitative spatial evidence. Direct interaction with the impacted communities is required to shed light on the underlying complexities surrounding the socio-economic and environmental consequences of mining. Moreover, the bottom-up approach is often more effective at identifying and resolving the fundamental causes of impacts. Geovisualization methods enable the rapid and effective communication of data patterns for aiding the decision-making process to evaluate where, how, and why changes have occurred.

As GIS and remote sensing technologies and applications continue to improve, more potential ways can be explored to incorporate multidisciplinary data capture and analysis, particularly to study socio-economic impacts which are often less tangible than e.g. physical ones. In order to achieve a more geographically integrated evaluation of socio-economic mining impacts, concerted efforts must also be made to improve data availability, quality, geographic characterisation, consistency, validation, and transparency. All of these are essential for effective data integration, inclusive analysis, and comprehensive planning across the mine life cycle, bringing us one step closer to attaining a sustainable future for the extractive industry and its surrounding community and landscapes.

References

Abdel-Rahman, E. M., Ahmed, F. B., & Ismail, R. (2013). Random forest regression and spectral band selection for estimating sugarcane leaf nitrogen concentration using EO-1 Hyperion hyperspectral data. *International Journal of Remote Sensing*, *34*(2), 712–728. https://doi.org/10.1080/01431161.2012.713142

Andersen, O., Crow, T. R., Lietz, S. M., & Stearns, F. (1996). Transformation of a landscape in the upper mid-west, USA: The history of the lower St. Croix river valley, 1830 to present. *Landscape and Urban Planning*. https://doi.org/10.1016/S0169-2046(96)00304-0

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). Land Use And Land Cover Classification System For Use With Remote Sensor Data. *U S Geol Surv, Prof Pap*.

Ang, M. L. E., Arts, D., Crawford, D., Labatos, B. v., Ngo, K. D., Owen, J. R., Gibbins, C., & Lechner, A. M. (2020). Socio-environmental land cover time series analysis of mining landscapes using Google Earth Engine and web-based mapping. *Remote Sensing Applications: Society and Environment*, *21*(July 2020), 100458. https://doi.org/10.1016/j.rsase.2020.100458

Antwi, E. K., Krawczynski, R., & Wiegleb, G. (2008). Detecting the effect of disturbance on habitat diversity and land cover change in a post-mining area using GIS. *Landscape and Urban Planning*, *87*(1), 22–32. https://doi.org/10.1016/j.landurbplan.2008.03.009

Aragon, F. M., & Rud, J. P. (2013a). Natural resources and local communities: Evidence from a peruvian gold mine. *American Economic Journal: Economic Policy*. https://doi.org/10.1257/pol.5.2.1

Aragon, F. M., & Rud, J. P. (2013b). Natural resources and local communities: Evidence from a peruvian gold mine. *American Economic Journal: Economic Policy*. https://doi.org/10.1257/pol.5.2.1

Arts, D., Crawford, D., & Lechner, A. M. (2019). Social change assessment : integrating social science , spatial analysis and participatory approaches to enhance social impact and risk management of mining projects or operations. *6th International Congress on Environment and Social Responsibility in Mining.*

Babidge, S., Kalazich, F., Prieto, M., & Yager, K. (2019). "That's the problem with that lake; it changes sides": Mapping extraction and ecological exhaustion in the Atacama. *Journal of Political Ecology*, *26*(1). https://doi.org/10.2458/V26I1.23169

Balaniuk, R., Isupova, O., & Reece, S. (2020). Mining and tailings dam detection in satellite imagery using deep learning. *Sensors (Switzerland)*, *20*(23), 1–26. https://doi.org/10.3390/s20236936

Baltzer, J. L., & Davies, S. J. (2012). *Rainfall seasonality and pest pressure as determinants of tropical tree species' distributions*. 2682–2694. https://doi.org/10.1002/ece3.383

Balzter, H., Cole, B., Thiel, C., & Schmullius, C. (2015). Mapping CORINE land cover from Sentinel-1A SAR and SRTM digital elevation model data using random forests. *Remote Sensing*. https://doi.org/10.3390/rs71114876

Bebbington, A., Hinojosa, L., Bebbington, D. H., Burneo, M. L., & Warnaars, X. (2008). Contention and ambiguity: Mining and the possibilities of development. *Development and Change*, *39*(6), 887–914. https://doi.org/10.1111/j.1467-7660.2008.00517.x

Belgiu, M., & Drăgu, L. (2016). Random forest in remote sensing: A review of applications and future directions. In *ISPRS Journal of Photogrammetry and Remote Sensing*. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Boakye, E., Anyemedu, F. O. K., Quaye-Ballard, J. A., & Donkor, E. A. (2020). Spatio-temporal analysis of land use/cover changes in the Pra River Basin, Ghana. *Applied Geomatics*, *12*(1), 83–93. https://doi.org/10.1007/s12518-019-00278-3

Botengan, R. F. P., Addawe, J. M., Botengan, H. J. P., Addawe, C. L., Belason, G. B., Gillado Jr., A. V., Mendoza, A. M., & Sioson, L. J. D. (2019). *Environmental Performance Report and Management Plan; Didipio Gold-Copper Project* (Issue April).

Braimoh, A. K. (2006). Random and systematic land-cover transitions in northern Ghana. *Agriculture, Ecosystems and Environment*, *113*(1–4), 254–263. https://doi.org/10.1016/j.agee.2005.10.019

Breiman, L. (2001). Random forests. *Machine Learning*. https://doi.org/10.1023/A:1010933404324

Brereton, D., Moran, C., Mcilwain, G., Mcintosh, J., & Parkinson, K. (2008). *Assessing the cumulative impacts of mining on regional communities: An exploratory study of coal mining in the Muswellbrook area of NSW*.

Briassoulis, H. (2019). *Analysis of Land Use Change: Theoretical and Modeling Approaches* (S. Loveridge & R. Jackson, Eds.). Regional Research Institute, West Virginia University.

Briones, P. S., & Sepúlveda-Varas, A. (2016). Systematic transitions in land use and land cover in a pre-Andean sub- watershed with high human intervention in the Araucania Region, Chile. *Ciencia e Investigacion Agraria*, *43*(3), 396–407. https://doi.org/10.4067/S0718-16202016000300006

Brown, G., Kangas, K., Juutinen, A., & Tolvanen, A. (2017). Identifying Environmental and Natural Resource Management Conflict Potential Using Participatory Mapping. *Society and Natural Resources*. https://doi.org/10.1080/08941920.2017.1347977

Brown, G., & Kyttä, M. (2014). Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. In *Applied Geography*. https://doi.org/10.1016/j.apgeog.2013.11.004

Brown, G., & Raymond, C. M. (2014). Methods for identifying land use conflict potential using participatory mapping. *Landscape and Urban Planning*. https://doi.org/10.1016/j.landurbplan.2013.11.007

Campbell, B. (2012). Corporate Social Responsibility and development in Africa: Redefining the roles and responsibilities of public and private actors in the mining sector. *Resources Policy*, *37*(2), 138–143. https://doi.org/10.1016/J.RESOURPOL.2011.05.002

Capuna, J. (2007, July 8). Deadly Viral Disease Threatens to Wipe Out Vizcaya Citrus Farms. *Northern Philippine Times*.

Carmona, A., Nahuelhual, L., Echeverría, C., & Báez, A. (2010). Linking farming systems to landscape change: An empirical and spatially explicit study in southern Chile. *Agriculture, Ecosystems and Environment*, *139*(1–2), 40–50. https://doi.org/10.1016/j.agee.2010.06.015

Chanthorn, W., Ratanapongsai, Y., Brockelman, W. Y., Allen, M. A., Favier, C., & Dubois, M. A. (2016). Viewing tropical forest succession as a three-dimensional dynamical system. *Theoretical Ecology*, *9*(2), 163–172. https://doi.org/10.1007/s12080-015-0278-4

Chavez, L. (2020, April 6). Standoff over Philippines' Didipio mines escalates despite COVID-19 lockdown. *Mongabay*.

Chen, Y., Liu, R., Barrett, D., Gao, L., Zhou, M., Renzullo, L., & Emelyanova, I. (2015). A spatial assessment framework for evaluating flood risk under extreme climates. *Science of the Total Environment*, *538*, 512–523. https://doi.org/10.1016/j.scitotenv.2015.08.094

Cocheci, R. M., Dorobanţu, R. H., & Sârbu, C. N. (2015). Environmental degradation in rural areas with high anthropic pressure - Impact and planning models. *Carpathian Journal of Earth and Environmental Sciences*, *10*(3), 25–36.

Cohen, W. B., Yang, Z., & Kennedy, R. (2010). Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync - Tools for calibration and validation. *Remote Sensing of Environment*. https://doi.org/10.1016/j.rse.2010.07.010

Comber, A., Fisher, P., & Wadsworth, R. (2005). What is land cover? *Environment and Planning B: Planning and Design*, *32*(2), 199–209. https://doi.org/10.1068/b31135

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing*. https://doi.org/10.1080/0143116031000101675

Cosimo, L. H. E., Martins, S. V., & Gleriani, J. M. (2021). Suggesting priority areas in the buffer zone of Serra do Brigadeiro State Park for forest restoration compensatory to bauxite mining in Southeast Brazil. *Ecological Engineering*, *170*(February). https://doi.org/10.1016/j.ecoleng.2021.106322

Craynon, J. R., Sarver, E. A., Ripepi, N. S., & Karmis, M. E. (2015). A GIS-based methodology for identifying sustainability conflict areas in mine design – a case study from a surface coal mine in the USA. *International Journal of Mining, Reclamation and Environment*, *30*(3), 197–208. https://doi.org/10.1080/17480930.2015.1035872

De Valck, J., Williams, G., & Kuik, S. (2021). Does coal mining benefit local communities in the long run? A sustainability perspective on regional Queensland, Australia. *Resources Policy*, *71*(July 2020), 102009. https://doi.org/10.1016/j.resourpol.2021.102009

Devenin, V., & Bianchi, C. (2019). Characterizing a mining space: Analysis from case studies in Chile and Australia. *Resources Policy*. https://doi.org/10.1016/j.resourpol.2019.101402

Dlamini, L. Z. D., & Xulu, S. (2019). Monitoring mining disturbance and restoration over RBM site in South Africa using landtrendr algorithm and landsat data. *Sustainability (Switzerland)*, *11*(24). https://doi.org/10.3390/SU11246916

D'Odorico, P., Rulli, M. C., Dell'Angelo, J., & Davis, K. F. (2017). New frontiers of land and water commodification: socio-environmental controversies of large-scale land acquisitions. *Land Degradation and Development*, *28*(7), 2234–2244. https://doi.org/10.1002/ldr.2750

Domaç, A., & Süzen, M. L. (2006). Integration of environmental variables with satellite images in regional scale vegetation classification. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431160500444806

Domingo, L. C. T. (2020, August 18). Australian mining firm's permit renewal pushed. *The Manila Times*.

Dorren, L. K. A., Maier, B., & Seijmonsbergen, A. C. (2003). Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. *Forest Ecology and Management*. https://doi.org/10.1016/S0378-1127(03)00113-0

Erb-Satullo, N. L. (2021). Technological rejection in regions of early gold innovation revealed by geospatial analysis. *Scientific Reports*, *11*(1), 1–12. https://doi.org/10.1038/s41598-021-98514-7

Everingham, J. A., Rolfe, J., Lechner, A. M., Kinnear, S., & Akbar, D. (2018). A proposal for engaging a stakeholder panel in planning post-mining land uses in Australia's coal-rich tropical savannahs. *Land Use Policy*. https://doi.org/10.1016/j.landusepol.2018.08.038

Fan, P., Chen, J., & John, R. (2016). Urbanization and environmental change during the economic transition on the Mongolian Plateau: Hohhot and Ulaanbaatar. *Environmental Research*, *144*(January 2016), 96–112. https://doi.org/10.1016/j.envres.2015.09.020

Ferring, D., & Hausermann, H. (2019). The Political Ecology of Landscape Change, Malaria, and Cumulative Vulnerability in Central Ghana's Gold Mining Country. *Annals of the American Association of Geographers*, *0*(0), 1–18. https://doi.org/10.1080/24694452.2018.1535885

Fisher, P., Comber, A. J., & Wadsworth, R. (2005). Land Use and Land Cover: Contradiction or Complement. In P. Fisher & D. J. Unwin (Eds.), *Re-presenting GIS* (3rd ed., pp. 85–98). John Wiley & Sons, Ltd.

Fohringer, C., Rosqvist, G., Inga, N., & Singh, N. J. (2021). Reindeer husbandry in peril?—How extractive industries exert multiple pressures on an Arctic pastoral ecosystem. *People and Nature*, *3*(4), 872–886. https://doi.org/10.1002/pan3.10234

Foody, G. M. (2002). Status of land cover classification accuracy assessment. In *Remote Sensing of Environment*. https://doi.org/10.1016/S0034-4257(01)00295-4

Foody, G. M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431160701442120

Franks, D. M., Brereton, D., & Moran, C. J. (2010). Managing the cumulative impacts of coal mining on regional communities and environments in Australia. *Impact Assessment and Project Appraisal*, *28*(4), 299–312. https://doi.org/10.3152/146155110X12838715793129

Ghaffar, M. A. A., McKinstry, A., Maul, T., & Vu, T. T. (2019). Data Augmentation Approaches for Satellite Image Super-Resolution. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *4*(2/W7), 47–54. https://doi.org/10.5194/isprs-annals-IV-2-W7-47-2019

Githiria, J. M., & Onifade, M. (2020). The impact of mining on sustainable practices and the traditional culture of developing countries. *Journal of Environmental Studies and Sciences*. https://doi.org/10.1007/s13412-020-00613-w

Gómez, C., White, J. C., & Wulder, M. A. (2016). Optical remotely sensed time series data for land cover classification: A review. In *ISPRS Journal of Photogrammetry and Remote Sensing*. https://doi.org/10.1016/j.isprsjprs.2016.03.008

Goodchild, M. F., Anselin, L., Appelbaum, R. P., & Herr Harthorn, B. (2000). Toward spatially integrated social science. In *International Regional Science Review* (Vol. 23, Issue 2).

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Greenberg, P. (2018). Coal Waste, Socioeconomic Change, and Environmental Inequality in Appalachia: Implications for a Just Transition in Coal Country. *Society and Natural Resources*, *31*(9), 995–1011. https://doi.org/10.1080/08941920.2018.1456593

Griffiths, S., Holmes, M., & Moore, J. (2014). *NI 43-101 Technical Report for the Didipio Gold / Copper Operation Luzon Island, Philippines*.

Gyawali, B., Fraser, R., & Wang, Y. (2004). *Land Cover and Socio-economic Characteristics in the Eight Counties of Alabama : A Spatial Analysis*.

Hajkowicz, S. A., Heyenga, S., & Moffat, K. (2011). The relationship between mining and socio-economic well being in Australia's regions. *Resources Policy*, *36*(1), 30–38. https://doi.org/10.1016/j.resourpol.2010.08.007

Haslam, P. A., & Tanimoune, N. A. (2016). The Determinants of Social Conflict in the Latin American Mining Sector: New Evidence with Quantitative Data. *World Development*, *78*, 401–419. https://doi.org/10.1016/j.worlddev.2015.10.020

Hausermann, H., Ferring, D., Atosona, B., Mentz, G., Amankwah, R., Chang, A., Hartfield, K., Effah, E., Asuamah, G. Y., Mansell, C., & Sastri, N. (2018). Land-grabbing, land-use transformation and social differentiation: Deconstructing "small-scale" in Ghana's recent gold rush. *World Development*, *108*, 103–114. https://doi.org/10.1016/j.worlddev.2018.03.014

He, T., Xiao, W., Zhao, Y. L., Deng, X., & Hu, Z. (2020). Identification of waterlogging in Eastern China induced by mining subsidence: A case study of Google Earth Engine time-series analysis applied to the Huainan coal field. *Remote Sensing of Environment*. https://doi.org/10.1016/j.rse.2020.111742

Hentschel, J., Lanjouw, J. O., Lanjouw, P., & Poggi, J. (2000). Combining census and survey data to trace the spatial dimensions of poverty: A case study of Ecuador. *World Bank Economic Review*. https://doi.org/10.1093/wber/14.1.147

Herrington, R. (2021). Mining our green future. *Nature Reviews Materials*, *6*(6), 456–458. https://doi.org/10.1038/s41578-021-00325-9

Holden, W. N. (2015). Mining amid typhoons: Large-scale mining and typhoon vulnerability in the Philippines. *Extractive Industries and Society*, *2*(3), 445–461. https://doi.org/10.1016/j.exis.2015.04.009

Hook, A. (2019). Mapping contention: Mining property expansion, Amerindian land titling, and livelihood hybridity in Guyana's small-scale gold mining landscape. *Geoforum*. https://doi.org/10.1016/j.geoforum.2019.07.008

Horsley, J., Prout, S., Tonts, M., & Ali, S. H. (2015). Sustainable livelihoods and indicators for regional development in mining economies. *Extractive Industries and Society*, *2*(2), 368–380. https://doi.org/10.1016/j.exis.2014.12.001

Hu, T., Myers Toman, E., Chen, G., Shao, G., Zhou, Y., Li, Y., Zhao, K., & Feng, Y. (2021). Mapping fine-scale human disturbances in a working landscape with Landsat time series on Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing*, *176*(August 2019), 250–261. https://doi.org/10.1016/j.isprsjprs.2021.04.008

Huang, H., Chen, Y., Clinton, N., Wang, J., Wang, X., Liu, C., Gong, P., Yang, J., Bai, Y., Zheng, Y., & Zhu, Z. (2017). Mapping major land cover dynamics in Beijing using all Landsat images in Google Earth Engine. *Remote Sensing of Environment*, *202*, 166–176. https://doi.org/10.1016/j.rse.2017.02.021

Jhanwar, M. L. (1996). *Application Monitoring of Remote in Bijolia Sensing for Environmental Mining Area of Rajasthan*. *24*(4).

Kamali, M., Alesheikh, A. A., Khodaparast, Z., Hosseinniakani, S. M., & Alavi Borazjani, S. A. (2015). Application of delphi-AHP and fuzzy-GIS approaches for site selection of large extractive industrial units in Iran. *Journal of Settlements and Spatial Planning*, *6*(1), 9–17.

Kazemi, F., Bahrami, A., & Abdolahi Sharif, J. (2020). Mineral processing plant site selection using integrated fuzzy cognitive map and fuzzy analytical hierarchy process approach: A case study of gilsonite mines in Iran. *Minerals Engineering*, *147*(November 2019), 106143. https://doi.org/10.1016/j.mineng.2019.106143

Kiere, L. M., Osorio-Beristain, M., Sorani, V., Prieto-Torres, D. A., Navarro-Siguenza, A. G., & Sánchez-González, L. A. (2021). Do metal mines and their runoff affect plumage color? Streak-backed Orioles in Mexico show unexpected patterns. *Condor*, *123*(3), 1–18. https://doi.org/10.1093/ornithapp/duab023

Kimijima, S., Sakakibara, M., Nagai, M., & Gafur, N. A. (2021). Time-series assessment of camp-type artisanal and small-scale gold mining sectors with large influxes of miners using LANDSAT imagery. *International Journal of Environmental Research and Public Health*, *18*(18). https://doi.org/10.3390/ijerph18189441

Kingston, R., Carver, S., Evans, A., & Turton, I. (2000). Web-based public participation geographical information systems: An aid to local environmental decision-making. *Computers, Environment and Urban Systems*. https://doi.org/10.1016/S0198-9715(99)00049-6

Kivinen, S., Vartiainen, K., & Kumpula, T. (2018). People and post-mining environments: PPGIS mapping of landscape values, knowledge needs, and future perspectives in Northern Finland. *Land*, *7*(4). https://doi.org/10.3390/land7040151

Koruyan, K., Deliormanli, A. H., Karaca, Z., Momayez, M., Lu, H., & Yalçin, E. (2012a). Remote sensing in management of mining land and proximate habitat. *Journal of the Southern African Institute of Mining and Metallurgy*, *112*(7), 667–672.

Koruyan, K., Deliormanli, A. H., Karaca, Z., Momayez, M., Lu, H., & Yalçin, E. (2012b). Remote sensing in management of mining land and proximate habitat. *Journal of the Southern African Institute of Mining and Metallurgy*, *112*(7), 667–672.

Kotey, B., & Rolfe, J. (2014). Demographic and economic impact of mining on remote communities in Australia. *Resources Policy*, *42*, 65–72. https://doi.org/10.1016/j.resourpol.2014.10.005

Krieger, G. R., Bouchard, M. A., de Sa, I. M., Paris, I., Balge, Z., Williams, D., Singer, B. H., Winkler, M. S., & Utzinger, J. (2012). Enhancing impact: Visualization of an integrated impact assessment strategy. *Geospatial Health*, *6*(2), 303–306. https://doi.org/10.4081/gh.2012.149

Kulkarni, A. D., & Lowe, B. (2016). Random Forest Algorithm for Land Cover Classification. *International Journal on Recent and Innovation Trends in Computing and Communication*, *4*(3).

Kumar, L., & Mutanga, O. (2018). Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sensing*, *10*(10), 1–15. https://doi.org/10.3390/rs10101509

Lagasca, C. (2007, July 20). Vizcaya citrus growers alarmed over spread of deadly diseases. *Philstar Global*.

Lagasca, C. (2014, August 3). Virus Threatens Vizcaya's Citrus Industry. *The Philippine Star*.

Lechner, A. M., Foody, G. M., & Boyd, D. S. (2020). Applications in Remote Sensing to Forest Ecology and Management. *One Earth*, *2*(5), 405–412. https://doi.org/10.1016/j.oneear.2020.05.001

Lechner, A. M., Kassulke, O., & Unger, C. (2016). Spatial assessment of open cut coal mining progressive rehabilitation to support the monitoring of rehabilitation liabilities. *Resources Policy*, *50*(March), 234–243. https://doi.org/10.1016/j.resourpol.2016.10.009

Lechner, A. M., Mcintyre, N., Witt, K., Raymond, C. M., Arnold, S., Scott, M., & Rifkin, W. (2017). Challenges of integrated modelling in mining regions to address social, environmental and economic impacts. *Environmental Modelling and Software*, *93*, 268–281. https://doi.org/10.1016/j.envsoft.2017.03.020

Lechner, A. M., Owen, J., Ang, M. L. E., Edraki, M., Che Awang, N. A., & Kemp, D. (2019). Historical socio-environmental assessment of resource development footprints using remote sensing. *Remote Sensing Applications: Society and Environment*. https://doi.org/10.1016/j.rsase.2019.100236

Lechner, A. M., Owen, J., Ang, M. L. E., & Kemp, D. (2019). Spatially integrated social sciences with qualitative GIS to support impact assessment in mining communities. *Resources*. https://doi.org/10.3390/resources8010047

Lechner, A. M., Raymond, C. M., Adams, V. M., Polyakov, M., Gordon, A., Rhodes, J. R., Mills, M., Stein, A., Ives, C. D., & Lefroy, E. C. (2014). Characterizing spatial uncertainty when integrating social data in conservation planning. *Conservation Biology*, *28*(6), 1497–1511. https://doi.org/10.1111/cobi.12409

Lechner, A. M., & Rhodes, J. R. (2016). Recent Progress on Spatial and Thematic Resolution in Landscape Ecology. *Current Landscape Ecology Reports*, *1*(98). https://doi.org/10.1007/s40823-016-0011-z

Li, J., Zipper, C. E., Donovan, P. F., Wynne, R. H., & Oliphant, A. J. (2015). Reconstructing disturbance history for an intensively mined region by time-series analysis of Landsat imagery. *Environmental Monitoring and Assessment*, *187*(9). https://doi.org/10.1007/s10661-015-4766-1

Li, X. Y., Chen, S. L., & Bian, K. (2014). Mine dynamic monitoring and integrated management based on RS and GIS. *Advanced Materials Research*, *955–959*, 3840–3844. https://doi.org/10.4028/www.scientific.net/AMR.955-959.3840

Li, Y. feng, Liu, Y. hua, Du, Z. ping, & Chen, J. (2009). Effect of coal resources development and compenasation for damage to cultivated land in mining areas. *Mining Science* *and Technology*, *19*(5), 620–625. https://doi.org/10.1016/S1674-5264(09)60115-0

Lima, A. T., Mitchell, K., O'Connell, D. W., Verhoeven, J., & Van Cappellen, P. (2016). The legacy of surface mining: Remediation, restoration, reclamation and rehabilitation. *Environmental Science and Policy*, *66*, 227–233. https://doi.org/10.1016/j.envsci.2016.07.011

Liu, L., & Zhou, J. (2018). Analyzing ecological functions in coal mining cities based on RS and GIS. *Polish Journal of Environmental Studies*, *27*(3), 1165–1174. https://doi.org/10.15244/pjoes/75190

Liu, W., & Agusdinata, D. B. (2020). Interdependencies of lithium mining and communities sustainability in Salar de Atacama, Chile. *Journal of Cleaner Production*, *260*, 120838. https://doi.org/10.1016/j.jclepro.2020.120838

Liu, X. H., Skidmore, A. K., & Van Oosten, H. (2002). Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*. https://doi.org/10.1016/S0924-2716(02)00061-8

Loayza, N., & Rigolini, J. (2016a). The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru. *World Development*. https://doi.org/10.1016/j.worlddev.2016.03.005

Loayza, N., & Rigolini, J. (2016b). The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru. *World Development*, *84*, 219–234. https://doi.org/10.1016/j.worlddev.2016.03.005

Londono Castaneda, C. L., Diaz, M. A., Devia, Y., Ballen, S., & Barrios, J. D. (2018). Multifunctional landscapes and socioeconomic impacts: A case study on productive sectors of Rancheria River Basin, Guajira, Colombia. *WIT Transactions on Ecology and the Environment*, *215*(June), 297–307. https://doi.org/10.2495/EID180271

Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2005). *Geographic Information Science and Systems, 4th Edition | Wiley* (4th ed.). Wiley. https://doi.org/https://doi.org/10.1111/j.1477-9730.2005.00343_5.x

Lunetta, R. S., Congalton, R. G., Fenstermaker, L. K., Jensen, J. R., McGwire, K. C., & Tinney, L. R. (1991). Remote sensing and geographic information system data integration: error sources and research issues. *Photogrammetric Engineering & Remote Sensing*.

Ma, Q., Wu, J., He, C., & Fang, X. (2021). The speed, scale, and environmental and economic impacts of surface coal mining in the Mongolian Plateau. *Resources, Conservation and Recycling*, *173*(May), 105730. https://doi.org/10.1016/j.resconrec.2021.105730

Macgregor, C., & Hugo, G. (2001). Defining Social Catchments in Australia : a Review of Recent Methods. *2nd International Conference on Landscape Futures*.

Marais, L. (2013). Resources policy and mine closure in South Africa: The case of the Free State Goldfields. *Resources Policy*, *38*(3), 363–372. https://doi.org/10.1016/J.RESOURPOL.2013.04.004

Marais, L., & Verna, N. (2019). *Space and planning in secondary cities : reflections from South Africa* (L. Marais & N. Verna, Eds.). UJ Press. https://books.google.com.my/books?hl=en&lr=&id=O5ddEAAAQBAJ&oi=fnd&pg=PR1&dq=lochner+%22marais%22+stakeholder+engagement+spatial+&ots=3I_MQ3xZy1&sig=Gf_3zDWeJNfq6k2KMU_sY1IG9xE#v=onepage&q=space&f=false

Matejicek, L., & Kopackova, V. (2010). Changes in croplands as a result of large scale mining and the associated impact on food security studied using time-series landsat images. *Remote Sensing*, *2*(6), 1463–1480. https://doi.org/10.3390/rs2061463

Matsuki, K., Kuperman, V., & Van Dyke, J. A. ; (2016). *The Random Forests statistical technique: An examination of its value for the study of reading*. *20*(1), 20–33. https://doi.org/10.1080/10888438.2015.1107073.The

McIntyre, N., Bulovic, N., Cane, I., & McKenna, P. (2016). A multi-disciplinary approach to understanding the impacts of mines on traditional uses of water in Northern Mongolia. *Science of the Total Environment*, *557–558*, 404–414. https://doi.org/10.1016/j.scitotenv.2016.03.092

McKenna, P. B., Lechner, A. M., Phinn, S., & Erskine, P. D. (2020). Remote Sensing of Mine Site Rehabilitation for Ecological Outcomes: A Global Systematic Review. *Remote Sensing*, *12*(21), 3535. https://doi.org/10.3390/rs12213535

Meerpohl, J. J., Herrle, F., Antes, G., & von Elm, E. (2012). Scientific Value of Systematic Reviews: Survey of Editors of Core Clinical Journals. *PLoS ONE*, *7*(5). https://doi.org/10.1371/JOURNAL.PONE.0035732

Meha, M., Rexha, B., Shala, I., & Dragusha, B. (2011). Using geographical information system for implementing resettlement strategies in mining areas in Kosovo. *WSEAS Transactions on Information Science and Applications*, *8*(1), 18–27.

Mihai, B., Nistor, C., & Simion, G. (2015). Post-socialist urban growth of Bucharest, Romania – a change detection analysis on landsat imagery (1984–2010). *Acta Geographica Slovenica*, *55*(2), 223–234. https://doi.org/10.3986/AGS.709

Molina, J. R., Silva, F. R. y., & Herrera, M. Á. (2016). Integrating economic landscape valuation into Mediterranean territorial planning. *Environmental Science and Policy*, *56*, 120–128. https://doi.org/10.1016/j.envsci.2015.11.010

Mudd, G. M. (2010). The Environmental sustainability of mining in Australia: key mega-trends and looming constraints. *Resources Policy*, *35*(2), 98–115. https://doi.org/10.1016/j.resourpol.2009.12.001

Mutanga, O., & Kumar, L. (2019). Google earth engine applications. *Remote Sensing*, *11*(5), 11–14. https://doi.org/10.3390/rs11050591

Myers, N., Mittermeier, R. A., Mittermeier, C. G., da Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*(6772), 853–858. https://doi.org/10.1038/35002501

Nuissl, H., Haase, D., Lanzendorf, M., & Wittmer, H. (2009). Environmental impact assessment of urban land use transitions-A context-sensitive approach. *Land Use Policy*, *26*(2), 414–424. https://doi.org/10.1016/j.landusepol.2008.05.006

OceanaGold. (2019). *Annual Information Form for the year 2018*.

OceanaGold. (2020). *Communities*. https://www.oceanagold.com/our-business/philippines/didipio-mine/communities/

Onencan, A. M., Meesters, K., & van de Walle, B. (2018). Methodology for participatory GIS risk mapping and Citizen Science for Solotvyno Salt Mines. *Remote Sensing*, *10*(11). https://doi.org/10.3390/rs10111828

Owen, J. R., & Kemp, D. (2013). Social licence and mining: A critical perspective. *Resources Policy*. https://doi.org/10.1016/j.resourpol.2012.06.016

Owen, J. R., Kemp, D., Harris, J., & Lechner, A. M. (2022). Fast track to failure? Energy transition minerals and the future of consultation and consent. *Energy Research & Social Science*, *89*(April), 102665. https://doi.org/10.1016/J.ERSS.2022.102665

Owen, J. R., Kemp, D., & Marais, L. (2021). The cost of mining benefits: Localising the resource curse hypothesis. *Resources Policy*, *74*(March), 102289. https://doi.org/10.1016/j.resourpol.2021.102289

Pactwa, K., & Górniak-Zimroz, J. (2021). Copper ore post-flotation settling tanks in Poland: social acceptance or objection? *Environment, Development and Sustainability*, *0123456789*. https://doi.org/10.1007/s10668-021-01646-z

Pal, M. (2005). Random forest classifier for remote sensing classification. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431160412331269698

Pan, D., Domon, G., De Blois, S., & Bouchard, A. (1999). Temporal (1958-1993) and spatial patterns of land use changes in Haut-Saint-Laurent (Quebec, Canada) and their relation to landscape physical attributes. *Landscape Ecology*. https://doi.org/10.1023/A:1008022028804

Pattanayak, S., Saha, S., Sahu, P., Sills, E., Singha, A., & Yang, J. (2010). Mine over matter? Health, wealth and forests in a mining area of Orissa. *Indian Growth and Development Review*, *3*(2), 166–185. https://doi.org/10.1108/17538251011084473

Pavloudakis, F., Galetakis, M., & Roumpos, C. (2009a). A spatial decision support system for the optimal environmental reclamation of open-pit coal mines in Greece. *International Journal of Mining, Reclamation and Environment*, *23*(4), 291–303. https://doi.org/10.1080/17480930902731935

Pavloudakis, F., Galetakis, M., & Roumpos, C. (2009b). A spatial decision support system for the optimal environmental reclamation of open-pit coal mines in Greece. *International Journal of Mining, Reclamation and Environment*, *23*(4), 291–303. https://doi.org/10.1080/17480930902731935

Pearce, T. D., Manuel, L., Leon, J., Currenti, R., Brown, M., Ikurisaru, I., Doran, B., Scanlon, H., & Ford, J. (2021). Mapping Social Values of the Sigatoka River Estuary, Nadroga-Navosa Province, Viti Levu, Fiji. *Human Ecology*, *49*(5), 579–594. https://doi.org/10.1007/s10745-021-00258-5

Peng, Y., Kheir, R. B., Adhikari, K., Malinowski, R., Greve, M. B., Knadel, M., & Greve, M. H. (2016). Digital mapping of toxic metals in qatari soils using remote sensing and ancillary data. *Remote Sensing*, *8*(12), 1–19. https://doi.org/10.3390/rs8121003

Pericak, A. A., Thomas, C. J., Kroodsma, D. A., Wasson, M. F., Ross, M. R. V., Clinton, N. E., Campagna, D. J., Franklin, Y., Bernhardt, E. S., & Amos, J. F. (2018). Mapping the yearly extent of surface coal mining in central appalachia using landsat and google earth engine. *PLoS ONE*, *13*(7), 1–15. https://doi.org/10.1371/journal.pone.0197758

Petrov, A. N., Graybill, J., Berman, M., Cavin, P., Kuklina, V., Rasmussen, R. O., & Cooney, M. (2018). Measuring impacts: A review of frameworks, methodologies, and indicators for assessing socioeconomic impacts of resource activity in the arctic. *Resources and Sustainable Development in the Arctic*, 107–131. https://doi.org/10.4324/9781351019101

Plourde, L., & Congalton, R. G. (2003). Sampling method and sample placement: How do they affect the accuracy of remotely sensed maps? In *Photogrammetric Engineering and Remote Sensing*. https://doi.org/10.14358/PERS.69.3.289

Polhill, J. G., Filatova, T., Schlüter, M., & Voinov, A. (2016). Modelling systemic change in coupled socio-environmental systems. *Environmental Modelling and Software*, *75*, 318–332. https://doi.org/10.1016/j.envsoft.2015.10.017

Prno, J., & Slocombe, D. S. (2014). A systems-based conceptual framework for assessing the determinants of a social license to operate in the mining industry. *Environmental Management*, *53*(3), 672–689. https://doi.org/10.1007/s00267-013-0221-7

Radulescu, C., & Radulescu, Virgil. M. G. (2011). Approaches of the management informational systems regarding the implementation of the geographic information systems (GIS) in the mining basins of Romania. *International Multidisciplinary Scientific GeoConference SGEM*, 215–223.

Rampellini, K., & Veenendaal, B. (2016). Analysing the spatial distribution of changing labour force dynamics in the pilbara. In *Labour Force Mobility in the Australian Resources Industry: Socio-Economic and Regional Impacts*. https://doi.org/10.1007/978-981-10-2018-6_3

Reeson, A. F., Measham, T. G., & Hosking, K. (2012a). Mining activity, income inequality and gender in regional Australia. *Australian Journal of Agricultural and Resource Economics*. https://doi.org/10.1111/j.1467-8489.2012.00578.x

Reeson, A. F., Measham, T. G., & Hosking, K. (2012b). Mining activity, income inequality and gender in regional Australia. *Australian Journal of Agricultural and Resource Economics*. https://doi.org/10.1111/j.1467-8489.2012.00578.x

Resources Environment and Economics Center for Studies (REECS). (2019). Impact Evaluation of OGPI's Social Investment and Development Programs: Terminal Report. In *OceanaGold*. https://doi.org/10.1016/s0149-2918(12)00253-6

Rich, K. J., Ridealgh, M., West, S. E., Cinderby, S., Ashmore, M., & Donath, T. W. (2015). Exploring the links between post-industrial landscape history and ecology through participatory methods. *PLoS ONE*, *10*(8), 1–14. https://doi.org/10.1371/journal.pone.0136522

Risk, C., Zamaria, S. A., Chen, J., Ke, J. J., Morgan, G., Taylor, J., Larsen, K., & Cowling, S. A. (2020). Using geographic information systems to make transparent and weighted decisions on pit development: Incorporation of interactive economic, environmental, and social factors. *Canadian Journal of Earth Sciences*, *57*(9), 1103–1126. https://doi.org/10.1139/cjes-2019-0119

Rivera, N. M. (2020). Is Mining an Environmental Disamenity? Evidence from Resource Extraction Site Openings. In *Environmental and Resource Economics* (Vol. 75, Issue 3). Springer Netherlands. https://doi.org/10.1007/s10640-019-00397-w

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., & Joachim, H. (2009). Planetary Boundaries : Exploring the safe operating space for humanity. *Ecology and Society*, *14*(2). https://doi.org/10.2174/1874282300802010217

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*. https://doi.org/10.1016/j.isprsjprs.2011.11.002

Saedpanah, S., & Amanollahi, J. (2019). Environmental pollution and geo-ecological risk assessment of the Qhorveh mining area in western Iran. *Environmental Pollution*, *253*, 811–820. https://doi.org/10.1016/j.envpol.2019.07.049

Schmid, T., Rico, C., Rodríguez-Rastrero, M., José Sierra, M., Javier Díaz-Puente, F., Pelayo, M., & Millán, R. (2013). Monitoring of the mercury mining site Almadén implementing remote sensing technologies. *Environmental Research*, *125*, 92–102. https://doi.org/10.1016/j.envres.2012.12.014

Schneider, K. (2017, June 8). The Philippines, a nation rich in precious metals, encounters powerful opposition to mining. *Mongabay*.

Schueler, V., Kuemmerle, T., & Schröder, H. (2011). Impacts of surface gold mining on land use systems in Western Ghana. *Ambio*. https://doi.org/10.1007/s13280-011-0141-9

Segura-Salazar, J., & Tavares, L. M. (2018). Sustainability in the minerals industry: Seeking a consensus on its meaning. *Sustainability (Switzerland)*, *10*(5). https://doi.org/10.3390/su10051429

Shackleton, R. T. (2020). Loss of land and livelihoods from mining operations: A case in the Limpopo Province, South Africa. *Land Use Policy*, *99*(June), 104825. https://doi.org/10.1016/j.landusepol.2020.104825

Shelestov, A., Lavreniuk, M., Kussul, N., Novikov, A., & Skakun, S. (2017). Exploring Google earth engine platform for big data processing: Classification of multi-temporal satellite imagery for crop mapping. *Frontiers in Earth Science*, *5*(February), 1–10. https://doi.org/10.3389/feart.2017.00017

Sieber, R. (2006). Public participation geographic information systems: A literature review and framework. In *Annals of the Association of American Geographers*. https://doi.org/10.1111/j.1467-8306.2006.00702.x

Sluiter, R., & Pebesma, E. J. (2010). Comparing techniques for vegetation classification using multi- and hyperspectral images and ancillary environmental data.

International Journal of Remote Sensing. https://doi.org/10.1080/01431160903401379

Smyth, E., & Vanclay, F. (2017). The Social Framework for Projects: a conceptual but practical model to assist in assessing, planning and managing the social impacts of projects. *Impact Assessment and Project Appraisal*, *35*(1), 65–80. https://doi.org/10.1080/14615517.2016.1271539

Sonter, L. J., Moran, C. J., Barrett, D. J., & Soares-Filho, B. S. (2014). Processes of land use change in mining regions. *Journal of Cleaner Production*, *84*(1), 494–501. https://doi.org/10.1016/j.jclepro.2014.03.084

Svobodova, K., Vojar, J., Yellishetty, M., & Janeckova Molnarova, K. (2020). A multi-component approach to conceptualizing the reputation of the mining industry from a stakeholder perspective. *Resources Policy*, *68*(December 2019), 101724. https://doi.org/10.1016/j.resourpol.2020.101724

Tao, Y., & Wang, Q. (2021). Quantitative recognition and characteristic analysis of production-living-ecological space evolution for five resource-based cities: Zululand, Xuzhou, Lota, Surf coast and Ruhr. *Remote Sensing*, *13*(8). https://doi.org/10.3390/rs13081563

Teluguntla, P., Thenkabail, P., Oliphant, A., Xiong, J., Gumma, M. K., Congalton, R. G., Yadav, K., & Huete, A. (2018). A 30-m landsat-derived cropland extent product of Australia and China using random forest machine learning algorithm on Google Earth Engine cloud computing platform. *ISPRS Journal of Photogrammetry and Remote Sensing*, *144*(February), 325–340. https://doi.org/10.1016/j.isprsjprs.2018.07.017

Ticci, E., & Escobal, J. (2015). Extractive industries and local development in the Peruvian Highlands. *Environment and Development Economics*, *20*(01), 101–126. https://doi.org/10.1017/S1355770X13000685

Tilahun, A., & Teferie, B. (2015). Accuracy Assessment of Land Use Land Cover Classification using Google Earth. *American Journal of Environmental Protection*, *4*(4), 193. https://doi.org/10.11648/j.ajep.20150404.14

Tsai, Y. H., Stow, D., Chen, H. L., Lewison, R., An, L., & Shi, L. (2018). Mapping vegetation and land use types in Fanjingshan National Nature Reserve using google earth engine. *Remote Sensing*, *10*(6). https://doi.org/10.3390/rs10060927

Uhlmann, V., Rifkin, W., Everingham, J. A., Head, B., & May, K. (2014). Prioritising indicators of cumulative socio-economic impacts to characterise rapid development of onshore gas resources. *Extractive Industries and Society*, *1*(2), 189–199. https://doi.org/10.1016/j.exis.2014.06.001

UN DESA. (2018). *World Urbanization Prospects: The 2018 Revision, Online Edition.* United Nations, Department of Economic and Social Affairs, Population Division. https://population.un.org/wup/Download/

UNFCCC. (2021). *End of Coal in Sight at COP26*. United Nations Framework Convention on Climate Change (UNFCCC). https://unfccc.int/news/end-of-coal-in-sight-at-cop26

Valle, D., & Tucker Lima, J. M. (2014). Large-scale drivers of malaria and priority areas for prevention and control in the Brazilian Amazon region using a novel multi-pathogen geospatial model. *Malaria Journal*, *13*(1), 1–13. https://doi.org/10.1186/1475-2875-13-443

Vanclay, F., Esteves, A. M., Aucamp, I., & Franks, D. M. (2015). *Social Impact Assessment: Guidance for assessing and managing the social impacts of projects*. *April*.

Virgone, K. M., Ramirez-Andreotta, M., Mainhagu, J., & Brusseau, M. L. (2018). Effective integrated frameworks for assessing mining sustainability. *Environmental Geochemistry and Health*, *40*(6), 2635–2655. https://doi.org/10.1007/s10653-018-0128-6

Walker, T. R., Habeck, J. O., Karjalainen, T. P., Virtanen, T., Solovieva, N., Jones, V., Kuhry, P., Ponomarev, V. I., Mikkola, K., Nikula, A., Patova, E., Crittenden, P. D., Young, S. D., & Ingold, T. (2006). Perceived and measured levels of environmental pollution: Interdisciplinary research in the subarctic lowlands of Northeast European Russia. *Ambio*, *35*(5), 220–228. https://doi.org/10.1579/06-A-127R.1

Wedding, L. M., Friedlander, A. M., Kittinger, J. N., Watling, L., Gaines, S. D., Bennett, M., Hardy, S. M., & Smith, C. R. (2013). From principles to practice: A spatial approach to systematic conservation planning in the deep sea. *Proceedings of the Royal Society B: Biological Sciences*, *280*(1773). https://doi.org/10.1098/rspb.2013.1684

Wen, B., Pan, Y., Zhang, Y., Liu, J., & Xia, M. (2018). Does the exhaustion of resources drive land use changes? Evidence from the influence of coal resources-exhaustion on coal resources-based industry land use changes. *Sustainability (Switzerland)*, *10*(8), 1–13. https://doi.org/10.3390/su10082698

Werner, T. T., Bach, P. M., Yellishetty, M., Amirpoorsaeed, F., Walsh, S., Miller, A., Roach, M., Schnapp, A., Solly, P., Tan, Y., Lewis, C., Hudson, E., Heberling, K., Richards, T., Chia, H. C., Truong, M., Gupta, T., & Wu, X. (2020). A geospatial database for effective mine rehabilitation in Australia. *Minerals*, *10*(9), 1–21. https://doi.org/10.3390/MIN10090745

Werner, T. T., Bebbington, A., & Gregory, G. (2019). Assessing impacts of mining: Recent contributions from GIS and remote sensing. *Extractive Industries and Society*, *6*(3), 993–1012. https://doi.org/10.1016/j.exis.2019.06.011

Wohlfart, C., Mack, B., Liu, G., & Kuenzer, C. (2017). Multi-faceted land cover and land use change analyses in the Yellow River Basin based on dense Landsat time series: Exemplary analysis in mining, agriculture, forest, and urban areas. *Applied Geography*, *85*, 73–88. https://doi.org/10.1016/j.apgeog.2017.06.004

Xiao, W., Chen, W., & Deng, X. (2021). Coupling and coordination of coal mining intensity and social-ecological resilience in China. *Ecological Indicators*, *131*, 108167. https://doi.org/10.1016/j.ecolind.2021.108167

Xiao, W., Deng, X., He, T., & Chen, W. (2020). Mapping annual land disturbance and reclamation in a surface coal mining region using google earth engine and the landtrendr algorithm: A case study of the shengli coalfield in Inner Mongolia, China. *Remote Sensing*, *12*(10). https://doi.org/10.3390/rs12101612

Xiao, W., Wang, Z., Zhang, R., & Li, S. (2017). The "golden ten years": Underground coal mining and its impacts on land use and subsequent social problems: A case study on the Jining city region, China. *International Journal of Mining and Mineral Engineering*, *8*(1), 19–34. https://doi.org/10.1504/IJMME.2017.082681

Xie, Y., Sha, Z., & Yu, M. (2008). Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology*. https://doi.org/10.1093/jpe/rtm005

Xue, M., Zhang, X., Sun, X., Sun, T., & Yang, Y. (2021). Expansion and evolution of a typical resource-based mining city in transition using the google earth engine: A case study of datong, China. *Remote Sensing*, *13*(20). https://doi.org/10.3390/rs13204045

Yan, X., Li, J., Shao, Y., Hu, Z., Yang, Z., Yin, S., & Cui, lvyuan. (2020). Driving forces of grassland vegetation changes in Chen Barag Banner, Inner Mongolia. *GIScience and Remote Sensing*, *57*(6), 753–769. https://doi.org/10.1080/15481603.2020.1794395

Yang, Y., Erskine, P. D., Lechner, A. M., Mulligan, D., Zhang, S., & Wang, Z. (2018). Detecting the dynamics of vegetation disturbance and recovery in surface mining area via Landsat imagery and LandTrendr algorithm. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2018.01.050

Yiran, G. A. B., Kusimi, J. M., & Kufogbe, S. K. (2012). A synthesis of remote sensing and local knowledge approaches in land degradation assessment in the Bawku East

District, Ghana. *International Journal of Applied Earth Observation and Geoinformation*, *14*(1), 204–213. https://doi.org/10.1016/j.jag.2011.09.016

Young, N. E., Anderson, R. S., Chignell, S. M., Vorster, A. G., Lawrence, R., & Evangelista, P. H. (2017). A survival guide to Landsat preprocessing. *Ecology*, *98*(4), 920–932. https://doi.org/10.1002/ecy.1730

Young, O. R., Berkhout, F., Gallopin, G. C., Janssen, M. A., Ostrom, E., & van der Leeuw, S. (2006). The globalization of socio-ecological systems: An agenda for scientific research. *Global Environmental Change*, *16*(3), 304–316. https://doi.org/10.1016/j.gloenvcha.2006.03.004

Zeng, X., Liu, Z., He, C., Ma, Q., & Wu, J. (2018). Quantifying surface coal-mining patterns to promote regional sustainability in Ordos, Inner Mongolia. *Sustainability (Switzerland)*, *10*(4), 1–17. https://doi.org/10.3390/su10041135

Zhang, B., Zhang, Q., Feng, C., Feng, Q., & Zhang, S. (2017). Understanding land use and land cover dynamics from 1976 to 2014 in Yellow River Delta. *Land*, *6*(1), 1–20. https://doi.org/10.3390/land6010020

Zhang, X., Bai, Z., Fan, X., Lu, Y., Cao, Y., Zhao, Z., Sun, Q., & Pan, J. (2016). Urban Expansion Process, Pattern, and Land Use Response in an Urban Mining Composited Zone from 1986 to 2013. *Journal of Urban Planning and Development*, *142*(4), 04016014. https://doi.org/10.1061/(asce)up.1943-5444.0000327

Zhang, Y., Wang, C., Xie, H., Zhang, J., & Wu, J. (2017). Analyzing spatial variations in land use/cover distributions: A case study of Nanchang area, China. *Ecological Indicators*, *76*, 52–63. https://doi.org/10.1016/j.ecolind.2017.01.007

Zhang, Z., He, G., Wang, M., Wang, Z., Long, T., & Peng, Y. (2015). Detecting decadal land cover changes in mining regions based on satellite remotely sensed imagery: A case study of the stone mining area in Luoyuan County, SE China. *Photogrammetric Engineering and Remote Sensing*, *81*(9), 745–751. https://doi.org/10.14358/PERS.81.9.745

Zhu, X., & Yu, X. (2016). Above-Ground Resource Analysis with Spatial Resolution to Support Better Decision Making. *Journal of Sustainable Metallurgy*, *2*(4), 304–312. https://doi.org/10.1007/s40831-016-0049-5

Appendix A – Chapter 2

Table A 1 List of study areas (as specified by the original literature authors) were grouped into regions based on the categories used in UN DESA (2018).

North America	South America	Africa	Europe	Central, West South Asia	East Asia	Southeast Asia (SEA)	Oceania	Multiple Countries
•US •Canada	•Brazil •Chile •Colombia •Latin America •Guyana •Peru	•Ghana •Africa •Botswana	•Sweden •Portugal •Poland •UK •Switzerland •Netherlands •Spain •Germany •Kosovo •Belgium •Ukraine •Finland •Romania •Turkey •Greece	•Tajikistan •Iran •India	•China	•Indonesia •Malaysia •Philippines	•Australia •New Zealand	•South Africa, China, Chile, Australia and Germany •Papua New Guinea and Laos

Table A 2 Full list of commodities as reported by the literature and categorized based on McKenna et al. (2020)'s mine commodity categories. The minerals in green, bold and italicised text are highlighted as part of Herrington (2021)'s list of top metalliferous commodities needed for green energy development. The respective percentage of increase in demand of these minerals by 2050 compared to 2018 of are included in brackets.

Category	Commodities (as listed by the original literature authors)	
Coal	Coal	
Metalliferous	• ***Lithium (+488%)*** • ***Copper-nickel (+7% to 99%)*** • ***Nickel minerals (+99%)*** • ***Silver (+56%)*** • ***Silver/base metal (+56%)*** • ***Lead (+18%)*** • ***Molybdenum (+11%)*** • ***Aluminum minerals (+9%)*** • ***Copper (+7%)*** • Mineral • Gold • Diamond	• Iron • Ironsand • Zinc • Iodine • Natural nitrates • Rhenium • Amethyst • Tin • Mercury • Polymetallic • Uranium • Bauxite • Chrome minerals
Quarry	• Hard rock • Igneous and metamorphic dimension stones and crushed rocks (DSCR) • Salt • Stone • Limestone • Sandstone	
Oil and Gas	• Oil • Gas • Shale oil • Gilsonite	

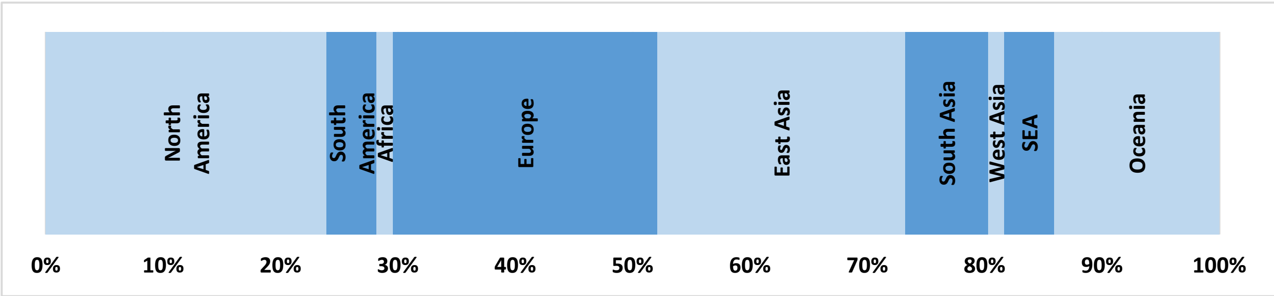


Figure A 1 Distribution of author origin based on study area region (N=71).

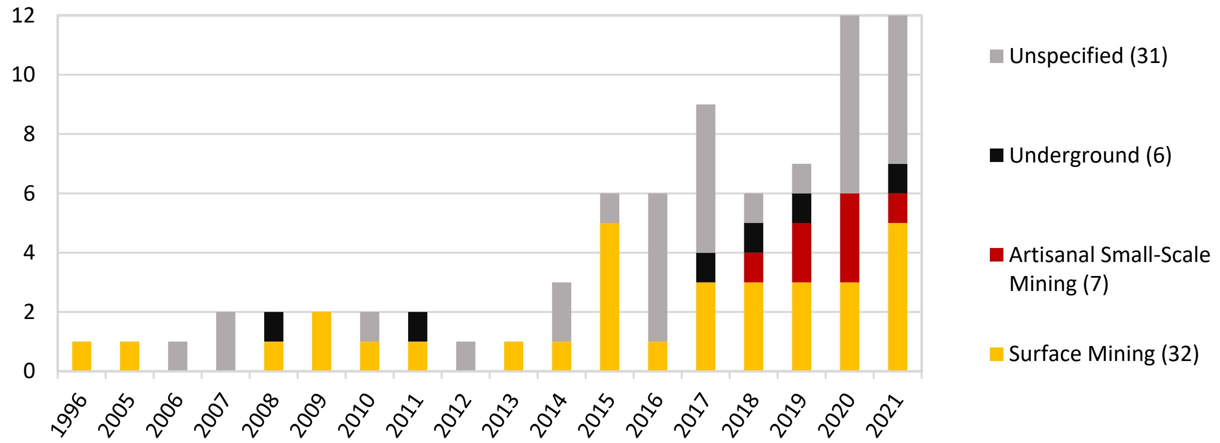


Figure A 2 The temporal distribution of the types of extraction studied. The total number of studies carried out for each type of extraction is indicated in brackets, ie: open cut/pit/cast aka surface mining (n=32). Note that certain studies may have more specified more than one type of extraction.

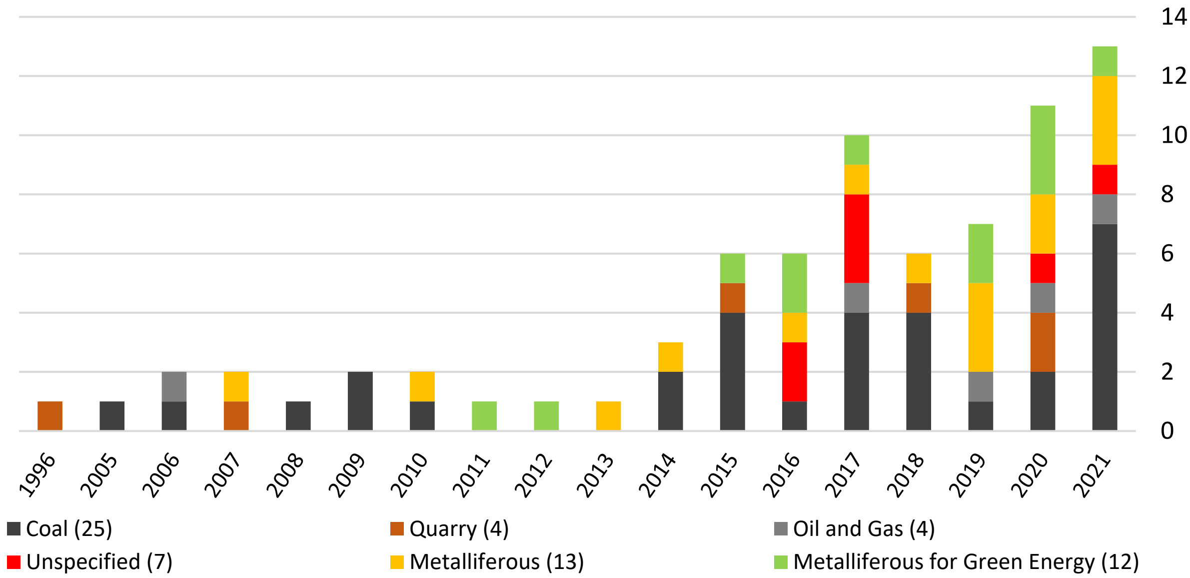


Figure A 3 Distribution of commodities based on year of study.

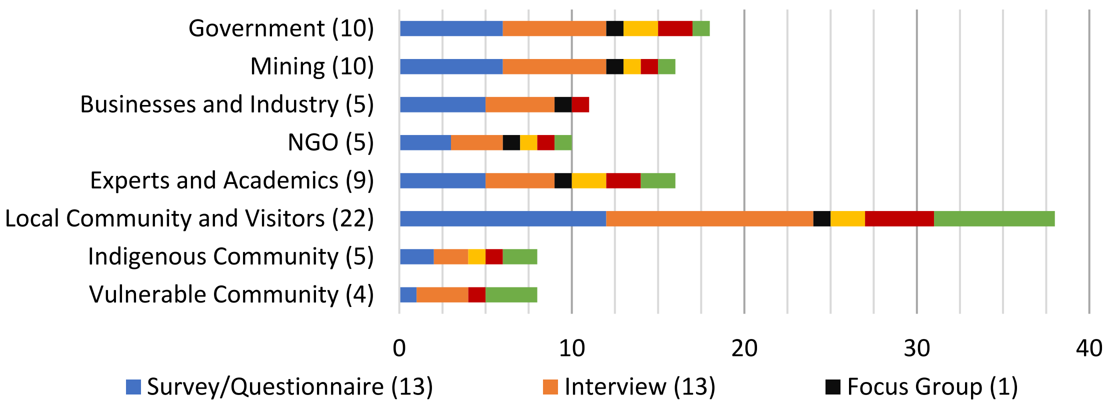


Figure A 4 Social Science methods applied, and the types of stakeholders engaged (n=25). The total number of studies of each implemented social science methods and type of engaged stakeholders are indicated in brackets. Note: some studies may apply one or more combinations of stakeholders and social science methods.

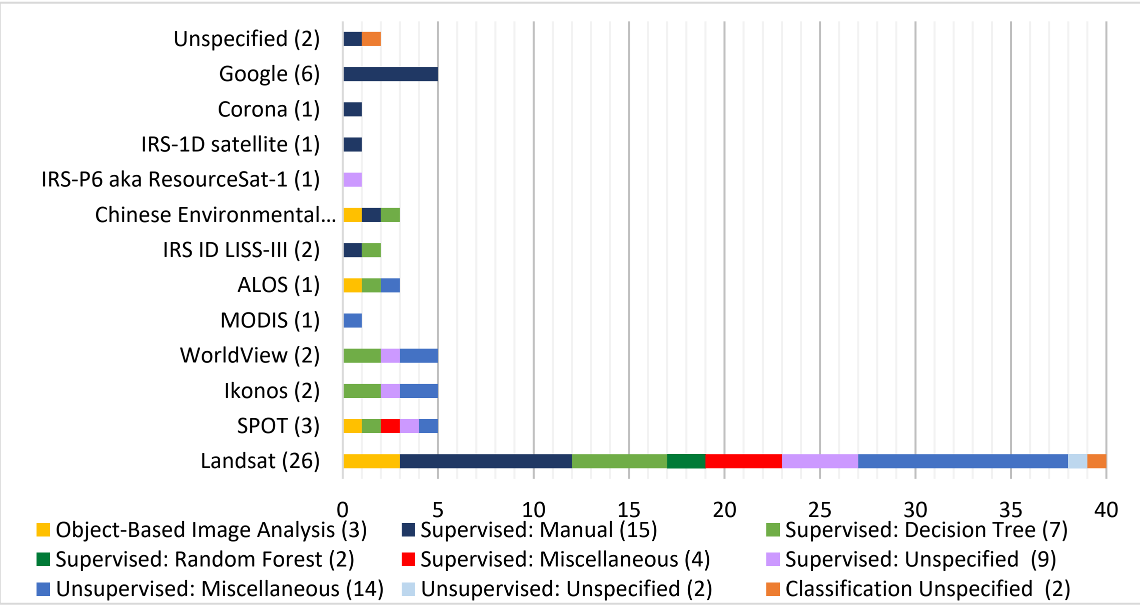


Figure A 5 The list of Remote Sensing imageries (satellite imageries and basemap) and the types of classification methods used (n=37). Note that some studies may use more than one of these products and methods. The total number of studies for each Remote Sensing classification method and satellite imagery are included in brackets, ie: 26 studies utilized Landsat imagery and 3 studies carried out object-based classification.

Table A 3 The list of Remote Sensing classification methods and keywords used by the original literature authors.

Remote Sensing Classification Methods		**Paper Keywords**
Unsupervised	**Index (Further Details In Table A 4)**	• Normalized Difference Vegetation Index • Enhanced Vegetation Index • Normalized Difference Water Index • Normalized Difference Build-Up Index • Built-Up Area Index • Normalized Difference Coal Index
	Unspecified	• Unspecified • Unsupervised Classification • Natural Breaks Classification Method (Jenks Method)
Supervised	**Decision Tree**	• Hierarchical Classification Trees • Svm • Cart • Classification And Regression Tree Algorithm • Decision Tree Classifier • Supervised Classification Using Regression Tree Algorithm
	Random Forest	• Random Forest (RF) Classifier • Supervised Random Forest
	Miscellaneous	• Principle Component Analysis (PCA) • Spectral Angle Mapping Technique • Spectral Analysis • Convolutional Neural Network (CNN) Method • Neural Net Interpretation
	Manual	• Visual Interpretation • Manual Image Interpretation
	Unspecified	• Supervised Classification
Geobia		• Object-Based Classification Using Segmentation • Object-Oriented Decision Trees (OODT) • Geographic Object-Based Image Analysis (GEOBIA) Classification Approach

Table A 4 Summary of indices used by the literature for unsupervised imagery classification.

Indices	**Description**	**Imagery used**	**Formula**	**No. of Studies**	**Literature applied**
NDVI	Normalized Difference Vegetation Index	Landsat	NDVI = (NIR − R) / (NIR + R)	10	(Ang et al., 2020; Ferring & Hausermann, 2019; Hausermann et al., 2018; Hu et al., 2021; Kimijima et al., 2021; Walker et al., 2006; Wohlfart et al., 2017; Yan et al., 2020; Zeng et al., 2018; Z. Zhang et al., 2015)
NDWI	Normalized Difference Water Index	Landsat	NDWI = (green band − midinfrared band) / (green band + midinfrared band)	3	(Ang et al., 2020; Ma et al., 2021; Z. Zhang et al., 2015)
EVI	Enhanced Vegetation Index	Landsat	EVI = 2.5 [(NIR-R) / (NIR + 6 R -7.5 B + 1)]	2	(Ang et al., 2020; Ma et al., 2021)
NDBI	Normalized Difference Build-up Index	Landsat	NDBI = (SWIR1-NIR) / (SWIR1+NIR)	2	(Wohlfart et al., 2017; Xue et al., 2021)
BAI	Built-up Area Index	Landsat	BAI = (B-NIR) / (B-NIR)	2	(Ma et al., 2021; Zeng et al., 2018)
NDCI	Normalized Difference Coal Index	Landsat	NDCI = (midinfrared band − nearinfrared band) / (midinfrared band + nearinfrared band)	2	(Ma et al., 2021; Zeng et al., 2018)

Table A 5 GIS methods used and categorized based (Longley et al., 2005)'s six types of spatial analysis

Categories of spatial method	Methods specified by literature	
Queries and reasoning	• Overlay Analysis • Reviewing Spatial Patterns	
Measurements	• Area Change • Area Trend • Buffer Analysis • Area Analysis • Distance Mapping • Distance Analysis • Cluster Analysis • Spatial Distribution • Expansion Scale • Proximity Analysis • Spatio-Temporal Analysis • Intersect Analysis	
Transformations	• Aggregate Data To Villages • Kernel Density • Spatially Align Data To Geo-Located Mine For Statistical Analysis • Spatially Referenced Social (SRS) Used To Determine Percentage Of Youth By Age And Sex Who Had Moved To Csg Regions	
Descriptive summaries	• NONE	
Optimization	• Weighted Overlay For Site-Location Analysis • Land Use Suitability Analysis Based On Indicator Ranking • Weight Spatial Data To Identify Land Use Preferences Spatially • Gis Database For Planning Resettlement Strategies • Analytical Hierarchy Process (AHP) Methodology	
Hypothesis testing	**Process Model**	• Conflict Potential Modeling • Fuzzy Cognitive Map (FCM) Method • Modified Ecological Footprint (EF) Model • Markov Model • Multi-Pathogen Geospatial Model • Value Compatibility Analysis (VCA) • Least-Cost Path • Least-Cost Corridor Analysis
	Index	• Weighted Preference Index (WPS) • Preference And Value Index (PVS) • Contingent Valuation Method (CVM) • Assess Water Stress Risk • Landscape Pattern Indexes: Total Class Area (CA) • Percentage Of Landscape (PLAND) • Landscape Metrics • Patch Density (PD) • Mean Patch Size (MPS) • Edge Density (ED) • Migration Effectiveness Index (MEI) • Mining Intensity Index; • Production-Living-Ecological Space (PLES) Analysis Using Proportion Of Ples Function (PPF); And Dominant Function (PDF); Landscape Shape Index; Largest Patch Index; Coupling Index And Coordination Index • Sustainability Index • Naturality Index • Binary Change Index • Social-Ecological Resilience Evaluation Index • Patch Cohesion Index (COHESION)
	Statistical Analysis	• Comparing Data Spatially For 3 Scenarios For Cost-Benefit Analysis • Disaggregated Analysis • Multilevel Analysis • Interaction Relationship • Quantify The Spatial Distribution Of The Driving Forces And Their Relative Importance To Vegetation Changes • Spatial Difference-In-Difference (DID) Approach • Kernel Density Method Used To Analyze The Spatial Pattern Of Coal Mines In China • Spatial Regression Model • Spatial Filtering Methodology (Moving Window) • Univariate Spatial Autocorrelation Global Moran's I Statistic
	PGIS and Geovisualisation	• Mapped Locations Of Complaints Received By Companies And LULC • Participatory GIS (PGIS) • On-Site Rapid Appraisal GIS (RAP-GIS) • Geospatial Data And Imagery Used To Visualize Impact For Presentation And Engaging With Stakeholders • Spatio-Temporal Analysis And Geovisualisation

*Table A 6 Summary of indices used by the literature for spatial analysis. * For formula details, please refer to literature source.*

Method Name (if applicable)	Index	Description	Method * Summary (if different from Description)	Data Input			Number of literature and reference	
				Geospatial	Remote Sensing	Social Science		
	Mining intensity index	Represents the level of mining disturbance to a local area	Normalized statistics were weighted and summarized	• Total coal production per county • Production capacity of coal mines per county • Number of coal mines per county • Spatial location of coal mines (via big-data search engine web crawler)			1	(Xiao et al., 2021)
	Social-ecological resilience evaluation index	Social-ecological resilience measures system adaptation to coal mining disturbances	A combination of threshold method, indicator evaluation method, and experimental modeling was used to quantify resilience. The entropy weight method was used to determine the indicator weight.	• Net primary production (NPP) Population density Gross domestic product (GDP) Soil erosion data Proportion of construction land Proportion of arable land	• Nighttime light Normalized difference vegetation index (NDVI) Digital elevation model (DEM) - for elevation and slope meteorological data - Annual average temperature and annual average precipitation		1	(Xiao et al., 2021)
Production -living-ecological space (PLES) analysis	Proportion of PLES function (PPF) and dominant function (PDF)	Used to analyze the scores of production living and ecological space (PLES) function in the study area (PPF). Function with the highest scores in an area is the dominant function (PDF).	Scores of PLES functions of each unit (pixels) were calculated based on the LULC classification.	• Administrative boundary data Socioeconomic statistics (Population, industrial economy, natural resources)	• Landsat imagery - LULC classification	• Socioeconomic statistics (Population, industrial economy, natural resources)	1	(Tao & Wang, 2021)
	Coupling and coordination index	The interactions between the different production-living-ecological space (PLES) functions in each city	The degree of interdependencies was calculated to study relationship					
	Migration Effectiveness Index (MEI)	The spatial impact of migration flows in each industrial sector	The degree of imbalance between migration flows (in-migration) and counter-flow (out-migration) was calculated	•	•	• Spatial labor mobility from the CHIM (CHilean Internal Migration) database	1	(W. Liu & Agusdinata, 2020)

Continue from Table A 6.

Method Name (if applicable)	Index	Description	Method * Summary (if different from Description)	Data Input			Number of literature and reference	
				Geospatial	Remote Sensing	Social Science		
Landscape metrics	Largest patch index (LPI)	Quantifies the percentage of total landscape area comprised by the largest patch.			• Landsat imagery - LULC classification		3	(L. Liu & Zhou, 2018; Tao & Wang, 2021; Zeng et al., 2018)
	Mean patch size (MPS)	The average area of all patches in the landscape					2	(L. Liu & Zhou, 2018; Zeng et al., 2018)
	Patch density (PD)	The number of patches per hectare					2	(L. Liu & Zhou, 2018; Zeng et al., 2018)
	Edge density (ED)	The total length of all edge segments per hectare for the class or landscape of consideration					2	(L. Liu & Zhou, 2018; Zeng et al., 2018)
	Landscape shape index (LSI)	A modified perimeter-area ratio of the form that measures the shape complexity of patch.					3	(L. Liu & Zhou, 2018; Tao & Wang, 2021; Zeng et al., 2018)
	Area-weighted mean fractal dimension (AWMFD)	The patch fractal dimension weighted by relative patch area, which measures the average shape complexity of individual patches for the whole landscape or a specific patch type.					1	(Zeng et al., 2018)
	Mean Euclidean nearest neighbor distance (NND)	The distance to the nearest neighboring forest patch, based on shortest edge-to-edge distance					1	(Zeng et al., 2018)
	Aggregation index (AI)	Aggregation index is calculated from an adjacency matrix, which shows the frequency with which different pairs of patch types (including like adjacencies between the same patch type) appear side-by-side on the map.					1	(Zeng et al., 2018)
	Patch cohesion index (COHESION)	Reflect the connection between patches					1	(L. Liu & Zhou, 2018)

Continue from Table A 6.

Method Name (if applicable)	Index	Description	Method * Summary (if different from Description)	Data Input			Number of literature and reference	
				Geospatial	Remote Sensing	Social Science		
	Weighted preference index (WPS)	Calculates conflict potential as a ratio between the number of mapped preferences for increasing and decreasing a particular land use, weighted by the total number of mapped preferences in each cell.				• Place-based values and landuse preferences mapped using PGIS	1	(Brown et al., 2017)
	Preference and value index (PVS)	Calculates conflict potential as a ratio between the number of mapped preferences for increasing and decreasing a particular land use, weighted by the number of mapped values.					1	(Brown et al., 2017)
	Contingent Valuation method (CVM)	Eliciting a willingness to pay value (WTP) for the preservation of landscape attributes.				• WTP mapped using PGIS	1	(Molina et al., 2016)
	Spatial 'sustainability index'	The potential for sustainability conflict	Computed by assigning equal weights to economic, environmental and social resources	• **Proximity of coal mines to streams and residents**				(Craynon et al., 2015)
	Expansion intensity	Intensity and speed of urban land expansion			• **Landsat imagery - LULC classification**		1	(X. Zhang et al., 2016)
	Barycenter of Urban Land Expansion	Transformation of urban barycenter can be used to describe the direction of urban expansion					1	(X. Zhang et al., 2016)
	Urban compactness	Compactness degree of urban land					1	(X. Zhang et al., 2016)

Appendix B – Chapter 3

Appendix B1

A 5-year Social Development and Management Program (SDMP) is a requirement for any mine Permit Holder operating in the Philippines and the program has to be approved by the Central Office of the Mines and Geosciences Bureau. The minimum expense that the Permit Holder must allocate annually for the SDMP is at least 1.5% of the direct costs of mining and milling operations (OceanaGold, 2020). Mining operators in the Philippines are obliged to fulfil these mandatory expenses in order to maintain their permit.

On the other hand, Community Development Program (CDP) is the community plan relevant to companies doing exploration in certain areas provided that they have the permit to explore. The companies' Corporate Social Responsibility (CSR) is voluntary contributions to social development of the local communities which may be through a Memorandum of Agreement (MOA).

Appendix B2

The links to the Google Earth Engine (GEE) codes are as indicated below. A GEE account will be required to view and run the codes:

Landsat 8: https://code.earthengine.google.com/5541c52ed56134f0342aafe0dcac0919

Landsat 5: https://code.earthengine.google.com/b4c719dda2b34dab1da8386bd9f0b12c

Alternatively, you may also access the codes via GitHub (https://github.com/michelleangliern/Didipio-Project.git) and Harvard Dataverse (https://doi.org/10.7910/DVN/HTYKVP).

Appendix B3

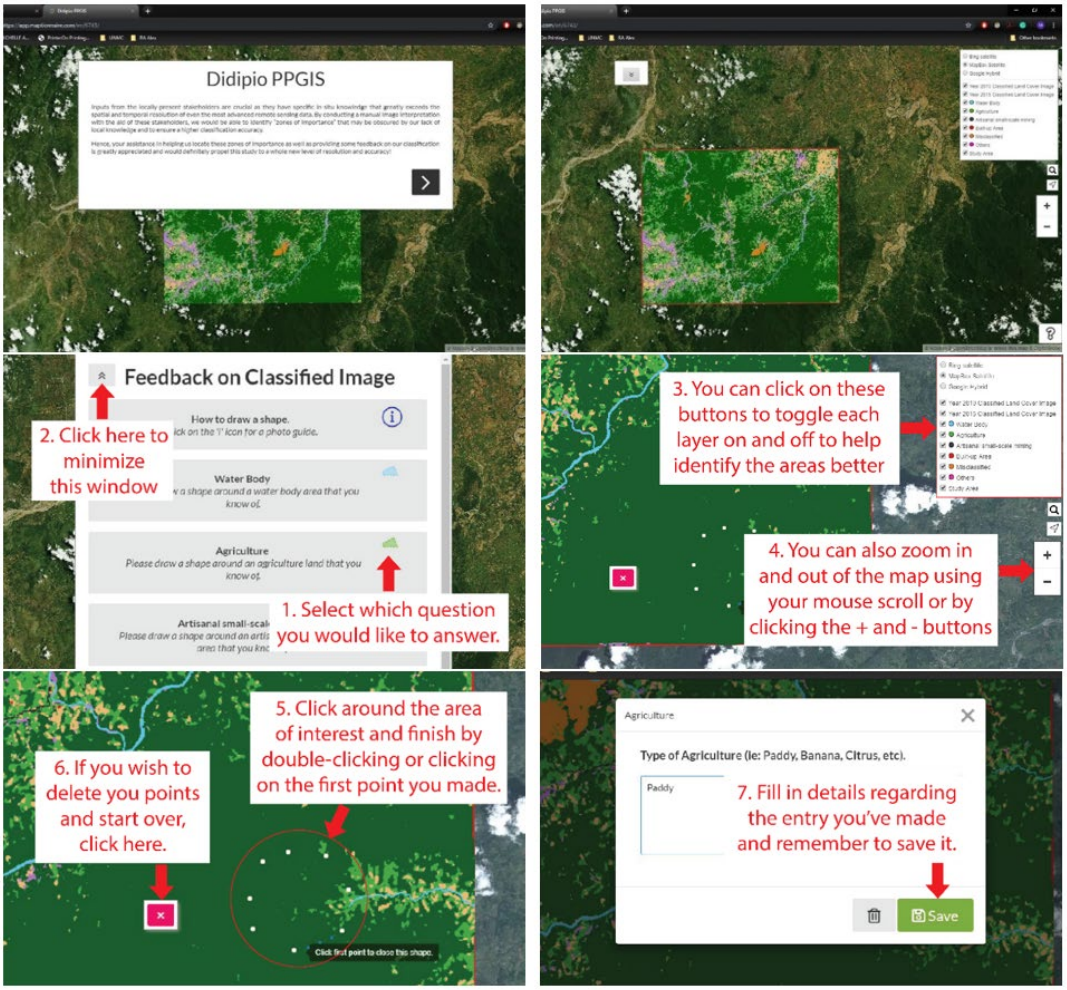


Figure B 1 A demo of the Didipio Web-Based Mapping survey using Maptionnaire, an interactive, online, crowdsourcing, geospatial web mapping application to obtain feedback from the stakeholders at Didipio. The survey can be accessed via this link: https://app.maptionnaire.com/en/6771/

Table B 1 ***Level of Certainty of the web-based mapping land cover.***

Level of Certainty	Application	Examples
100%	Land use and land cover that can be 100% validated using available ground truth imagery.	With reference to high resolution ground truth imagery.
50%	Land use and land cover that can be 50% validated due to relation to past/present timesteps that has available ground truth data (100% certainty).	Land use was agriculture in 2010 according to the basemap (100% certainty) so in 2005, if the area in the Landsat image appears to be similar to 2010, we can assume that it is agriculture as well with a 50% uncertainty.
Less than 50%	Land use and land cover was based mostly on rough estimation using only the Landsat Imagery without any relation to past/present timesteps that has 100% certainty.	Land use was agriculture in 2010 according to the basemap (100% certainty) and also similar in 2005 (50% certainty). But in 1994, the area in the Landsat image appears to be bare land/builtup area but there is no way to 100% prove that it is what it is. In this case, we'd label it as bare land or built-up area (depending on the relation of the area to the adjacent land cover) and we have to categorize this class with the highest level of uncertainty

Table B 2 The list of composites for the 2010 timestep with different combinations of bands and their respective accuracy assessment scores. The band combination composite with the highest score is highlighted in Green.

Random Forest Using 100 Trees	Landsat 8 Bands 2 to 7 and the following Indices													Landsat Bands 2 to 7 Only
	NDWI, NDVI, EVI, SRTM	NDVI, EVI, SRTM	NDWI, EVI, SRTM	NDWI, NDVI, SRTM	NDWI, NDVI, EVI	SRTM	NDWI, SRTM	NDWI	NDVI, SRTM	NDVI	EVI, SRTM	EVI	NDVI, EVI	
Kappa	0.95	0.92	0.90	0.88	0.92	0.86	0.90	0.87	0.91	0.87	0.86	0.89	0.86	0.93
Overall Accuracy	0.96	0.94	0.92	0.90	0.93	0.89	0.91	0.90	0.92	0.89	0.88	0.91	0.88	0.94

Table B 3 The classifiers available in Google Earth Engine (GEE) and their respective accuracy assessment scores for the 2010 timestep. The classifier with the highest score is highlighted in Green.

	Random Forest	CART	GmoMaxEnt	SVM	Minimum Distance	Naïve Bayes
Kappa	0.95	0.93	0.93	0.71	0.80	0.87
Overall Accuracy	0.96	0.94	0.94	0.76	0.83	0.89

Table B 4 The accuracy assessment results for the original Google Earth Engine (GEE) 2010 classified image and after applying the post-classification processing and the Majority Filter.

2010		Original GEE Classified Image	After Majority Filter
Kappa		0.97	0.96
Overall Accuracy		0.98	0.97
Producer Accuracy	Water Body	0.98	0.96
	Vege Primary	0.99	1.00
	Vege Secondary	0.96	0.96
	Bareland	0.96	0.96
	Built-up Area	1.00	0.79
	Agriculture	0.98	1.00
Consumer Accuracy	Water Body	0.98	1.00
	Vege Primary	0.99	1.00
	Vege Secondary	0.96	0.98
	Bareland	0.96	0.91
	Built-up Area	1.00	1.00
	Agriculture	0.98	0.94

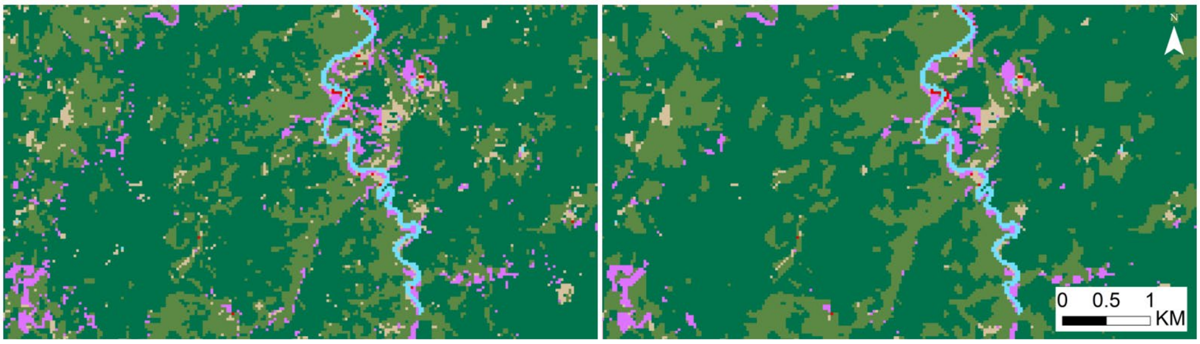


Figure B 2. A comparison of the original 2010 Google Earth Engine (GEE) classified image output (left) vs the processed Majority Filter output (right).

Table B 5 A compilation of the accuracy assessment results for all five timesteps after applying the post-classification processing.

Year		1994	2005	2010	2015	2018
Kappa		0.92	0.89	0.94	0.88	0.93
Overall Accuracy		0.93	0.91	0.95	0.90	0.95
Producer Accuracy	Water Body	0.79	0.78	0.98	0.94	0.95
	Vege Primary	0.98	0.95	0.94	0.90	0.97
	Vege Secondary	0.89	0.95	0.94	0.83	0.96
	Bareland	0.96	0.85	0.92	0.96	0.97
	Built-up Area	1.00	0.98	0.84	0.77	0.96
	Agriculture	0.97	0.93	1.00	1.00	0.88
Consumer Accuracy	Water Body	1.00	0.95	1.00	0.98	0.91
	Vege Primary	0.99	0.96	1.00	0.98	0.97
	Vege Secondary	0.90	0.82	0.93	0.85	0.98
	Bareland	0.89	0.97	0.90	0.79	0.97
	Built-up Area	1.00	0.87	1.00	0.96	1.00
	Agriculture	0.90	0.91	0.92	0.88	0.90

Table B 6 A list of the Social Development and Management Program (SDMP), Community Development Program (CDP) and Corporate Social Responsibility (CSR) social investment projects that were identified by local experts via the Maptionnaire Web-Based Mapping Survey.

Land use	Main Description	Detailed Description
Social Development and Management Program (SDMP)	SDMP funded project (Solar dryer)	Utilized by the community for drying harvested rice.
	SDMP funded project (Solar dryer)	Utilized by the community for drying harvested rice.
	SDMP counterpart on building of administrative building and covered court of Brgy. Capisaan.	-
	SDMP funded project (day care center)	-
	SDMP Project - Box Culvert	-
Community Development Program (CDP)	Vegetable farm	-
	Vegetable farm	-
Corporate Social Responsibility (CSR)		-
		-
	Old reforestation area	OGPI's Old Reforestation Area
	Track oval	Part of MOA with BLGU Didipio.
	Kasibu Sanitary Landifill	Part of company MOA commitment which instead of building in Didipio, was agreed to be placed in Brgy. Lupa in Kasibu to cater the whole municipality's residual waste. Kasibu SLF construction is on hold due to present situation of the company.
	Senior highschool classrooms	$US1M, 3 storey, 16 senior high school classrooms. Part of MOA with Didipio Barangay Council (CSR).
	Family Health Center	PhP10,895,904.67 Barangay Health Center. Part of MOA with Didipio Barangay Council (CSR).
	Didipio Water System	PhP35,932,209.66 worth Level III water system. Part of MOA with Barangay Didipio.
	Gymnasium	Didipio Gymnasium P7,500,000 (Phase 1). P21,706,790.00 (Phase 2). Part of MOA with Didipio BLGU.

Table B 7 Land Use and Land Cover Transition Matrix for timestep 1994 to 2018 in km². Note that the diagonal line (highlighted in grey) does not track across the table because some land use and land cover classes (e.g. Mining, Small-Scale Mining and SDMP) were not detected in the former timestep but present in the latter timestep. Additionally, the variables labelled with 0.00 km² indicated areas of land use and land cover classes detected that were less than 0.01 km².

		Land Use and Land Cover 2018 (km²)													
		Water Body	**Vegetation Primary**	**Vegetation Secondary**	**Bareland**	**Mining**	**Small-Scale Mining**	**Built-Up Area**	**SDMP**	**CDP**	**Agriculture - Irrigated**	**Agriculture - Citrus**	**Agriculture - Paddy**	**Agriculture - Swidden**	**Grand Total (km²)**
Land Use and Land Cover 1994 (km²)	**Water Body**	11.37		0.88	0.34	0.02	0.02	0.06	0.00		0.52	0.01	0.07	0.00	13.29
	Vegetation Primary	1.38	337.22	186.18	31.96	1.61	0.00	0.28		0.00	13.89	0.18	0.21	0.28	573.19
	Vegetation Secondary	1.44		202.39	61.84	1.42	0.01	1.12	0.00	0.61	17.71	0.68	1.36	1.19	289.77
	Bareland	0.71		41.71	32.13	0.72	0.00	1.53	0.00	0.02	11.02	0.09	0.27	0.04	88.24
	Built-Up Area	0.12		0.38	0.35	0.07		0.18			0.18		0.00		1.28
	CDP			0.00	0.01			0.00		0.10	0.00				0.11
	Agriculture - Irrigated	1.27		6.43	4.33	0.26	0.00	0.23		0.00	17.02	0.02	0.26	0.00	29.82
	Agriculture - Citrus	0.01		0.13	0.08			0.00			0.03	2.83	0.33	0.09	3.50
	Agriculture - Paddy	0.07		0.41	0.14		0.00	0.02	0.00		0.38	0.14	5.01	0.02	6.19
	Agriculture - Swidden	0.00		0.22	0.07		0.07	0.00	0.00	0.00	0.01	0.00	0.03	1.83	2.23
	Grand Total	16.37	337.22	438.73	131.25	4.10	0.10	3.42	0.00	0.73	60.76	3.95	7.54	3.45	1007.62