GEOSPATIAL MODELLING OF RELATIONSHIPS BETWEEN SELECT RECREATIONAL USER GROUPS' SOCIAL VALUES AND ECOSYSTEM SERVICES IN THE CAPE PENINSULA OF SOUTH AFRICA

by

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Thesis presented in fulfilment of the requirements for the degree of Master of Arts in the Faculty of Arts and Social Sciences at Stellenbosch University.

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March 2023

DECLARATION

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SUMMARY

Integrative ecosystem service (ES) assessments are crucial to completely assess the benefits of ES and to evaluate synergies and trade-offs among ES. Numerous ES studies have investigated biophysical ES assessments and economic valuation, although social values (SVs) remain under-represented. Integrated modelling of SV maps and biophysically modelled services (BpSs) provide an integrated approach to incorporating SV into ES assessments, through social-ecological hotspot mapping of ES and regression analysis.

This study aimed to investigate the relationships between recreational users' social values and ecosystem services in the Cape Peninsula of the Western Cape province in South Africa. The following four objectives were set to achieve the overall aim of the study: 1) review literature to determine the current discourses and state of research on ES determination; 2) investigate the types and spatial distribution of social values linked to ecosystems in the Cape Peninsula using a participatory mapping exercise; 3) evaluate and quantify the spatial distribution of biophysically modelled services in the Cape Peninsula and 4) investigate the relationships of social values and distribution of biophysical services within the Cape Peninsula.

Social values for Ecosystem services (SolVES) was used to model 11 SV for the Cape Peninsula based on questionnaire results. The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) tool was used to model four BpSs based on geospatial biophysical data. A hotspot analysis on cumulative SV and BpS layers was conducted using the Getis-Ord Gi* statistic, to produce hotspot and coldspot maps of SVs and BpS. A regression analysis using the Ordinary Least Squares (OLS) tool was done to determine the relationships between SVs and BpSs

These findings of the study provided areas of potential trade-offs conflict where there is a disconnect between SVs and BpSs, and where SVs and BpSs overlap, but are possibly not complementary. The study also highlighted potential areas (where SVs and BpSs values overlap) for stakeholder engagement in ES conservation. The weak relationship between biological diversity and habitat quality indicated limited respondents' recognition of habitat quality. These findings can be incorporated within the management plans of conservation decision-makers such as South African National Parks (SANParks) to improve sustainable and inclusive ES conservation and planning, and to ensure SVs are included in ES assessments for the Cape Peninsula.

Keywords: ecosystem services, social values, PPGIS, SolVES, InVEST, social-ecological systems, hotspot analysis, regression analysis.

OPSOMMING

Assesserings van geïntegreerde ekosisteemdienste (ED) is noodsaaklik om die voordele daarvan volledig te evalueer en om sinergieë en afwykings tussen dienste te evalueer. Talle ED-studies het biofisiese ED-assesserings en ekonomiese waardasie ondersoek, hoewel sosiale waardes (SW's) onderverteenwoordig bly. Geïntegreerde modellering van SW-kaarte en biofisies-gemodelleerde dienste (BpS) bied 'n geïntegreerde benadering om SW's by ES-assesserings in te sluit deur middel van sosiaal-ekologiese brandpuntkartering van ED en regressieanalise.

Hierdie studie het ten doel gehad om die verwantskappe tussen ontspanningsgebruikers se sosiale waardes en ekosisteemdienste in die Kaapse Skiereiland van die Wes-Kaap Provinsie in Suid-Afrika te ondersoek. Die volgende vier doelwitte is gestel om die oorhoofse doel van die studie te bereik: 1) hersien literatuur om die huidige diskoerse en stand van navorsing oor ES-bepaling te bepaal; 2) ondersoek die tipes en ruimtelike verspreiding van sosiale waardes gekoppel aan ekosisteme in die Kaapse Skiereiland deur van 'n deelnemende geografiese inligtingstelseloefening gebruik te maak; 3) evalueer en kwantifiseer die ruimtelike verspreiding van biofisies-gemodelleerde dienste in die Kaapse Skiereiland; en 4) ondersoek die verwantskappe van sosiale waardes en verspreiding van biofisiese dienste binne die Kaapse Skiereiland.

SolVES is gebruik om 11 SW-kaarte te genereer wat op vraelysdata gebaseer is. InVEST is gebruik om vier biofisies-gemodelleerde dienste te modelleer gebaseer op georuimtelike biofisiese data. 'n Warmkolanalise op kumulatiewe SW- en BpS-lae was uitgevoer deur die Getis-Ord Gi*-statistiek te gebruik om warmkol- en kouekolkaarte van SW's en BpS'e te produseer. 'n Regressieanalise is gedoen deur gebruik te maak van die Ordinary Least Squares (OLS)-instrument om die verwantskappe tussen SW's en BpS'e te bepaal.

Hierdie bevindinge van die studie het gebiede van potensiële konflik verskaf waar daar 'n skeiding tussen SW's en BpS'e is en waar SVs en BpSs oorvleuel, maar moontlik nie komplementêr is. Die studie het ook potensiële gebiede (waar die waardes van SW's en BpS'e oorvleuel) waar belanghebbendes op die gebied van ES-bewaring kan betrokke raak. Die swak verband tussen biologiese diversiteit en habitatkwaliteit het daarop gedui dat beperkte respondente erkenning gee aan habitatkwaliteit. Hierdie bevindinge kan opgeneem word in die bestuursplanne van bewaringsbesluitnemers soos Suid-Afrikaanse Nasionale Parke (SANParks) om volhoubare en inklusiewe ES-bewaring en -beplanning te verbeter, en om te verseker dat SW's by ED-assesserings vir die Kaapse Skiereiland ingesluit word.

Sleutelwoorde: ekosisteemdienste, sosiale waardes, PPGIS, SolVES, INVEST, sosiaal-ekologiese stelsels, warmkolanalise, regressieanalise

ACKNOWLEDGEMENTS

I would sincerely like to thank:

- My supervisor, Dr Samantha Williams for her never-ending support and guidance;
- My co-supervisor, Dr Eric Mashimbye for his insightful comments and assistance;
- The South African Weather Service (SAWS) for providing their rainfall data;
- My dad and my brother for their love and motivation;
- My mom for being my guardian angel and supporting me from heaven, I dedicate this thesis to you;
- My friends and family for always checking up on the progress of this thesis;
- The staff of the Stellenbosch University Department of Geography and Environmental Studies and fellow students for their overall support and insight.

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ACRONYMS AND ABBREVIATIONS

BpSs	Biophysically modelled services
CFR	Cape Floristic Region
CoCT	City of Cape Town
CSV	Comma-separated value
ES	Ecosystem services
GIS	Geographical Information Systems
InVEST	Integrated Valuation of Ecosystem Services and Trade-offs
LULC	Land use/Land cover
MEA	Millennium Ecosystem Assessment
OLS	Ordinary Least Squares Regression
PPGIS	Public Participation Geographical Information Systems
SES	Social-ecological systems
SolVES	Social Values for Ecosystem Services
SVs	Social values
TMNP	Table Mountain National Park

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

An estimated 60% (15 out of 24) of the ecosystem services (ES) globally are being used in an unsustainable manner or are being degraded (Millennium Ecosystem Assessment (MEA) 2005). According to the MEA (2005: 5), ES entails benefits that people acquire from ecosystems, either directly or indirectly and critically supports human well-being for example, mitigating the rise of disease and crop production (Costanza et al. 1997; MEA 2005; Hallouin et al. 2018; Talbot et al. 2018; Cerda et al. 2020). ES thus provides a connection between people and ecosystems (Costanza et al. 1997; Reyers et al. 2013). ES are currently facing degradation due to measures used to increase the provisioning of other ES, such as mining and food production (Yang et al. 2021; Li et al. 2022). Therefore, it is essential to evaluate and monitor the state of ES to inform sustainable utilisation (MEA 2005; Crossman et al. 2014; Brown et al. 2014; Harrison et al. 2018). The measurement, modelling and monitoring of ecosystem functions provide a basis for ES assessments and as a result, a foundation to inform the sustainable utilisation of biodiversity, ecosystems, and natural resources overall (Anton et al. 2010). A dominant challenge for ES management is managing several ES simultaneously within a landscape (Karimi, Yazdandad & Fagerholm 2020; Shaikh et al. 2021), investigating ES synergies and trade-offs have also been a crucial focus to assess multiple ES at once (Bagstad et al. 2017; Karimi, Yazdandad & Fagerholm 2020). Such methods for assessing and managing ES still need to be better incorporated into the ES framework (Bagstad et al. 2016).

The ES framework has increasingly been used as a sustainable natural resource management tool to inform spatial planning and conservation-based planning processes (MEA 2005; Crossman et al. 2013; Harrison et al. 2018). According to the MEA (2005), and Turner and Daily (2008), the ES framework emphasises the persistent function that robust ecosystems serve for the sustainable supply of human well-being, poverty mitigation, and economic growth and on a global scale. This framework enables a basis for the efficient and adequate conservation of ecosystems that maintain critical ES supply (Turner & Daily 2008). Incorporating social values (SVs) information is essential to apprise efficient ES assessments and decision frameworks that assist ES-based approaches within natural resource management and conservation (Daily et al. 2009; Bryan et al. 2011; Stanturf et al. 2012; Ives & Kendal 2014; Sherrouse, Semmens & Clement 2014; De Vreese et al. 2016; Lin et al. 2017). Numerous ES studies have investigated biophysical ES assessments and economic valuation, although SVs remain under-represented (Raymond et al. 2009; Vihervaara, Rönkä & Walls 2010; Chan, Satterfield & Goldstein 2012; Nieto-Romero et al. 2014).

In this study, SVs for ES can be defined as values (usually corresponding to cultural ES such as spiritual and therapeutic values) that people assign to places on the landscape (Sherrouse, Clement & Semmens 2011). Biophysical and economic valuation methods cannot encompass the complete range of ES that ecosystems provide to people (Karimi, Yazdandad & Fagerholm 2020). Consequently, research that incorporates SVs information into ES assessments is required for complete ES assessments. Biophysical assessments and economic valuation dominate ES research and policy due to the contrasting methods to map, conceptualise and measure SVs (Kenter et al. 2014). It is now more straightforward to map and model SVs with the GIS application Social Values for Ecosystem Services (SolVES) (Sherrouse, Clement & Semmens 2011). SolVES is used to evaluate, map, and quantify SVs according to environmental characteristics such as vegetation type and elevation (Sherrouse, Clement & Semmens 2011; Van Riper et al. 2017; Sherrouse & Semmens 2015). The quantification of SVs comparable to monetary terms provides an opportunity for SVs to be better incorporated into ES assessments in a manner that is informative to decision-makers and scientists (Sherrouse et al. 2011).

ES assessments serve to assess the influence of policy decisions and to outline benefits and trade-offs regarding environmental management (Schmidt, Sachse & Walz 2016). ES assessments are useful to demonstrate the benefits of ecosystem preservation to various stakeholders and for contending biodiversity conservation (Schmidt, Sachse & Walz 2016). Methods and tools used for assessing ES are increasing (Harrison et al. 2018). One example is Geographical Information Systems (GIS) mapping of ES with GIS software, provided spatially explicit data are available (Nemec & Raudsepp-Hearne 2013). Another approach includes ES modelling, where ES models evaluate the supply of multiple ES frequently in a particular GIS software environment (Vihervaara et al. 2018). Three categories of approaches for assessing ES include economic methods, biophysical methods, and socio-cultural approaches, (MEA 2005; Scholte, Van Teeffelen & Verburg 2015; Harrison et al. 2018; Vihervaara et al. 2018). The biophysical and economic ES modelling tool Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) has been used to quantify ES, which is a freely available GIS tool that produces spatially explicit estimations of multiple ES (Goldstein et al. 2014; Lin et al. 2017a; Lin et al. 2017b; Kadaverugu, Rao & Viswanadh 2020; Sharp et al. 2020). Lin et al. (2017) demonstrated the use of InVEST and SolVES to model ES and SV within a social-ecological systems (SES) framework for a more integrative ES assessment.

Incorporating a s SES view within ES assessments provides a basis to ensure SVs are included in ES assessments (Reyers et al. 2013). Within SES, ecological and social systems are inextricably linked (Ostrom 2009). Many ES studies have acknowledged the concept of SES to comprehend the influential interconnections between environmental and social change (Martínez-Harms & Balvanera 2012; Reyers et al. 2013; Bagstad et al. 2017; Lin et al. 2017b; Quintas-Soriano et al. 2018; Masterson et al. 2019). Integrating social and ecological elements could help conflict mitigation and solutions when resolving resource shortages and utilisation change problems (Brown & Fagerholm 2015; De Vreese et al. 2016; Lin et al. 2017b). These methods are crucial for preventing ES degradation, considering the intensifying impacts of these influences (Climate change, urbanisation, habitat destruction, unsustainable resource use, alien invasive species).

Despite ES being known to arise from elaborate relations between ecological and social systems, it is uncertain what exact incorporations of ecological and social contributions are needed to produce services. People and ES are also inextricably linked in SES (Alessa, Kliskey & Brown 2008; Zhu et al. 2010). Consequently, ES should be quantified using biophysically modelled services (BpS) and SVs to resolve the increasing demand for ES within communities as well as to thoroughly assess the benefits of ES (Cowling et al. 2008; Reyers et al. 2013; De Vreese et al. 2016; Bagstad et al. 2017; Lin et al. 2017b). BpS are ES that can be assessed with biophysical methods (such as flood mitigation and carbon storage) (Sharp et al. 2020). Although BpS and SVs modelling have largely been conducted separately (Bagstad et al. 2016), there is a potential for SVs and BpS modelling to serve as complementary methods (Bagstad et al. 2016; Lin et al. 2017b; Smart et al. 2021).

Integrated modelling of SVs and BpSs offers a method to identify synergies and trade-offs among ES and to integrate SVs into ES assessments (Bagstad et al. 2016). Mapping social-ecological hotspots and coldspots has been used as a method for integrated modelling of SVs and BpSs (Alessa, Kliskey & Brown 2008; Bagstad et al. 2016; Smart et al. 2021). Social-ecological hotspots display spatial correspondence of highly recognised landscape values (i.e., SVs) and high ranking in the biophysical environment (Alessa, Kliskey & Brown 2008). Social-ecological coldspots are the inverse thereof (Bagstad et al. 2016). Various hotspot depiction approaches have been progressively used along with ES mapping. These approaches include quantile cut-offs, such as the highest 10, 20 or 30% of values (Alessa, Kliskey & Brown 2008) and statistical methods, e.g., the Getis-Ord Gi* statistic (Bagstad et al. 2016). ES studies have also used regression analysis as a method to determine relationships between SVs and BpSs, also for concurrent GIS modelling (Alessa, Kliskey & Brown 2008; Bagstad et al. 2016).

GIS techniques have enabled the combination of ecological and social data for the establishment of spatial preferences for the managing of ecosystems along with the people which rely on them (Alessa, Kliskey & Brown 2008; Whitehead et al. 2014; Lin et al. 2017b; Van Riper et al. 2017). GIS enables the visualisation of how ES are scattered throughout the landscape (Nemec &

Raudsepp-Hearne 2013). Indicators of ES are selected and mapped to understand where ES are situated on a landscape. It is possible to contrast the arrangement of numerous ES to provide a comprehensive level of understanding for synergies and trade-offs, and to outline areas of hotspots where high allocation of single or several ES exists (Alessa, Kliskey & Brown 2008; Nemec & Raudsepp-Hearne 2013; Bagstad et al. 2017).

Mapping ES using Public Participation GIS (PPGIS) has also recently emerged in the literature (Brown & Fagerholm 2015). PPGIS is a joint group of techniques for incorporating public comprehension of places which aim to apprise decision-making and land use planning (Sieber 2006; Dunn 2007; Brown 2012). PPGIS is mainly used for obtaining and investigating SVs for ES regarding environmental characteristics (Sherrouse, Clement & Semmens 2011; Brown & Fagerholm 2015). Information from social-ecological ES assessments can outline management options that enhance human well-being throughout multiple ES and for averting possibly substantial degradation resulting from neglecting trade-offs for specific ES (Förster et al. 2015; De Vreese et al. 2016; Bagstad et al. 2017).

1.2 PROBLEM STATEMENT

Globally, ES are being degraded at an unprecedented rate primarily due to human activities that abruptly alter the structure and function of ecosystems and decrease their potential to sustain human well-being (MEA 2005; Masterson et al. 2019). The City of Cape Town (CoCT) ES assessment by O'Farrell et al. (2012) investigated how anthropogenic transformation would impact numerous ES, which is based on the scenario of all undeveloped land which do not fall within protected areas converted into formal housing. The scenario revealed that the capacity of all ES had been reduced. This specifically related to provisioning services that were explicitly impacted, with decreases from 30 to 50% relative to the ES. The study points out the importance of reducing regulating ES that are not as threatened as other ES. However, they are possibly more complicated when degraded since these ES must be provided in situ. It is possible for provisioning ES to be sourced from areas outside the city borders (such as water), although this is unfeasible with the majority regulating ES (e.g., flood mitigation). Most ES and the biodiversity and ecological infrastructure that underpin them have experienced degradation (O'Farrell et al. 2012). However, integrative ES assessments that can ensure the adequate conservation of ES and biodiversity within the CoCT are currently lacking (Elmqvist et al. 2013). Particularly ES assessments that use an SES framework.

To ensure the conservation and tailoring of policies for ES regarding current and future use, social and ecological factors should be assessed to achieve more complete ES assessments and sustainable natural resource use (Cowling et al. 2008; Reyers et al. 2013). Establishing a prosperous assessment for multiple ES for national and local-level policies embedded in BpSs and SVs is difficult (Lin et al. 2017b). As a result, conventional approaches for mapping and measuring all elements of ES are notably omitted from most natural resource management decision-making processes (Villa et al. 2014; Lin et al. 2017b). Applying conservation policies without the consideration of local communities' values can result in social conflicts for management and use within the landscape (Ernston 2013). This can frequently be the case when only biophysical and economic ES assessments are considered in decision-making (Bagstad et al. 2016; Ernston 2013). ES conservation thus also needs to be socially acceptable to avoid such conflicts, by ensuring the inclusion of stakeholder SVs in landscape management decision-making (Lin et al. 2017b). Additionally, for ES conservation to be socially acceptable, it is also essential to ensure that users and stakeholders recognize areas for important ES provision and their value (Elmqvist et al. 2013; Ernston 2013). Conservation policy makers have previously neglected SVs because of inadequate quantification methods, although one can now potentially evaluate both SVs and BpSs more precisely (Bagstad et al. 2016; Lin et al. 2017b).

These evaluation techniques enable the concurrent modelling of SVs and BpSs to inform decision-making processes (Bagstad et al. 2016; Lin et al. 2017b). Additionally, several recent studies have gained insight into the associations among ecological and social systems through methods that use a SES framework (De Vreese et al. 2016; Bagstad et al. 2016; Lin et al. 2017b). To ensure that future ES provision is an emphasised public-policy topic, mapped ES assessments of measured ES provision and demand should apprise the decision-making process (Maes et al. 2012; Ban et al. 2013; Brown & Fagerholm 2015; Lin et al. 2017b). Spatially explicit ES assessments can ensure policy implementation and management that provide methods to incorporate biodiversity conservation and the numerous services supplied by ecosystems (Cowling et al. 2008, Anton et al. 2010).

There has been limited research on biophysical and social ES assessment studies conducted for the Cape Peninsula. Consequently, information from spatially explicit ES assessments on the state of ES and values, and ES synergies and trade-offs within the Cape Peninsula lack. Up-to-date information on ES assessments will be crucial for informing future management actions to conserve ES, prevent degradation, and ensure that ES conservation measures and strategies are socially accepted. Concurrent modelling of SV and ES in the form of hotspot and coldspot ES mapping provides a promising method for integrative ES assessments, and to ensure social aspects are included in them (Bagstad et al. 2017).

This study seeks to answer the following research questions:

1. What is the spatial distribution of social-ecological hotspots and coldspots within the Cape Peninsula?

2. Do respondents recognise important areas of ES provision?

3. Can the spatial concurrence or disconnect between SVs and BpS hotspots and coldspots be used to identify important synergies and trade-offs among multiple ES relevant to decision-making within the Cape Peninsula?

1.3 AIM(S) AND OBJECTIVES

This study aims to investigate the relationships between recreational users' social values and ecosystem services in the Cape Peninsula of the Western Cape Province in South Africa.

To achieve the overall aim of this study, the following objectives have been set:

1. Review literature to determine the current discourses and state of research on ES determination.
2. Investigate the types and spatial distribution of social values linked to ecosystems in the Cape Peninsula using a participatory mapping exercise.
3. Evaluate and quantify the spatial distribution of biophysically modelled services in the Cape Peninsula.
4. Investigate the relationships of social values and the distribution of biophysically modelled services within the Cape Peninsula.

1.4 METHODOLOGY AND RESEARCH DESIGN

An outline of research design is depicted in Figure 1.1. This research is predictive as it uses existing methods of integrating SVs and ES to predict relationships between them and subsequent significant synergies and trade-offs. The research approach is deductive, as the research uses existing methods to map social-ecological hotspots of SVs and BpSs and to model relationships thereof. As a result of the approach, a mixed-method approach was used to map and quantify SVs and ES in the Cape Peninsula. The study qualitatively analysed SVs to understand perceived SV types. The research quantitatively analysed quantified SVs and biophysical variables using hotspot and regression analysis methods to identify statistically significant relationships. The study made use of primary and secondary data sources, primary data comprised questionnaire survey data collected through online questionnaire surveys and secondary data consisted of geospatial biophysical data.

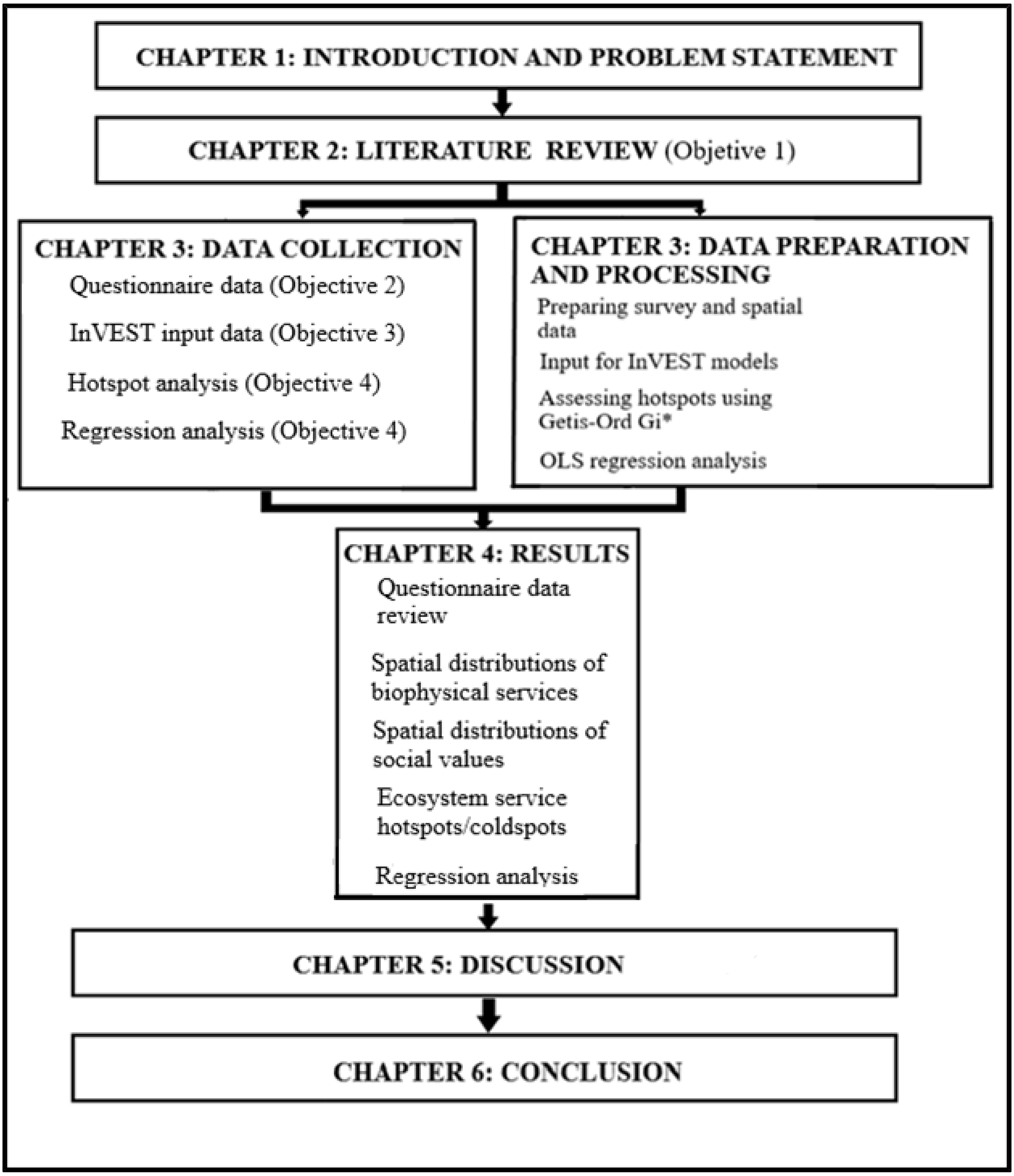


Figure 1. 1 The research design.

1.5 THESIS STRUCTURE

Four objectives have been set to achieve the overall aim of this study (refer to section 1.3). The study is organised into six chapters of which Chapter 2 to Chapter 4 respond to the set objectives. Chapter 1 provides an introductory background to the study and problem formulation. The aims, objectives, research questions and rationale of this study are given, followed by the study's research methodology and design.

The next chapter (Chapter 2) responds to Objective 1 where a literature overview covering social-ecological systems, ecosystem services assessment approaches, ecosystem services relationships and mapping of ecosystem services is provided. The state of ES research known in these aspects is uncovered and gaps are identified.

This is succeeded by Chapter 3 which outlines the data used, preparations and analysis procedures. The study area description is given first. This is followed by data collection and preparation procedures. Questionnaire design and administration are outlined. Data requirements and preparation for use in InVEST modelling are then outlined. This includes the creation of SVs maps from the questionnaire survey results and biophysical ES modelling (namely carbon storage, habitat quality, flood risk mitigation and annual water yield modelling). Then, an analysis of social values and BpSs based on hotspots and regression analysis is provided.

Objectives 2 – 4 are addressed in Chapter 4. Chapter 4 presents the research findings based on the data collection and analysis procedures for this research. These results include various maps, graphs, and tables.

Chapter 5 interprets questionnaire results, social values, and biophysically modelled services maps, as well as the hotspot and regression analysis. The results are put in the context of other studies. The chapter then discusses the implications of these results for future landscape management.

Chapter 6 concludes the study by revising the aims and objectives of the study. The extent to which the aims and objectives were met is outlined. Concluding remarks, study limitations and recommendations for future research are also provided in this chapter.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

This chapter reviews literature covering social-ecological systems (SES), ecosystem services and their importance for human well-being and biodiversity. It continues by outlining the state of ES research, approaches for ES assessment and public participation GIS (PPGIS) to underpin the theoretical framework of this study. The framework of SES and its relevance for this study is presented first, followed by a brief background of ES and its importance for human well-being and biodiversity. After that, the state of ES research and current trends is offered. Following this, an overview of different methods of ES assessments is outlined. Furthermore, the role of PPGIS and GIS in ES assessments and mapping is reviewed. This review examines methods to determine ES relationships and outline synergies and trade-offs among ES. The chapter concludes with a summary of the literature review.

2.2 SOCIAL-ECOLOGICAL SYSTEMS

The SES framework explains how interconnections of sophisticated human-environmental systems provide a basis to explain global environmental challenges (Berkes, Colding & Folke 2008; Karimi, Brown & Hockings 2015). The SES framework also outlines evaluating social and ecological factors that promote sustainable resource use and management (Ostrom 2009). Within an SES, the natural environment is linked with and incorporated into a specific social system which consists of a group of governance rules and institutions (Ostrom 2009). An SES is an intelligible yet influential and complicated arrangement of social and biophysical factors that frequently link in a consistent form at numerous temporal, spatial, and organisational scales to monitor the delivery of essential resources (Berkes, Colding & Folke 2008; Ostrom 2009; Karimi, Brown & Hockings 2015). Human activities affect ecosystems, where significant alterations produce feedbacks which changes prospective management actions. Ecosystems are best understood and maintained by incorporating social aspects within biophysical realms where natural resources are viewed as complex SES (Ostrom 2009). An effective equilibrium between users (e.g., communities) and biological systems that provide resources (e.g., estuarine ecosystems) can be achieved through persistent adaptation and ecological resilience (Ostrom 2009).

The ES concept also focuses on relations between people and the environment, combining social and ecological characteristics (Reyers et al. 2013; Rüdisser, Leitinger & Schirpke 2020). The inextricable relationships among environmental and social systems highlight that ES assessments should focus on the complicated relationship between ecosystem processes, structures, capacities, and the provisioning and evaluation of stakeholders' benefits with diverse demands (Reyers et al. 2013; Lin et al. 2017b; Rüdisser, Leitinger & Schirpke 2020). An SES approach is crucial for developing effective policy and management measures that conserve ES, which considers both social and biophysical dimensions of ES (Reyers et al. 2013; Lin et al. 2017b). However, the relationships between social and ecological characteristics of ES remain underrepresented in the literature (Lin et al. 2017b; Korpilo et al. 2018). Specifically, the incorporation of SVs has been neglected in ES mapping and assessments (Reyers et al. 2013; Bagstad et al. 2016; Korpilo et al. 2018). The ES concept fits within the research field of SES (Vihervaara, Rönkä & Walls 2010).

Three dominant fields of ES include ecology and the additional social sciences, economics, natural sciences, and interdisciplinary integrations of these, as well as the ecosystem approach (Vihervaara, Rönkä & Walls 2010; Wang, Zhang & Cui 2021). Most approaches to ES research include economic valuation, spatially explicit methodologies, and conceptual frameworks which are used to investigate, assess, and quantify ES (Torres, Tiwari & Atkinson 2021; Wang, Zhang & Cui 2021). Economic valuation approaches aim to quantify the value of ES based on monetary terms (Torres, Tiwari & Atkinson 2021). Spatially explicit methodologies outline the spatial characteristics within the study of ES (Torres, Tiwari & Atkinson 2021). Conceptual framework approaches utilise analytical methods to prescribe structure and organisation to advance ES research (Torres, Tiwari & Atkinson 2021). Computational modelling (an approach that utilises mathematical models for producing predictions and simulations of ecosystems and corresponding ES) and non-monetary valuation (an approach to determine the value of ES in units instead of monetary terms) approaches occur the least within ES studies (Torres, Tiwari & Atkinson 2021; Wang, Zhang & Cui 2021). This is due to their recent emergence in the literature (Torres, Tiwari & Atkinson 2021; Wang, Zhang & Cui 2021). Conservation of biodiversity is the leading theme within ES research, followed by landscape planning and urbanisation, and land use change (Torres, Tiwari & Atkinson 2021). The main research themes of ES include the conservation of biodiversity which safeguards the conservation of species, populations, and movement of genes within an ecosystem (Torres, Tiwari & Atkinson 2021). Landscape planning and urbanisation is a research theme that integrates ES in policy, decision-making and planning (Torres, Tiwari & Atkinson 2021). Land use change pertains to a research theme which looks at the socioeconomic and environmental effects of land use change and urbanisation on ES (Torres, Tiwari & Atkinson 2021).

For example, Thapa et al. (2020) investigated the economic value of wetland ES for the Begnas Watershed System in Nepal. The economic value of ES provided by the Begnas Watershed System was determined through surveys and interviews, integrated with market- and non-market-based valuation methods such as market values and travel expenses. The study concluded that wetland ES was valued at 3.91 million USD annually, which is equivalent to 650.67 USD for every household and 799.79 USD per hectare.

Nikodinoska et al. (2018) assessed and mapped regulating and provisioning ES for Uppsala city in Sweden. These ES were mapped with GIS biophysical assessment and economic valuation methods for agricultural, forest and green urban areas. The study found ES had a monetary value of €198 million per year, forests provided 80% of this value, agricultural areas provided 19%, and green urban areas provided 1%. In a conceptual framework study, Cortinovis & Geneletti (2019) presented a framework for understanding how urban planning decisions impact regulating ES at the city scale. The conceptual framework detailed the way demand, capacity, and the provisioning of urban regulating ES along with associated benefits are connected to dominant factors influenced with urban planning, such as typology and location. The study then demonstrated how planners could consider the quantification and geographical distribution of urban regulating ES for decision-making at the city scale.

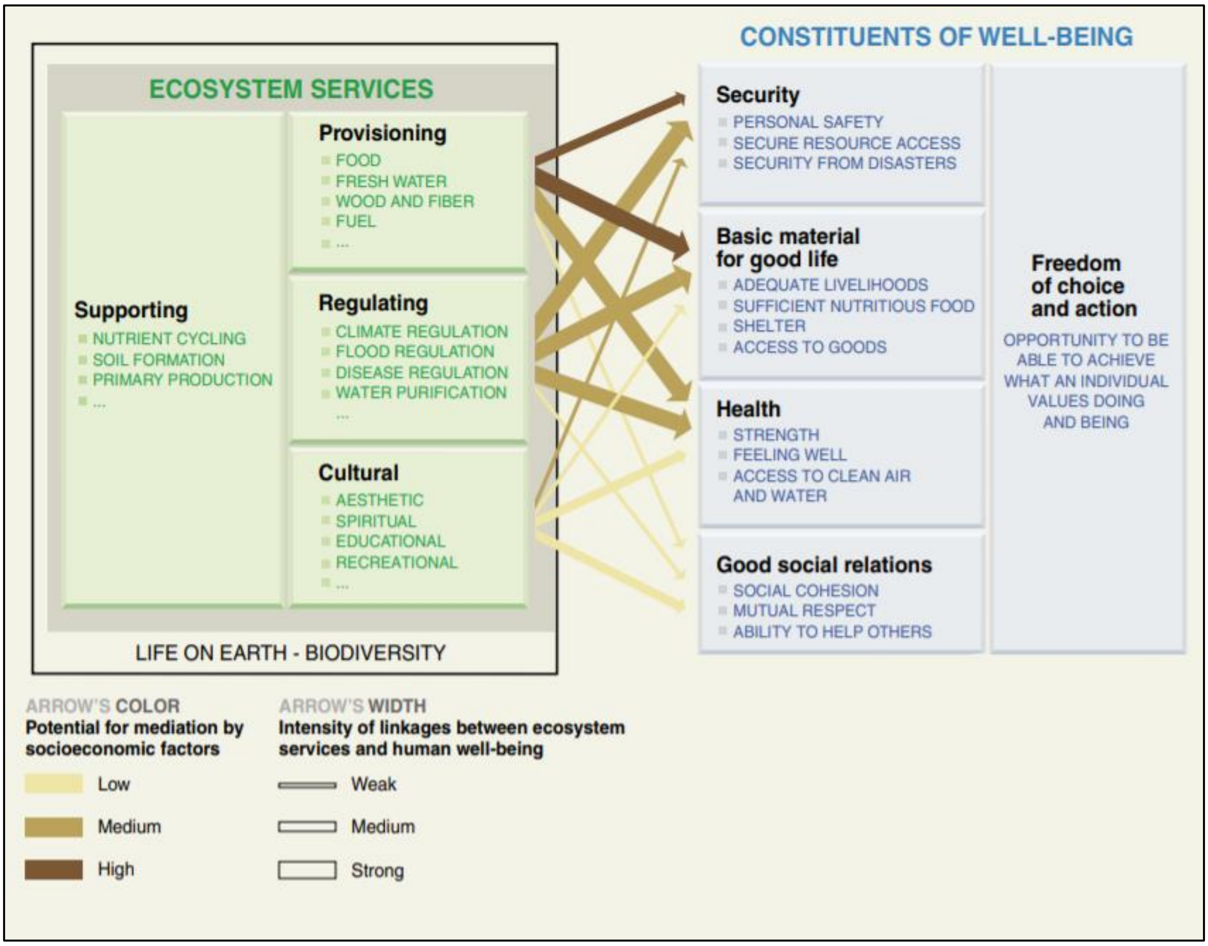
Both studies by Thapa et al. (2020) and Nikodinoska et al. (2018) focus on the valuation of different ES, from an economic perspective. Nikodinoska et al. (2018) make integrated use of both biophysical and economic methods of ES assessment and determine the spatial distribution of ES using GIS mapping. Both studies present their outputs in monetary terms, while Nikodinoska et al. (2018) also link these economic valuations to specific ecosystems from a spatial perspective. Cortinovis & Geneletti (2019) also consider the valuation and distribution of ES. However, it varies since the study considers how the distribution and demand of ES can be used to inform urban planning beyond the valuation of ES. Although these studies provide examples of how ES can be assessed and incorporated into planning decisions, they do not evaluate ES in non-monetary terms. Not all ES (many regulating and cultural ES) provided by ecosystems constitutes marketable commodities that explicitly indicate a monetary value (Schmidt, Sachse & Walz 2016). Economic valuation approaches overlook less tangible services such as education and aesthetics, while non-monetary approaches still appear limited in the literature (Schmidt, Sachse & Walz 2016; Torres, Tiwari & Atkinson 2021). Thus, monetary valuation approaches cannot express the total value of ES and further research into non-monetary approaches is required (Schmidt, Sachse & Walz 2016). Non-monetary approaches can highlight the connection between people’s values and ES, which might also improve decision-making and management strategies for ES (Torres, Tiwari & Atkinson 2021).

Research on ES assessments has also recently increased (Harrison et al. 2018). ES assessments have developed into one of the dominant domains of environmental land-use planning and conservation from an academic point of view (MEA 2005). As mentioned in the introduction, many studies have concentrated on biophysical and monetary methods for assessing ES, however studies that focus on socio-cultural approaches are uncommon (Nieto-Romero et al. 2014). Social elements outlined in these socio-cultural approaches usually determine whether ES management practices succeed or fail (Nieto-Romero et al. 2014). Thus, omitting socio-cultural values from ES assessments can result in poor decision-making and planning regarding ES management and conservation (Ernston 2013). Further research into methods that integrate these ES assessment approaches is required, as there are limited studies that investigate both the social demand and biophysical supply of ES (Quintas-Soriano et al. 2014; Bagstad et al. 2016).

2.3 ECOSYSTEM SERVICES

Ecosystem services (ES) are described as "the conditions and processes through which natural ecosystems, and the species that make them up, sustain and fulfil human life…" (Daily 1997: 3). The various conditions and processes of ecosystems become ES when humans benefit from them directly or indirectly (Costanza et al. 1997; MEA 2005). ES are derived from ecosystem functions, which refers to "habitat, biological or system properties or processes of ecosystems" (Costanza et al. 1997: 1). These ecosystem functions thus enable important ES delivery for human welfare (Costanza et al.1997). Humans and ecosystems jointly produce ES because of relationships between ecological functions, societal management, and demand (Reyers et al, 2013). MEA (2005: 40) classifies ES into four categories: provisioning, regulating, cultural and supporting services. Provisioning services pertain to products from ecosystems such as fibre, water, food, timber, and genetic resources (MEA 2005: 40). Regulating services pertain to benefits acquired from regulatory ecosystem processes such as regulating climate, floods, disease, and water quality and waste treatment (MEA 2005: 40). Cultural services are the intangible benefits of ecosystems such as recreation, aesthetic enjoyment, and spiritual fulfilment (MEA 2005: 40). Supporting services are those required for producing every other service such as nutrient cycling, pollination, and soil formation (MEA 2005: 40).

Humans depend on these four ES categories for various features of their well-being (such as essential resources for a good health, life, and security) and prosperity (Figure 2.1) (MEA 2005; Bennett et al. 2015; Rendón et al. 2019; Wang, Zhang & Cui 2021). Therefore, ES are essential for socio-economic development and poverty reduction at a local and national level (MEA 2005; Bennett et al. 2015; Rendón et al. 2019; Wang, Zhang & Cui 2021).



Source: MEA (2005: 6)

Figure 2. 1 The strength of relationships between categories of ES and aspects of human well-being.

According to Anton et al. (2010) and Maes et al. (2012), ES are also significant for contending biodiversity conservation when these benefits are made clear, as biodiversity plays a substantial role in underpinning many ES (MEA 2005; Anton et al. 2010; Reyers et al. 2012 Sandifer, Sutton-Grier & Ward 2015). Biodiversity conservation, apart from its innate value, is also crucial for human well-being (Reyers et al. 2012; Sandifer, Sutton-Grier & Ward 2015). ES provide a connection between people and nature, highlighting humans' interdependence on ecosystem-based processes that produces the products that sustain our lives (MEA 2005; Reyers et al. 2013; Sandifer, Sutton-Grier & Ward 2015).

2.3.1 State of ES research

ES research has received increased attention in the last decade for the purpose of promoting the advancement of methods and policies that mainstream the ES framework into decision-making and planning (MEA 2005; Seppelt et al. 2011). Most ES studies focus on "function", which explains the functioning of ecosystems, "assessment", including studies assessing ES states or values, and "management", including studies focusing on specific management concerns

(Vihervaara, Rönkä & Walls 2010). For example, Gownaris et al. (2018) examined the ecosystem functioning of lakes and water level fluctuations. They used the Least Absolute Shrinkage and Selection Operator (LASSO) regression to investigate relationships among ecosystem characteristics (such as total biomass and production) and seven physical attributes (for example, climatic, hydrologic, and morphologic). The results indicated that yearly water level fluctuations had positive relationships with primary and overall production, and negative relationships with food chain length, fish diversity, and transfer efficiency. In an ES assessment study, Imran (2021) investigated the state of carbon stock for the Bagrote Valley, Pakistan. Carbon stock was modelled geospatially using the ES assessment tool InVEST. Carbon stock was estimated based on land use/land cover (LULC) data and carbon pools (aboveground and belowground biomass, soil, and dead organic matter) (Imran 2021; Sharp et al. 2020: 73). Based on the InVEST modelling, they found that carbon stock ranged from 0 to 491 tonnes (t) of carbon/ha. They also recorded that dense forests stored the highest amount of carbon (292.1 to 390 t/ha) while sparse forests stored the lowest (0.1 to 79.5 t/ha).

Birgé et al. (2016) investigated how to manage multiple ES to understand cross-scale trade-offs among ES adaptively. They presented a framework that considers adaptive management for ES which considers cross-scale trade-offs within ES provision. The framework seeks to determine important spatiotemporal scales (such as patch and landscape) including internal and cross-scale dynamics, management controllability, and ES trade-offs (Birgé et al. 2016). Both Gownaris et al. (2018) and Imran (2021) investigated ES and ecosystem function from a biophysical perspective, while Birgé et al. (2016) prescribe how to manage multiple ES in a framework study adaptively. Gownaris et al. (2018) found positive and negative regression relationships among lake water level fluctuations and ecosystem and physical attributes. The findings of Imran (2021) included carbon stock maps linked to forest land cover classes.

These studies provide comprehensive knowledge of ES function, assessment, and management. However, these studies overlook the social aspects of these ES focus areas. For example, forests also provide cultural, historical, spiritual, and religious ES which are not readily assessed with biophysical and economic methods of ES assessment (Bagstad et al. 2016; Beckmann-Wübbelt et al. 2021). ES should then not always only be assessed using biophysical assessments such as Imran (2021), but also with socio-cultural methods that capture intangible benefits to provide more complete ES assessments. Birgé et al. (2016) provide a framework for assessing ES trade-offs with adaptive management. However, the study does not account for trade-offs in the form of conflict among various stakeholder concerns and values. Various ongoing studies indicate that ES research should include various stakeholders' SVs in ES assessment and management strategies that seek to conserve ES (Ives & Kendal 2014; Lin et al. 2017b).

More studies tend to focus on assessing ES and management (Vihervaara, Rönkä & Walls 2010). For example, Vihervaara, Rönkä & Walls (2010) evaluated the status of ES research on a global scale. Of the 353 ES research articles reviewed, 217 articles (61.5%) pertained to "assessment", 97 (27.5%) in "management", while only 39 (11%) fell in the "function" category. Thus 89% of these studies fell in the "management" and "assessment" categories. Although ES studies focusing on specific management concerns still require a larger focus (Vihervaara, Rönkä & Walls 2010; Bagstad et al. 2016). Concerning MEA (2005) defined ES categories, majority studies concentrate on provisioning and regulating ES, or a combination of two or more categories (Vihervaara, Rönkä & Walls 2010). Cultural ES are considered essential, although tools for their assessment have been insufficient (Vihervaara, Rönkä & Walls 2010; Bagstad et al. 2017). Cultural ES subsequently have been inadequately considered in numerous ES assessments (Vihervaara, Rönkä & Walls 2010; Plieninger et al. 2013; Mengist, Soromessa & Legese 2020). Of these, 41 investigated provisioning ES, 82 focused on regulating ES, three focused on supporting ES, and only one on cultural ES. The rest focused on a combination of these service types (Vihervaara, Rönkä & Walls 2010). Mengist, Soromessa & Legese (2020) investigated the status of mountain ES research globally. The study identified 74 publications including 317 different ES types. Of these 317 ES types, 115 (36.3%) belonged to regulating services, 86 (27.1%) to provisioning services, 63 (19.9%) to supporting services, and cultural ES was the least at 53 (16.7%) (Mengist, Soromessa & Legese 2020). Thus, more studies are required which include cultural ES in assessments.

Regarding the geographical distribution of ES studies, the North American and European scientific community dominates ES research (Le Maitre, O'Farrell & Reyers 2007; Vihervaara, Rönkä & Walls 2010; Rüdisser, Leitinger & Schirpke 2020; Wang, Zhang & Cui 2021). ES researchers have given marine areas and Africa comparably less attention (Vihervaara, Rönkä & Walls 2010; Mengist, Soromessa & Legese 2020). Many ES studies also concentrate on biogeographical zones instead of states or units such as forest patches or drainage basins (Vihervaara, Rönkä & Walls 2010). Several studies are constrained to comparably small regions located in individual states (Vihervaara, Rönkä & Walls 2010). Using socially demarcated boundaries enables the identification of various SES within a landscape (Raudsepp-Hearne, Peterson & Bennett 2010).

The demand of people benefitting from ES and the provision of ES through biodiversity, function and interrelate at various temporal and spatial scales (Anton et al. 2010; Castro et al. 2014; Lee & Lautenbach 2016). ES are also facing numerous pressures from human activities which can constrain their ability to sustain human well-being and often cause irreversible damage to ecosystems (MEA 2005; Lin et al. 2017b; Mahmoud & Gan 2018). Measures to increase the provisioning of specific services, such as crop production and firewood, decrease numerous other services (MEA 2005; Raudsepp-Hearne, Peterson & Bennett 2010; Karimi, Yazdandad & Fagerholm 2020). A crucial challenge of ecosystem management is establishing a way to manage numerous ES throughout landscapes instead of concentrating on a few services separately (MEA 2005; Raudsepp-Hearne, Peterson & Bennett 2010; Martín-López et al. 2011; Lee & Lautenbach 2016). As such, resolving this challenge necessitates outlining trade-offs and synergies that occur at various scales (MEA 2005; Raudsepp-Hearne, Peterson & Bennett 2010; Lee & Lautenbach 2016). Consequently, obtaining a fundamental comprehension of the scales where ES function is essential for advancing all conservation programmes at the landscape scale (MEA 2005; Anton et al. 2010). Conservation plays an essential role to ensure the long-term sustainability of ES (MEA 2005; Lin et al. 2017b). A multi-disciplinary research method is essential for this, which is possible with an integrated ES assessment (MEA 2005; Anton et al. 2010; Crossman et al. 2013; Bagstad et al. 2017; Harrison et al. 2018).

2.4 ECOSYSTEM SERVICE ASSESSMENTS

ES assessments, aim to evaluate the supply and conditions of ES along with the interlinkages among them, and to determine trade-offs and synergies regarding environmental management (Nieto-Romero et al. 2014; Schmidt, Sachse & Walz 2016; Bagstad et al. 2017; Harrison et al. 2018). ES assessments provide practical information for strategies, policies, and ecosystems management for stakeholders (Cowling et al. 2008; Nieto-Romero et al. 2014). The number of methods and tools created for evaluating ES in particular instances is increasing (Harrison et al. 2018). Categories of methods for assessing ES include biophysical methods for mapping or modelling ES (Buckhard et al. 2018; Vihervaara et al. 2018; Trégarot & Failler 2021), socio-cultural approaches for comprehending SVs for ES and preferences (Scholte, Van Teeffelen & Verburg 2015; Schmidt, Sachse & Walz 2016), and economic methods for evaluating economic value for services (Harrison et al. 2018). This research will only focus on biophysical and socio-cultural methods for ES assessments. Information from ES assessments enables the planning of management options that enhance human well-being throughout multiple ES and for averting possibly substantial degradation resulting from neglecting indications for certain ES (Bagstad et al. 2017). Integrating these various methods provides a basis for an integrative methodological framework for assessing ES (Castro et al. 2014; Bagstad et al. 2017).

2.4.1 Biophysical Approaches

Biophysical approaches for mapping ES are used to measure the capability of ecosystems to supply ES (i.e., supply) along with the quantity of accumulated yield of this capability for people (i.e., use or demand), usually mapped in physical units (e.g., ha, kg, m^3) (Burkhard et al. 2018; Vihervaara et al. 2018; Trégarot & Failler 2021). Biophysical measurement is established with spatial and temporal quantifications of ecosystem processes (Cowling et al. 2008; Burkhard et al. 2018; Vihervaara et al. 2018). Biophysical methods consist of three essential categories regarding the aspects of quantification and the way required information is obtained (Vihervaara et al. 2018). Biophysical data are typically obtained either by, "direct observations and measurements, indirect methods such as proxies or spatial extrapolation, or by modelling" (Vihervaara et al. 2018: 14). The application of direct examinations and quantifications is usually unfeasible for extensive areas due to resource constraints and inadequate data (Harrison et al. 2018; Vihervaara et al. 2018). In such circumstances, it is essential to examine different modelling and mapping approaches to assess ES at the chosen spatial scale (Olosutean 2015; Burkhard et al. 2018; Vihervaara et al. 2018).

For example, Kadaverugu, Rao & Viswanadh (2020) quantified flood risk mitigation (rainfall run-off retention service) of urban green spaces for Hyderabad city, India. They used the InVEST model to quantify and map flood risk mitigation, based on elevation, land cover, and soil characteristics. The study revealed that run-off retention was higher in vegetated land cover classes and open spaces.

Biophysical models provide details concerning the connection between biophysical aspects (processes and functions) which regulate ES provision (Harrison et al. 2018; Vihervaara et al. 2018). Types of biophysical modelling relevant for ES assessments include phenomenological, process-based, state and transition, macro-ecological, statistical ecological, connectivity models, and integrated modelling frameworks (Harrison et al. 2018; Vihervaara et al. 2018). Integrated modelling tools are particularly suitable for ES mapping and modelling, which can enable the evaluation of trade-offs and scenarios for numerous ES (Burkhard et al. 2018; Harrison et al. 2018; Vihervaara et al. 2018), although these tools usually need substantial amounts of quantitative data and have considerable time requirements (Harrison et al. 2018). The methods are frequently grouped into modules, each fitting to assess a specific ecosystem service (Vihervaara et al. 2018). Integrated modelling frameworks use GIS software in order to provide maps and to manipulate spatial data (Vihervaara et al. 2018). They are normally add-ons to web-based applications, stand-alone tools, commercial or open-source software packages (Vihervaara et al. 2018). The biophysical integrated modelling tool InVEST has been widely used in ES mapping and valuation in numerous studies around the world, mainly to evaluate multiple ES and contrast various scenario-based options of possible prospective land-use management (Crossman et al. 2013; Posner et al. 2016; Vihervaara et al. 2018; Sharp et al. 2020). However, ES assessment tools such as InVEST have parameter values and primary data to model ES mainly for western countries (Leh et al. 2013; Cabral et al. 2017; Belete et al. 2018). Further research is still required to adjust these parameter values for data scarce regions such as Africa (Leh et al. 2013; Cabral et al. 2017; Belete et al. 2018). InVEST is a set of freely available software models that can perform spatially explicit mapping often utilised for assessing multiple ES, allowing decision-makers to evaluate trade-offs among ES (Sharp et al. 2020). Four ES (among others) that InVEST can model include Carbon Storage, Flood Risk Mitigation, Habitat Quality, and Annual Water Yield (Sharp et al. 2020).

Within the InVEST model, carbon storage is evaluated in terms of the amount of carbon within a landscape at any given time (Sharp et al. 2020). The carbon model works by examining four carbon pools (aboveground biomass, belowground biomass, soil organic matter, and dead organic matter) according to land use/land cover (LULC) type (Sharp et al. 2020: 73). Aboveground biomass pertains to all existing plant material on top of the soil (such as plants, shrubs, and trees) (Sharp et al. 2020; Yang et al. 2021). Belowground biomass pertains to "the living root systems of the aboveground biomass…" (Sharp et al. 2020: 73). Soil organic matter pertains to, "the organic component of the soil…" (Sharp et al. 2020: 73). Decaying organic matter includes dead wood and litter (Sharp et al. 2020: 73; Yang et al. 2021). The total value of carbon stored within the study area is calculated as the sum of all four carbon pools in megagrams (Mg) (Sharp et al. 2020; Gong et al. 2021). Regarding the flood risk mitigation model, it calculates the volume of rainfall retained by the landscape following a storm event (Sharp et al. 2020; Gong et al. 2021). In the model, rainfall-runoff works with precipitation received over the study area along with LULC and soil characteristics (Sharp et al. 2020; Gong et al. 2021). Concerning the habitat quality model, it evaluates biodiversity status within a landscape by combining LULC and threats data (e.g., roads and urban areas) to generate habitat quality maps (Sharp et al. 2020). Habitat quality pertains to an ecosystems' capacity to support environments suitable for biodiversity preservation (Sharp et al. 2020). Habitat quality is demeed as, "a continuous variable in the model, ranging from low to medium to high…" (Sharp et al. 2020:25). Habitat quality is dependent on existing resources for population perseverance, reproduction, and survival (Sharp et al. 2020). Habitat quality is calculated based on four elements (Sharp et al. 2020). These four elements include the level of land conservation, sensitivity of habitats towards threats, the relative threat, and distance from threat to habitat (Sharp et al. 2020). Concerning the Annual Water Yield model, annual water yield is estimated as how much run-off water flows from the landscape annually (Sharp et al. 2020). Water yield is calculated as total annual evapotranspiration (water lost due to evaporation and plant transpiration) subtracted from total annual rainfall (Sharp et al. 2020).

Various studies investigated ES using biophysical methods. For example, Lin et al. (2017b) analysed BpS based on the InVEST model to produce spatially explicit estimations of carbon storage, water yield, soil retention habitat quality and nitrogen retention in the Datuan watershed, Taiwan. These BpS models were integrated with SVs maps obtained using an online questionnaire and the GIS application SolVES. Most of the input biophysical data to map these ES were based on LULC, terrain, vegetation, habitat, and soil data. Nyanthi and Musakwa (2020) investigated the impact of LULC changes on ES modelled with InVEST within the Nzhelele river catchment, South Africa. Carbon sequestration and crop production were modelled based on two different LULC input data from 1999 to 2018. The study revealed a spatial increase for both carbon sequestration and crop production within the study area and a highly significant correlation between these ES. Lin et al. (2017a) investigated systematic conservation planning to conserve habitat quality and multiple ES within the Wutu watershed, Taiwan. InVEST was used to model phosphorus retention, soil retention, carbon storage, habitat quality, and water yield. They also used local Indicators of Spatial Association (LISA) to outline ES hotspots based on the five modelled ES. The conservation software Zonation was used for systematic conservation planning based on alternative scenarios of ES distribution derived from InVEST outputs. The study found that ES distributions and hotspots occurred mainly in forest areas. Scenarios of InVEST ES quantifications and LISA hotspots, and LISA ES hotspots, provided more efficient techniques to conserve ES than using InVEST ES quantifications in isolation.

These studies similarly modelled the spatial distribution of multiple ES based on InVEST within the study's findings. Nyanthi and Musakwa (2020) also investigated the temporal changes in ES states. All these studies also modelled multiple ES in hydrological features, including watersheds and a river catchment. However, Raudsepp-Hearn, Peterson & Bennett (2010) recommend using administrative boundaries (such as states) as the study area to model ES since social processes form the creation and utilisation of ES. Lin et al. (2017a) and Nyanthi and Musakwa (2020) do not integrate SVs data with InVEST modelled BpSs such as in the study of Lin et al. (2017b). Lin et al. (2017b) and Bagstad et al. (2017) noted that it is crucial to quantify and map both BpSs and SVs for more complete ES assessments and to ensure SVs are incorporated into management decisions. More research is required that integrates BpSs and SVs (Lin et al. 2017; Bagstad et al. 2017).

Biophysical quantifications of ES are also jointly associated with other methods and establishes the foundation for natural capital accounting and frequently provides a basis for economic and social mapping methods and (Cowling et al. 2008; Burkhard et al. 2018; Vihervaara et al. 2018). Biophysical methods for assessing ES should assist in evaluating the extent of sustainable use and to apprise decision-making with this information (Vihervaara et al. 2018). Biophysical measurements and delineation of ES mapping are essential for social and economic mapping and evaluation (Cowling et al. 2008; Vihervaara et al. 2018). Economic and social mapping can be carried out beyond exact biophysical measurements for isolated studies. However, biophysical ES quantifications are necessary to inform sustainable utilisation and planning of ecosystems, natural capital accounting, and ES (Vihervaara et al. 2018).

Biophysical models for assessing ES are crucial for the sustainable management of ES, however, Bagstad et al. (2017) and Cowling et al. (2008) contend that biophysical models for assessing ES should not be used in isolation when aiming for complete ES assessments. Biophysical models cannot encapsulate the full scope of benefits supplied to people by ecosystems (Karimi, Yazdandad & Fagerholm 2020). For example, Ma et al. (2019) aimed to comprehensively assess ES provided by Dongting Lake Wetland, China. The study modelled multiple ES of snail control and schistosomiasis prevention, soil conservation, water yield, and carbon storage using the InVEST modelling tool. The study's results revealed spatial and temporal variations for these multiple ES. However, lake ecosystems are also known to provide cultural ES such as aesthetic experiences, educational opportunities, and inspirational, spiritual, and symbolic benefits (Schirpke et al. 2021), that was not considered in the study of Ma et al. (2019). Biophysical models for assessing ES cannot model such intangible benefits due to the intangible and incommensurable characteristics of cultural ES (Bagstad et al. 2017).

Numerous biophysical ES modelling tools have advanced from previous ecological, hydrological, and additional biophysical process models, which were demonstrated advantageous in measuring provisioning, regulating, and supporting ES (Bagstad et al. 2017). Cultural ES remains more complicated to quantify with these models (Bagstad et al. 2017). There are a few cultural ES such as the viewshed element of aesthetic values that can be quantified by biophysical models, although they are inadequately equipped to quantify all cultural ES (Bagstad et al. 2017). As Semmens, Sherrouse & Ancona (2019) pointed out, unlike how provisioning and regulating ES can be assessed, it is not possible to assess cultural ES provision supplied by ecosystems from the biophysical attributes of the environment without input from cultural ES beneficiaries. Cultural ES assessments thus require input from stakeholders to adequately model cultural ES and for more complete ES assessments.

Researchers are also including socio-cultural valuation approaches for the assessment of cultural ES and other ES, to incorporate a wider group of social perspectives into the ES framework (Sherrouse, Clement& Semmens 2011; Scholte, Van Teeffelen & Verburg 2015; Schmidt, Sachse & Walz 2016).

2.4.2 Socio-cultural Approaches

Socio-cultural values of ES pertain to the significance the public, as groups or as individuals, assign to ES (Scholte, Van Teeffelen & Verburg 2015) and are regarded as assigned values (Schmidt, Sachse & Walz 2016). Social valuation refers to the valuation through people contrary to existing proxies such as monetary values (Schmidt, Sachse & Walz 2016). Socio-cultural values of ES are usually determined through questionnaires, observation approaches, in-depth interviews, document research, approaches to account for spatial factors, expert-based approaches, and focus groups (Schmidt, Sachse & Walz 2016; Harrison et al. 2018). For example, Sanyé-Mengual et al. (2018) investigated the social acceptance and perceived ES of urban agriculture in Bologna, Italy. Preferences for urban agricultural ES were obtained through an on-site quantitative survey conducted with Bologna citizens. Survey respondents were asked to rank how much they accept the influence of urban agriculture on the environment and socio-cultural ES. Results of the study revealed that respondents widely accepted vegetable production, and intensive farming systems were least accepted.

Richards & Tunçer (2018) investigated cultural ES using geo-tagged social media photographs for Singapore. The study utilised a machine learning algorithm for evaluating the content of pictures captured in Singapore and were grouped using hierarchical clustering. The study found that many photographs consisted of nature (animals and plants). These photographs were located mainly in specific natural sites, and they were most likely to appear in parks and places with dense vegetation cover. Dai et al. (2019) investigated perceptions of cultural ES on social media for urban parks within Xuzhou, China. The study used word searching software to review online social media comments which were divided into keywords. The study revealed that urban parks are valued for different cultural ES, including cultural heritage, aesthetics, education, inspiration, recreation, sports, and spiritual satisfaction.

These socio-cultural ES studies provide straightforward techniques to determine cultural ES and preferences of certain areas. However, these methods do not outline where these socio-cultural values for ES are located within the study area in a spatially explicit manner (Schmidt, Sachse & Walz 2016). Mapping people's socio-cultural values for ES can be beneficial for ecological management and can also be incorporated with biophysical data and used in conservation management and planning (Ives & Kendal 2014). Numerous techniques to collect socio-cultural ES values disregard the spatial variations of ES supply (Scholte, Van Teeffelen & Verburg 2015). These techniques typically require respondents to broadly describe their socio-cultural values of a landscape, with no reference to the specific ecosystems that supply ES (Schmidt, Sachse & Walz 2016). Subsequently, ecological managers would not be able to derive an understanding of specific locations of high and low values (Zhou et al. 2020). They will also not be able to understand what the driving factors are for SVs (Zhou et al. 2020). Thus, socio-cultural ES assessments still require further research, particularly studies that apply spatially explicit methods to elicit socio-cultural values (Karimi, Yazdandad & Fagerholm 2020).

Within methods to account for spatial factors, most approaches used for mapping socio-cultural values of ES use either specific place mapping or generic feature mapping (Scholte, Van Teeffelen & Verburg 2015). In specific place mapping, respondents identify where particular values are found by marking points on locations as a form of a participatory mapping exercise (Scholte, Van Teeffelen & Verburg 2015). These studies offer an understanding of the spatial distribution of ES provision and relative corresponding values, where relationships among values and environmental characteristics such as elevation, vegetation cover, and/or distance to features, e.g., trail pathways or water can be deduced (Scholte, Van Teeffelen & Verburg 2015). Maps depicting ES and corresponding values thereof can be remarkably effective in the case of sustainable decision-making for ecosystems (Sherrouse, Clement & Semmens 2011; Schmidt, Sachse & Walz 2016; Van Riper et al. 2017).

Socio-cultural ES values have also been associated with spatial characteristics through participatory mapping, where respondents identify the locations of ES. For example, Sherrouse, Clement & Semmens (2011) sent a mail questionnaire survey to residents within the Pike and San Isabel (PSI) forests in Colorado, USA, to map the SVs most important to them by using specific place mapping and the GIS application SolVES. Respondents were asked to hand-mark points on numerous maps of the PSI where they associated their specific SVs. They discerned the many SVs that the PSI held for the survey respondents and the relationships of underlying environmental characteristics (elevation, slope, distance to features, landforms, and land cover) with these SVs.

SolVES is a GIS application used for examining and mapping questionnaire-survey response data (Sherrouse, Clement & Semmens 2011). SolVES combines and measures the spatial data of SVs to inform natural resource managers and stakeholders (Sherrouse & Semmens 2015). SolVES additionally enables an understanding of the relationship between the endpoints of ES (the things people care about) and the underlying environmental characteristics in protected areas (such as land cover, elevation, terrestrial vegetation, and slope) (Sherrouse & Semmens 2015). SVs information can be used to assess the relationship between SVs endpoints to outline the importance of SVs intensities relative to physical environmental characteristics and socio-demographic factors. SolVES measures and maps SVs in spatial models with non-spatial and spatial responses from questionnaire surveys pertaining to public preferences. SolVES afterwards determines a measurable value index ranging from 0 to 10, with 10 indicating the greatest value, with the use of value allocations obtained from a questionnaire (Sherrouse & Clement 2015: 3). The value index is the indicator obtained from values allocated by stakeholders in response to questionnaires and subsequently associated with underlying environmental variables. The relationship between SVs and environmental attributes such as land cover, vegetation cover, and other physical landscape characteristics is examined relative to where respondents marked locations linked with each SV type (Sherrouse & Semmens 2015). SolVES additionally examines variations in values along with distinct groups of respondents contingent to socio-demographics and other respondent characteristics (Sherrouse & Semmens 2015).

Sherrouse, Clement & Semmens (2011) investigated SVs within a PPGIS context. SVs were defined as identical to non-monetary landscape values (values people assign to areas on the landscape), and characterised by type (such as historical, intrinsic, and life-sustaining values), comparably to monetary valuations. This definition of SVs is then slightly different from the broader term “socio-cultural values”. Socio-cultural values pertain to peoples’ values for the full range of MEA (2005) ES categories including provisioning, regulating and cultural ES (Scholte, Van Teeffelen & Verburg 2015), while SVs mainly pertain to values for cultural ES (Bagstad et al. 2016). However, biological diversity pertains to supporting ES, economic values correspond to provisioning and cultural ES, and life-sustaining values generally pertain to regulating ES (Bagstad et al. 2016). Brown & Reed (2000) explained 13 of these place-based values within a forest value typology setting including, “aesthetic, biological diversity, cultural, economic, future, historic, intrinsic, learning, life-sustaining, recreation, subsistence, spiritual, and therapeutic” values (Brown & Reed 2000: 4). These forest values are also referred to as SVs for ES (Sherrouse, Clement & Semmens 2011).

Specific place mapping uses PPGIS methods to map SVs (Brown & Fagerholm 2015). PPGIS has been used to derive GIS social information for incorporation with ecological data within GIS (Alessa, Kliskey & Brown 2008; Bagstad et al. 2016). PPGIS aims to include the public in participatory procedures using GIS tools for apprising decisions with spatial consequences (Sieber 2006; Dunn 2007; Brown 2012). An example of using PPGIS includes respondents being asked to point out places on a map, either digital or hardcopy, using digital indications, markers, or stickers

(Brown 2012). Respondents are recruited through on-site surveys, social media, mailing lists, workshops, or online panels (Brown 2012). Within the social sciences, an effort has been made for mapping expert and public socio-cultural values of ES using PPGIS (Bagstad et al. 2017). These methods ask respondents to map areas where they think ES are provided. PPGIS can also comprise a value-allocation exercise which enables respondents to identify the value types most important to them (Sherrouse, Clement & Semmens 2011). These SVs mapping methods are applicable to comprehend cultural ES, comprising non-use values. SVs mapping subsequently provides a method to quantify cultural ES and other ES to apprise environmental planning and management (Sherrouse, Clement & Semmens 2011; Bagstad et al. 2016).

SVs approaches for assessing ES can complement biophysical valuations, although they should not be seen as an alternative (Cowling et al. 2008; Scholte, Van Teeffelen & Verburg 2015; Bagstad et al. 2017). An SVs focus within planning can occasionally deviate considerably from biodiversity planning (Plieninger et al. 2015). A study by Whitehead et al. (2014) investigated a scenario of using only the highest ranked areas of SVs as a foundation for conservation planning in the Lower Hunter region, Australia. SVs for conservation in this study were defined as areas that people perceived as important for biodiversity conservation. These SVs were obtained with a community PPGIS questionnaire survey. The study established that more than 50% of the highest ranked areas in biodiversity values (represented by distribution data of seven fauna species) would not be conserved anymore.

Nevertheless, researchers have acknowledged socio-cultural ES valuation approaches (Daily et al. 2009; Sherrouse, Clement & Semmens 2011; Sherrouse, Semmens & Clement 2014; Nahuelhual et al. 2016; Schmidt, Sachse & Walz 2016), for the potential to raise awareness of ES, to integrate public knowledge in management decision-making, and to encourage local inspiration (Daily et al. 2009; Sherrouse, Clement & Semmens 2011; Sherrouse, Semmens & Clement 2014; Nahuelhual et al. 2016; Schmidt, Sachse & Walz 2016). However, biophysical and economic ES assessment approaches still lead ES research and policy (Nahuelhual et al. 2016; Karimi, Yazdandad & Fagerholm 2020). The absence of SVs in ES assessments is intensified through the overall association of SVs with cultural ES, which is not sufficiently incorporated within the ES framework (Sherrouse, Semmens & Clement 2014; Bagstad et al. 2016). SVs are usually the most difficult to evaluate due to their intangible and incommensurable character. At the same time, a large focus has been placed on those ES which are readily measured and marketed (García-Díez, García-Llorente & González 2020). However, the spatial representation of SVs with participatory mapping presents an opportunity to resolve this difficulty (Sherrouse Clement & Semmens 2011; Bagstad et al. 2016; García-Díez, García-Llorente & González 2020). Mapping of SVs within ES assessments offers a way to convey cultural ES in a manner comparable to monetary terms of economic value (Sherrouse, Clement & Semmens 2011).

ES assessments are receiving increasing attention, although there is still doubt whether they sufficiently assess the benefits of ecosystems (Förster et al. 2014; Posner, Getz & Ricketts 2016). ES are made by ecosystems and consumed by people (Reyers et al. 2013). Thus, ES obtained from biophysical processes should not be viewed separate from people but rather as intertwined in political and social processes (Ernston 2013). As a result, methods of ES assessment that solely concentrate on social or biophysical factors will not accurately assess the supply and use of ES (Bennet, Peterson & Gordon 2009; Reyers et al. 2013). Inadequate participation of stakeholders and their SV within the implementation of ES assessments can separate the outcomes from the requirements of decision-makers and existing policy arrangements (Trégarot & Failler 2021).

Contemporary methods concentrate on ecological production functions, which comprise a group of biophysical variables (such as soil type and tree cover) to model the supply of ES (Nemec & Raudsepp-Hearne 2013; Reyers et al. 2013; Hamann, Biggs & Reyers 2015). Modelling ES supply based on ecological production functions highlights ecological aspects linked to ES supply, although it frequently omits the social aspects (Reyers et al. 2013; Hamann, Biggs & Reyers 2015). Diaz et al. (2015) also highlights how monetary ES assessments overlook cultural ES (Daiz et al. 2015). For example, farmers that value agriculture for cultural heritage reasons would not have these values captured by monetary methods (Diaz et al. 2015). Another example is the provision of drinking water from vegetated watersheds are valued for entitlement reasons and not as a commodity ES, thus extending beyond market logic (Diaz et al. 2015). Thus, ES valuation approaches need to account for the value systems of all relevant stakeholders for adequate consideration of their values and preferences (Diaz et al. 2015). This in turn could reduce conflict among stakeholders for ES allocation. Studies that do include social aspects usually do so after service production, as quantifications of use or value (Reyers et al. 2013).

Cowling et al. (2008) state that social ES assessments should be conducted before biophysical ES assessments. This is because it determines the owners and beneficiaries of biophysical functions which provide ES and subsequently need a biophysical ES assessment. A social ES assessment identifies the values, requirements, actions of people, standards, societies, and relevant groups within the study area (Cowling et al. 2008). That is, it reveals how a site functions concerning socioeconomic characteristics and the reasons for it (Cowling et al. 2008). Omitting the comprehension of the social system derived from a social ES assessment could result in inadequate targeted implementation (Cowling et al. 2008). Smart et al. (2021) stated that overlooking local community values but still expecting them to conform to planning regulations is unreasonable and possibly undermines their cooperation and ability to adhere to land-use regulations. This possibly results in the development of controversial, inequitable, and ineffective policies. If possible, data should be collected spatially and conform to the biophysical ES assessment scale (Cowling et al. 2008).

An SES approach expands the idea of ecological production functions by acknowledging that within a human environment, ES production also involves social aspects such as stakeholder values, skills, management regimes, and technology (Ernston 2013; Reyers et al. 2013; Hamann, Biggs & Reyers 2015). However, this is not evident in the ES framework (Reyers et al. 2013). Cultural ES have specifically robust aspects involved in their production (such as recreational infrastructure and preferences, sacred site practices and management) which have not been adequately modelled with ecological production functions (Reyers et al. 2013).

Academics producing models to incorporate ES assessments for water and land use decision-makers have recommended that ES valuation ought to comprise data from biophysical and social evaluations (Cowling et al. 2008; Sherrouse, Clement & Semmens 2011; Bagstad et al. 2017; Lin et al. 2017b). Integrating an SES approach within ES enables a method of making these ES assessments more applicable to decision-making, combining social and biophysical characteristics of ES (Lin et al. 2017b; Rüdisser, Leitinger & Schirpke 2020). An SES approach regarding ES enables an examination of how human dependencies entail possible services, comprehension of trade-offs amid management prescriptions, and the outlining how people rely on ES (Förster et al. 2015). One method to integrate a social-ecological approach into ES assessments is the concurrent modelling of SVs and BpSs (Lin et al. 2017b). As biophysical modelling and SVs mapping of ES have mainly taken place separately, simultaneous mapping of biophysical ES and SVs could offer a better strategy to incorporate SVs into ES assessments (Bagstad et al. 2017).

Felipe-Lucia, Comín & Escalera-Reyes (2015) highlights that many social ES assessment studies only evaluate cultural ES, not provisioning, regulating, and supporting ES. Although studies have noted that making respondents map complicated ecosystem processes, supporting these ES is quite cognitively demanding for respondents (Brown & Fagerholm 2015; Bagstad et al. 2017). This could affect the efficiency of mapping these ES with the use of PPGIS (Brown & Fagerholm 2015; Bagstad et al. 2017). More specifically, Brown & Fagerholm (2015) noted that studies that used MEA-defined ES instead of ES indicators relating to uses and values for these ES were fairly cognitively demanding for respondents. In response to this, Bagstad et al. (2016) suggested a technique which involves simultaneously mapping SVs obtained through PPGIS methods in conjunction with those services, which are more accurately assessed biophysically. This technique superimposes SVs and BpSs derived hotspot maps and determines possible conflict areas with a conflict between these services (Bagstad et al. 2016). This approach offers cultural ES to be more equivalent in decision making with more straightforwardly monetised provisioning and regulating ES, and to assess multiple ES at once (Bagstad et al. 2016). Mapping SVs and BpSs also outlines trade-offs and synergies between many SVs and BpSs (De Vreese et al. 2016; Lin et al. 2017b; Smart et al. 2021).

2.5 ECOSYSTEM SERVICE RELATIONSHIPS

ES can create synergy, trade-off, or neutral relationships, that is, ES can either be independent or negatively or positively related to one another at various spatial scales (Mengist, Soromessa & Legese 2020). A trade-off relationship in ES is when the provisioning or value of one or many ES are negatively affected by alterations in other services (Castro et al. 2014). That is, the supply or value of a single or several ES is increased to the detriment of negatively affecting other services. Trade-off relationships also possibly arise in the event of a disconnect between stakeholders' economic and socio-cultural values on one or several services and the biophysical capability of a specific landscape to supply ES (Castro et al. 2014). For example, such a trade-off can arise when people do not acknowledge the importance (regarding economic and social benefits) of groundwater recharge in an arid region (Castro et al. 2014). A synergy relationship entails when both ES are increased concurrently (Mengist, Soromessa & Legese 2020). Concerning a neutral relationship, it is when there are no interconnections or no impact between ES (Mengist, Soromessa & Legese 2020).

An extensive comprehension of multiple ES is essential in natural resource management to increase synergies between ES and to avert unintended and frequently negligent trade-offs and (Förster et al. 2015; Lee & Lautenbach 2016). Comprehending ES synergies and trade-offs can assist landscape managers in choosing appropriate management interventions at the local level, specifically, those that appear because of conflict among different stakeholder concerns (Qiu & Turner 2013; Castro et al. 2014; Bagstad et al. 2016; Karimi, Yazdandad & Fagerholm 2020). Ernston (2013) provides an example where an unintentional fire occurred within the Tokai Forest, Cape Town, which resulted in conflict about the importance of different ES. The Tokai Forest was initially a pine plantation that was used for timber production and job creation, although the fire in 1998 promoted the growth of fynbos seeds, an indigenous and endangered vegetation.

The evidence of potential fynbos to grow in the area led to an influential alliance which wanted the pines removed, and fynbos replanted. Pine trees undermined the biodiversity of fynbos and affected water quality and quantity in this drought-prone area. Conservation ecologists, non-governmental organisations (NGOs), and public agencies formed government-funded programmes for the purpose of eradicating the pine trees and additional alien invasives. However, this caused conflict between conservation biologists and forest user groups. Conservation biologists contended that the replantation of fynbos could maintain ecological functions and freshwater streams in the watershed area, at the same conserving biodiversity for inherent values and enduring ecosystem-based adaptation. However, forest users argued for the retention of the pine trees, for recreation, access for mushroom picking, and for well-being purposes. This was seemingly more convenient with pine trees that provided little underbrush and shade. The pine trees were also associated with socio-cultural values linked to identity and belonging since a lot of the users grew up with the pine trees, and not fynbos. The pine trees were removed, although a few trees were left for shaded walks.

When managing ecosystems only from an ecological perspective, managers could unknowingly make choices that cause counterproductive trade-offs for visitors (Ernston 2013). Elmqvist et al. (2013) noted that places with high SVs are not always synergistic with areas essential for ES and biodiversity established with scientific analysis or government. Thus, perceptions regarding the legitimacy of conservation vary (Elmqvist et al. 2013). To make sure measures to conserve ES are applied and accepted by the public and stakeholders, it is crucial to improve communications regarding ES, particularly for ES that are less recognised and poorly understood, such as by applying social learning (Rüdisser, Leitinger & Schirpke 2020). A biophysical ES assessment alone would not have captured the specific SVs linked to the Tokai Forest.

Such trade-offs motivate assessing multiple elements of ES (Ernston 2013; Castro et al. 2014). The question concerning which ES have a greater importance than others, that is, the value of an ES, hinges on to a substantial extent upon stakeholders' values (Ernston 2013; Hauck et al. 2013). However, Ernston (2013) acknowledges that "finding the right trade-off" can be difficult. Notably, a social ES assessment outlines stakeholders' concerns and values regarding places to establish possible consequences where a specific decision can impact them (Sherrouse, Clement & Semmens 2011; Karimi, Yazdandad & Fagerholm 2020). As stated before, there is an inadequacy of research examining trade-offs which concurrently consider biophysical ES provision and social ES demand (Quintas-Soriano et al. 2014; Bagstad et al. 2016). Multiple techniques to determine synergies and trade-offs between ES exist (Bagstad et al. 2016: Lee & Lautenbach 2016; Mengist, Soromessa & Legese 2020). The next section provides an overview of techniques for mapping ES synergies and trade-offs.

2.6 MAPPING ES SYNERGIES AND TRADE-OFFS

2.6.1 Modelling ES relationships

Methods to determine relationships between ES include descriptive techniques, correlation coefficients, regression analysis and multivariate statistics (Lee & Lautenbach 2016). Regression analysis can be used to model, assess, and investigate spatial relationships among ES, with the aim of better understanding the aspects behind observed spatial patterns or anticipating spatial outcomes (Scott & Janikas 2010; Bagstad et al. 2016). Regression analysis has been widely used in studying complex interactions among multiple ES (Alessa, Kliskey & Brown 2008; Bagstad et al. 2016; Liu et al. 2019). Alessa, Kliskey & Brown (2008) analysed the relationship between biological diversity and net primary productivity using linear regression for the Kenai Peninsula, Alaska study area. The study yielded a relatively significant positive relationship, highlighting the connection between spatial patterns of net primary productivity and respondents' perceived biological diversity values (Alessa, Kliskey & Brown 2008). Bagstad et al. (2016) used the Ordinary Least Squares Regression (OLS) linear regression tool to analyse relationships between SVs and BpSs for the PSI forest in the USA. However, the study's OLS results were non-significant. This indicated public perceptions of ES provision areas were limited. OLS is the most well-known regression approach, which provides a suitable starting point for all spatial regression analysis (Environmental Systems Research Institute (ESRI) 2021b). However, Agudelo, Bustos & Moreno (2020) argued that modelling multiple ES with a single approach is often not enough. Methods should be integrated to meet decision-makers' requirements (Agudelo, Bustos & Moreno 2020). Using more than one modelling approach can include a larger number of ES and compensate for the weaknesses in other methodologies (Agudelo, Bustos & Moreno 2020). One limitation of regression models is that it differentiates multiple ES into dependent and independent variables (Lee& Lautenbach 2016). Errors are not accounted for in the independent variable and are only considered within the dependent variable (Lee& Lautenbach 2016). Another method to determine ES relationships is the social-ecological hotspot mapping of ES (Bagstad et al. 2016).

2.6.2 Social-ecological hotspot mapping

Social-ecological hotspot mapping provides a method to identify trade-offs and synergies between SVs and other ES (Bagstad et al. 2016). It also provides a means to consider some non-monetary cultural ES in quantitative and spatial ES assessments (Bagstad et al. 2016). As stated in the introduction, social-ecological hotspots pertain to areas that display spatial correlation of both high ranking for ecological conditions and high perceived landscape values (in this case SVs) (Alessa, Kliskey & Brown 2008). An example of an SES hotspot can occur within a region highly valued for biological diversity by community members together and biological productivity determined through quantitative scientific investigation (Alessa, Kliskey & Brown 2008). In the context of this study, social-ecological hotspots are areas with high SVs and BpSs values. Areas with low perceived SVs and low BpS values are coldspots.

Different hotspot analysis methods have been used together with ES mapping. These include expert definition, quantile cut-offs such as the top 10, 20 or 30% of values, and statistical methods such as the Local Moran's I and the Getis-Ord Gi* (Bagstad et al. 2017). Expert definition can provide reliable information for once-off studies and/or regional or national assessments (Bagstad et al. 2017). However, the possibility to provide various information subject to the expert group's organisation and, the relative bias makes expert definition suboptimal for mainstream ES assessments (Bagstad et al. 2017). Statistical methods refer to methods used to delineate hot spots along with Jenks natural breaks, maximising the variation between classes relative to the clusters contained in the data. (Schröter & Remme 2016:). The Getis-Ord Gi* statistic determines spatial clustering within the data to outline hotspots or coldspots. The Getis-Ord Gi* statistic determines clustering of pixels containing high values (hotspots) and low values (coldspots) according to a certain distance (Schröter & Remme 2016). The Getis-Ord Gi* statistic forms part of the Local Indicators of Spatial Association (LISA) (Anselin 1995). A LISA refers to any local statistic that outlines clusters of similar values above or less than the average which express local patterns of spatial dependence, usually referred to as hotspots and coldspots correspondingly (Anselin 1995). These include local indicators of local Getis-Ord G and Gi*, Moran's I, and local Geary's C (Anselin 1995). The Getis-Ord Gi* statistic has been applied across a variety of different fields including criminology and has also particularly been used to outline spatial clustering (hotspots) of SVs and ES (Bagstad et al. 2016; Li et al. 2017; Smart et al. 2021).

Spatial clustering methods may overlook crucial small, dispersed, or linear elements such as springs or riparian corridors, which could appear as high-value areas in the quantile cut-off method (Bagstad et al. 2017). However, quantile cut-off methods frequently overlook landscape connectivity among or within the outlined hotspots, which could result in detrimental and serious landscape fragmentation (Schröter & Remme 2016; Li et al. 2017). The output hotspots from the Getis-Ord Gi* statistic can provide improved continuous hotspots surfaces, representing an example of landscape connectivity (Bagstad et al. 2017; Li et al. 2017). Thus, spatial clustering approaches provide the opportunity to outline more continuous hotspots (Li et al. 2017; Lin et al. 2017a). The Getis-Ord Gi* statistic is well suited to evaluate and outline ES hotspots that have good spatial connectivity (Bagstad et al. 2017; Li et al. 2017).

In a comparative study, Bagstad et al. (2017) evaluated different methods for generating ES hotspots and coldspots for six US national forests. ES hotspots and coldspots were mapped based on BpSs modelled using Artificial Intelligence for Ecosystem Services (ARIES) and SVs modelled using SolVES. For comparison, ES hotspots and coldspots were mapped with, "two quantile approaches (top and bottom 10% and 33% of values), two area-based approaches (top and bottom 10 and 33% of area), and two statistical approaches (Getis-Ord Gi* at α= 0.05 and 0.10 significance levels)" (Bagstad et al. 2017: 8). The study revealed that these hotspot delineation methods differ concerning the degree of conservatism (confidence levels) for hotspot and coldspot extents and spatial clustering. The study concluded that statistical hotspots of intermediate conservatism (such as Getis-Ord Gi*, α= 0.10) could offer the best ES hotspot and coldspot mapping method to apprise landscape-scale management.

Social-ecological landscape attributes are geographically diverse and budgets for conservation are small, and thus geographical focusing on conservation hotspots for biodiversity and ES presents an opportunity to improve the effectiveness of conservation (Bagstad et al. 2017). Bagstad et al. (2016) mapped social-ecological hotspots for SVs and BpS using the Getis-Ord Gi* statistic for PSI forests in Colorado, USA. Hotspot maps were based on SVs modelled using SolVES and BpSs modelled based on ARIES. The study demonstrated that hotspots of SVs and BpSs were immensely situated in wilderness areas of the PSI. Coldspots of SVs and BpSs were located more outside of wilderness areas. The study presented an opportunity for landscape managers to overlay the spatial location of prospective management actions above SVs and ES maps. This could improve the visualisation of human/landscape relations.

Smart et al. (2021) mapped hotspots and coldspots based on BpSs and cultural ES with the Getis-Ord Gi* statistic for Johns Island, South Carolina, USA. Cultural ES were mapped using PPGIS stakeholder workshops. BpS were mapped using the InVEST model. The study recorded that cultural ES hotspots infrequently (3% of the area) overlapped with hotspots of BpS. The study highlighted the significance of stakeholder engagement for mapping cultural ES, which enables them to be on equal terms with BpSs in landscape planning.

2.7 CONCLUSION

ES research has been increasing since MEA (2005) development, although ES research that evaluates social dimensions of ES, particularly cultural ES, and integrative ES assessments, is still lacking. Particularly, ES research that explores ES trade-offs among social and biophysical ES assessments lack. This literature review highlighted the importance of evaluating multiple dimensions of ES assessments to better identify synergies and trade-offs among ES, and to improve decision-making. Conducting ES assessments in isolation can result in neglecting trade-offs for ES and the values of stakeholders. ES assessment studies that also use an SES framework have the potential to make ES assessments more applicable to decision making, by incorporating social aspects within ES assessments. Regression analysis of ES and social-ecological hotspot mapping of ES and SVs provide a preferable approach to identify synergies and trade-offs among ES, and to incorporate cultural ES within ES assessments. Statistical methods (such as Getis-Ord Gi*) could offer the best method to map ES hotspots.

CHAPTER 3: METHODOLOGICAL APPROACH

This chapter introduces the methodological approach used in the study. It presents how the data was collected, pre-processed, and analysed to achieve the overall aim and objectives (specifically objectives 2, 3 and 4). The study area description is provided first, and then questionnaire design and administration. After that, data pre-processing procedures for input in InVEST modelling are given. This is succeeded by an outline of data analysis techniques that incorporate social values (SVs), biophysically modelled services (BpSs), hotspot, and regression analysis.

3.1 STUDY AREA

The study area is located within the Cape Peninsula, situated in the CoCT in the Western Cape Province of South Africa (Figure 3.1). The Cape Peninsula is located at the southwestern tip of Africa and includes an area of internationally recognised aesthetic beauty and extraordinary biodiversity (Cowling, MacDonald & Simmons 1995). The area is designated by the existing Cape Peninsula mountain chain, stretching from Lion's Head and Signal Hill in the North to Cape Point in the South (Helme & Trinder-Smith 2006: 1). The Cape Peninsula covers a ground area of 470km^2 of which approximately 220 km^2 is a conservation area called the Table Mountain National Park (TMNP), (comprising 80% of the mountain chain) (Cowling, MacDonald & Simmons 1995). According to Elmqvist et al. (2013), the TMNP forms a vital conservation area for preserving ES and biodiversity that sustains residents (Elmqvist et al. 2013).

Sites such as Table Mountain, the Silvermine area, and Cape Point within the TMNP were initially declared as individual nature reserves, managed by 14 different authorities during the 1900s (SANParks 2016). These areas were eventually incorporated into the Cape Peninsula Nature area with regards to the Physical planning act in 1983. This was then replaced by the Cape Peninsula Protected Natural Environment (CPPNE) with regards to the Environmental Conservation Act in 1989 (SANParks 2016). However, it was recommended that land within the CPPNE be established as a national park in 1998 and managed by a single management authority South African National Parks (SANParks) (SANParks 2016). The TMNP was then established in 2004 under declaration of the UNESCO serial Cape Floral Region Protected Area World Heritage (CFRPAWHS) (SANParks 2016).

The Cape Peninsula is also largely distinguished physiographically. It has exceptionally great topographical diversity, lengthy and abrupt gradients in yearly rainfall, and a large variation of nutrient-deficient soils (Cowling, MacDonald & Simmons 1995). Consequently, the Cape Peninsula underpins many habitats and ecological groups. The Peninsula falls under the Cape Floristic Region (CFR), an area of remarkably high endemism and diversity, including all taxonomic levels and is acknowledged as one of the six major floral kingdoms within the globe (Cowling, MacDonald & Simmons 1995). One notable characteristic of the Cape Peninsula is its abundance of flora biota (Helme & Trinder-Smith 2006). There are approximately 2285 indigenous plant species within the Cape Peninsula, the highest concentration of plant species within the CFR (Helme & Trinder-Smith 2006). Concerning the Cape Peninsula's vegetation, it mainly consists of fynbos, a fire-driven shrubland, which includes twelve (12) different fynbos species in the Peninsula (Helme & Trinder-Smith 2006). Two internationally recognised landscape features found here include Table Mountain and Cape Point. The Cape Peninsula has a high abundance of fauna for its size, with many amphibian species, reptiles, birds, and terrestrial mammals). The northern section of the Cape Peninsula consists of heavy and light industries, dense residential suburbs, and an extensive road network (Okes & O'Riain 2017). The southern section of the Peninsula consists of lower levels of urban development since most of the southern parts are protected by the TMNP (Okes & O'Riain 2017). The rivers of the Cape Peninsula mostly occur within the TMNP protected area. The Cape Peninsula also includes the CoCT (City of Cape Town) residential suburbs including the City Bowl, Atlantic Seaboard, Southern Suburbs, and the Peninsula. The Peninsula is surrounded by the greater Cape Town area, leading to intensifying threats to scenic quality and biodiversity (Cowling, MacDonald & Simmons 1995).

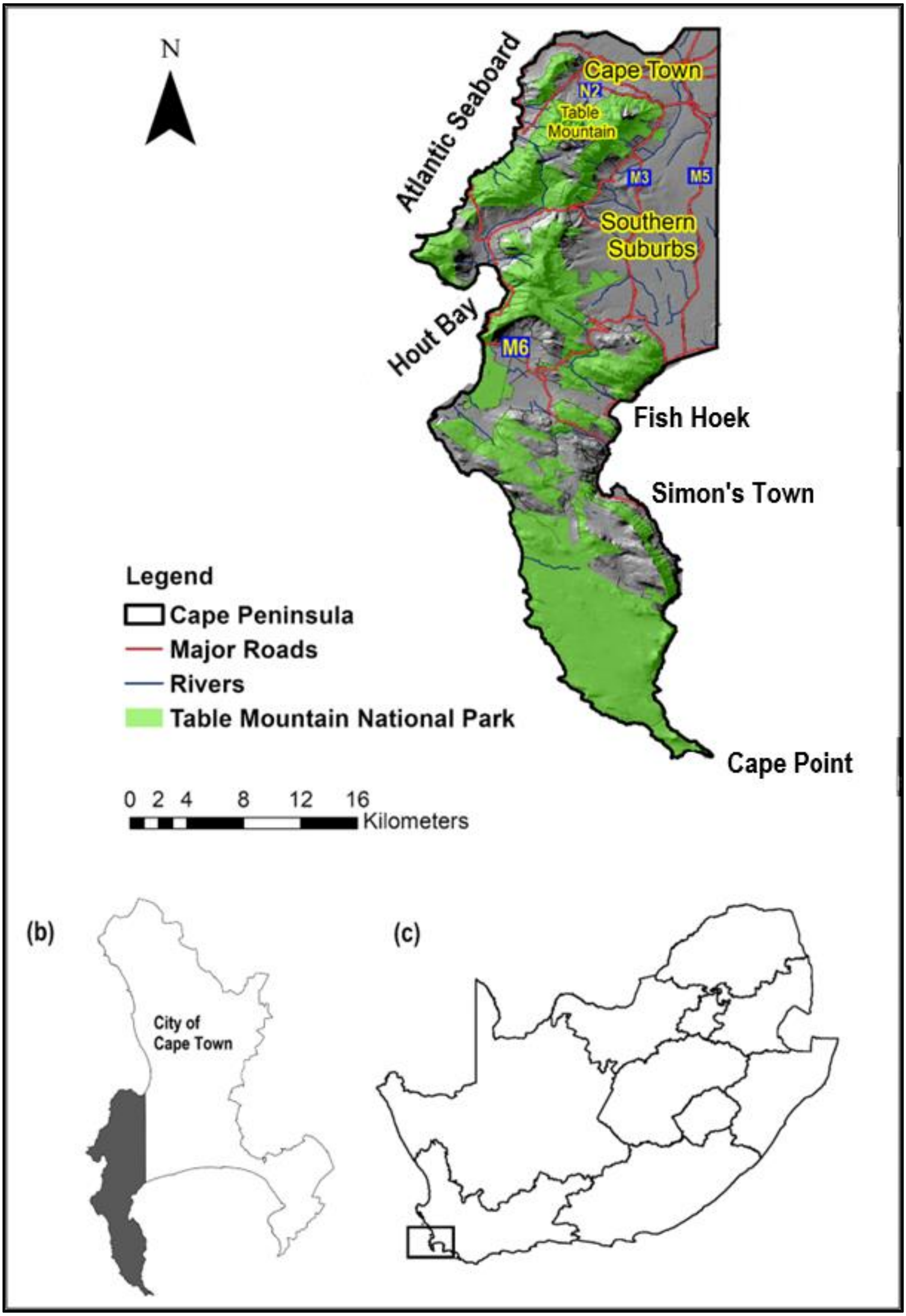


Figure 3. 1 (a) The Cape Peninsula study area, (b) the location of the study area within the CoCT, and (c) the location of the study area within South Africa.

3.2 DATA COLLECTION AND ANALYSIS FRAMEWORK

Questionnaire data was collected online through Facebook using the SUNSurveys application. The questionnaire comprised four sections. The first section consisted of questions relating to respondents' familiarity with the Cape Peninsula. The second section recorded respondents' attitudes towards the uses of the Cape Peninsula. The third section entailed SV allocation and a PPGIS mapping exercise by respondents. Regarding the fourth section, it asked for respondents' demographic information. Data from section three served as input data for SolVES analysis. To prepare the questionnaire input data for SolVES, the questionnaire data were digitised in ArcGIS. SolVES also requires data on environmental characteristics to run along with questionnaire data. Data that characterised the study areas' physical environment was also obtained, such as LULC, slope, elevation, and distance to certain features, to explain the physical context of SVs mapping. To map the four BpSs of carbon storage, habitat quality, flood risk mitigation annual water yield, InVEST required various land cover, biophysical CSV tables, climate, soil and vegetation input data. The respective input datasets were obtained from various sources such as government GIS data portals and past research. Input data for the four BpS models were prepared in ArcGIS for use in InVEST.

The SolVES questionnaire point and environmental characteristics data were processed to generate 11 SVs maps based on the generation of a spatially explicit Value Index. The four BpS maps were generated using various biophysical equations within InVEST. A regression analysis using the Ordinary Least Squares (OLS) tool was done on three independent SV variables and the respective value allocation data, and three dependent BpSs variables. This was to determine whether there is a relationship between SVs and BpSs. Thereafter, hotspot analysis was carried out on cumulative SV and BpS layers using the Getis-Ord Gi* statistic, to produce hotspot and coldspot maps of SVs and BpSs. Figure 3.2 depicts the flowchart of the research methodology followed.

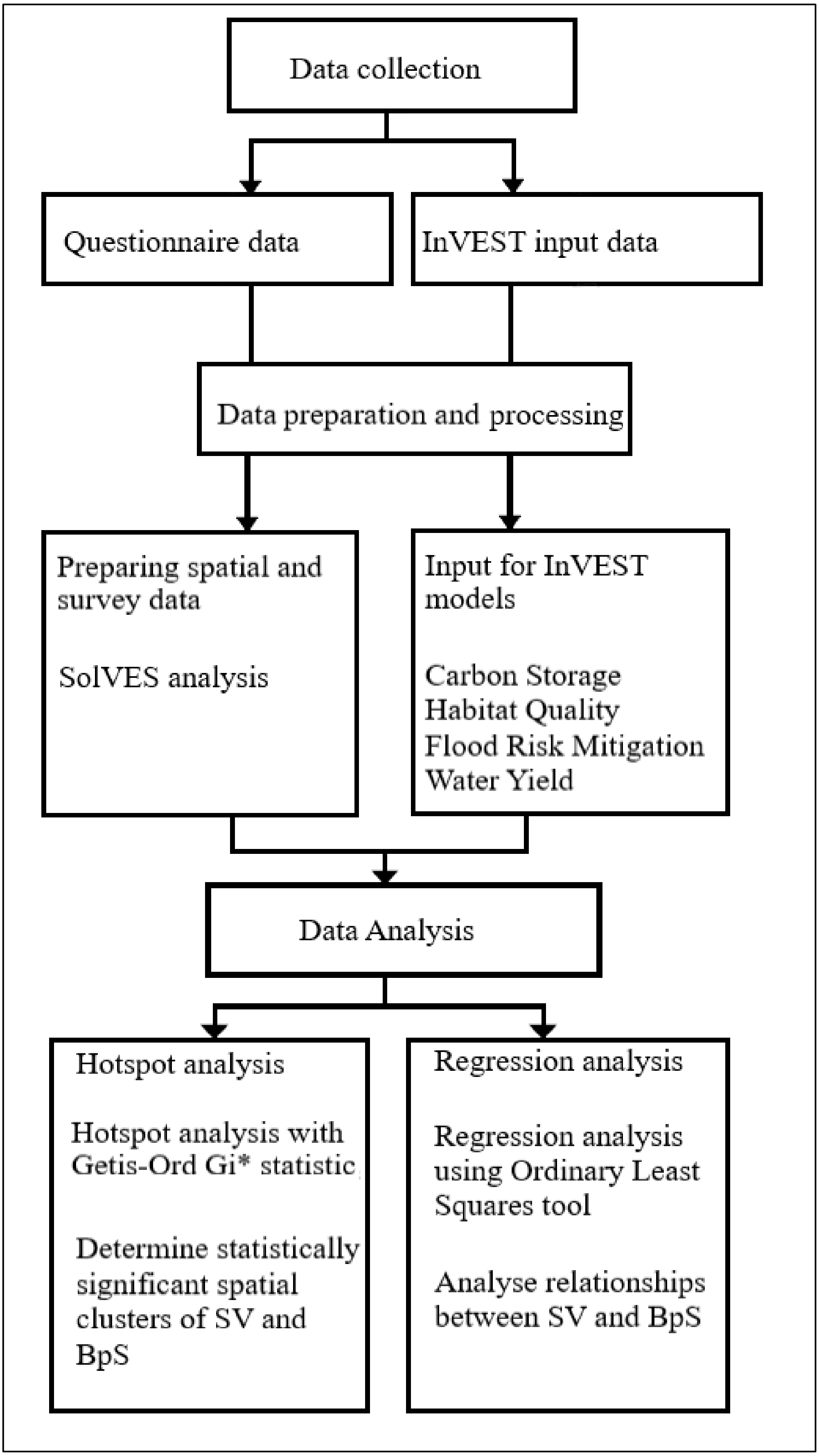


Figure 3. 2 Generalised research methods and materials flow chart demonstrating how the data for this research was collected and analysed.

3.2.1 Questionnaire Survey Design

A questionnaire was used to record opinions about respondents' familiarity with the Cape Peninsula, preferences, and spatial distribution of the SVs. The questionnaire design process is based on the methods from Lin et al. (2017b) and the questionnaire comprised four sections. The first section sought to document respondents' familiarity with the Cape Peninsula (for example when, and how frequently they visit). In the second section, a five-point Likert scale ranging from strongly in favour to strongly oppose, was used to record respondents' attitudes toward the uses of the Cape Peninsula for other types of ES such as recreation (Joshi et al. 2015). Section three consisted of two parts, first asking respondents to designate 100 "preference points" throughout 12 SVs incrementally. The descriptions of these SVs are provided in Table 3.1. The designated preference points indicated the extent to which respondents value each SV. The second part of section three of the questionnaire comprised a Public Participation Geographical Information Systems (PPGIS) mapping exercise, which entailed locating these values on a map of the Cape Peninsula. Respondents were asked to select areas on the map that represented designated SVs selected in the first part of section three of the questionnaire. The map had an approximate scale of 1:110 000 and displayed numerous locations within the Cape Peninsula, for example, Table Mountain, Cape Point, and Boulders Beach. Respondents could list up to ten locations they preferred, and the SVs assigned to those locations. Section four asked for demographic information such as age, gender, and education, to explain the social context of SVs allocations. No personal identification information was asked in the questionnaire.

3.2.1.1 Questionnaire Administration

The online questionnaire targeted recreational users above eighteen (18) years of age on Facebook. For this study, recreational users are those who use the Cape Peninsula for activities such as hiking, walking, running, mountain climbing, sight-seeing, picnicking, biking, camping, and swimming. A pilot questionnaire survey was conducted before a full-scale survey was launched. The pilot questionnaire was sent to the administrator of the Facebook groups. The pilot questionnaire received a total of 10 responses. Necessary adjustments to the questionnaire and structure were then made based on the pilot survey. The questionnaire was made available on various Facebook groups focused on outdoor recreation via Stellenbosch University's official SUNSurveys platform. Administrators of the online Facebook groups were contacted to ask permission to distribute the questionnaire. The pilot questionnaire was sent to the administrator of the Facebook groups. The pilot questionnaire received a total of 10 responses. The questionnaire was finalised after the pilot questionnaire phase. The final questionnaire was administered by making the online SUNSurveys link available to the participating groups. All members of these groups were invited to participate in the questionnaire survey. The online SUNsurveys questionnaire posted on Facebook groups was open for a period from the beginning of February 2022 to the end of May 2022. The SUNsurveys platform also has a feature to prevent duplicates which was used for the questionnaire survey.

Table 3.1 The 12 social value typology definitions used in this study. These are landscape-based values that could be assigned to areas on the Cape Peninsula to determine stakeholder preferences on the landscape.

Value typology	Explanation of value
Aesthetic	Scenery, views, sounds, smells etc.
Biological diversity	Presence of different plant life, wildlife etc.
Cultural	Place to maintain and pass down insight and knowledge, practices and the culture of one's predecessors.
Economic	Provision of fisheries, recreation, and opportunities for tourism, e.g., outfitting and guiding.
Future	Continuation of the Cape Peninsula's current state for future generations.
Historic	Historical and natural human history important for oneself, others, or the nation.
Intrinsic	Area itself, notwithstanding other's perceptions on it.
Learning	Opportunities to study ecosystems with scientific observation or experimentation.
Life-sustaining	Sustainable services such as renewing air, soil and water.
Recreation	Provision of favourite outdoor recreational activities.
Spiritual	Sacred, religious, or spiritually personal reasons.
Therapeutic	Physical and/or mental improvement of people.

Adapted from Sherrouse, Clement & Semmens (2011: 6)

In deciding which online platform to distribute the questionnaire, Facebook has the most engagement across social media platforms, where 63% of those on Facebook make use of the platform at least once daily and 40% use it on numerous occasions during the day (Bonson, Royo & Ratkai 2015). This made Facebook a suitable online platform for distributing the questionnaire.

One drawback frequently experienced with online-based PPGIS questionnaires is low response rates (Brown, Kelly & Whitall 2013; Brown & Kyttä 2014). One way to increase participation rates is to target populations that are probably more interested in the research focus (Saleh & Bista

2017). In this study, recreational users of the Cape Peninsula were targeted, as they presumably frequently use the Cape Peninsula. This also ensures that the project is related to their everyday life, another factor that can draw more interested participants in PPGIS applications (Tang & Liu 2016). Compared to online surveys, hardcopy and onsite PPGIS questionnaire surveys generally lead to more responses, better mapping engagement, and less respondent bias (Brown & Fagerholm 2015). However, due to the COVID-19 pandemic, online survey research was encouraged, and the study also received ethical clearance to conduct the research in that manner. Internet-based PPGIS applications can, however, improve productivity by decreasing data entry time, enhance accuracy in the mapping, and reduce data collection costs (Pocewiz et al. 2012). It also enables users to access information about the topic being discussed and to provide comments on and express opinions about them, from any place with internet access (Garcia et al. 2020).

3.2.1.2 Social Values Map Generation

SolVES was used to generate 11 SV maps with data obtained from questionnaire results. Not all 12 SVs were mapped since questionnaire respondents mapped no spiritual values. SolVES has been used in numerous planning applications, such as forest planning (Sherrouse, Clement & Semmens 2011), watershed planning (Petrakis et al. 2020), and to depict social-ecological hotspots by integrating BpS models (Bagstad et al. 2016; Lin et al. 2017b). Section three’s spatial and non-spatial responses functioned as primary questionnaire data inputs for SolVES analysis.

3.2.2 InVEST Input Data

InVEST was utilised to generate four BpS maps derived from geospatial biophysical data. These four BpS models include Carbon Storage, Annual Water Yield, Habitat Quality, and Flood Risk Mitigation. The input data required for these four InVEST models pertain to spatially explicit files and tabular datasets that correlate to the biophysical attributes of each land cover (Sharp et al. 2020). Table 3.2 provides the specific data inputs of the four BpS models. Input data required for the four InVEST models was obtained from GIS data portals, reports, government websites, and past research. The InVEST tool mainly uses biophysical equations to estimate ES within the chosen study area (Sharp et al. 2020). The models then generate maps where pixels contain the ES information (Sharp et al. 2020). InVEST can map numerous ES that allows users to assess land use trade-offs or management scenarios (Sharp et al. 2020). InVEST has been used frequently in applications such as urban planning (Kadaverugu, Rao & Viswanadh 2020), land use planning (Goldstein et al. 2014), and systematic conservation planning (Lin et al. 2017a). InVEST has also been used to map social-ecological hotspots by integrating social variables (Lin et al. 2017b; Smart et al. 2021).

Table 3.2 InVEST input data requirements.

Model	Input Data	Description	Source
Carbon Storage	Current Land Use/Land Cover	Raster of LULC for each pixel (Sharp et al. 2020: 75).	Geoterraimage (2021)
	Carbon pools	Comma-separated value (CSV) table of LULC classes, comprising information pertaining to carbon stored for LULC classes (Sharp et al. 2020: 76).	Prepared using Excel.
Habitat Quality	Current Land Use/Land Cover	Raster of LULC for each pixel.	Geoterraimage (2021)
	Threat's data	CSV table of threat sources, such as roads. This the threat's relative weight and their impact through space listed in the table (Sharp et al. 2020: 30).	Prepared using Excel.
	Threat's raster	Raster datasets of the threats' distribution and the concentration of each threat.	CoCT (2022)
	Land cover sensitivity to threats	CSV table of every LULC that is believed to be habitat, and its sensitivity to every threat.	Prepared using Excel.
	Half-saturation constant	The scaling parameter/constant which is set by default to 0.5 (Sharp et al. 2020: 33).	Provided by the model.
Flood Risk Mitigation	Watershed vector	Shapefile outlining areas of interest, that are hydrological units: watersheds or sewersheds.	ArcGIS watershed delineation tool, derived from DEM
	Digital Elevation Model (DEM)	Light Detection and Ranging (Lidar) 10m DEM of the Cape Peninsula in metres. Used to delineate the watershed vector.	CoCT (2022)
	Land Cover Map	Raster of LULC for each pixel.	Geoterraimage (2021)
	Soils Hydrological Group Raster	Raster dataset comprising categorical hydrological soil groups (Sharp et al. 2020: 265). Soils hydrological group describes a group of soils which are similar in terms of run-off potential when facing similar storm and cover circumstances.	Ross et al. (2018a)
	Rainfall depth	Numerical value in mm of a single extreme rainfall event.	Rosenzweig et al. (2019)
	Biophysical table	CSV table containing values for each LULC.	Prepared using Excel.

Continued Overleaf

Table 3.2 continued

Annual Water Yield	Average annual precipitation	Raster dataset comprising the average annual precipitation (in mm) for every cell (Sharp et al. 2020: 110).	South African Weather Service (SAWS)
	Average annual reference evapotranspiration	Raster dataset comprising average annual evapotranspiration value (in mm) for every cell (Sharp et al. 2020: 110). Reference evapotranspiration pertains to the possible amount of water lost from plant transpiration and evaporation (Sharp et al. 2020: 110).	ORNL DAAC (2018) and Running (2017).
	Root restrict layer depth	Raster dataset comprising average root restricting layer depth (mm) value for every cell (Sharp et al. 110). Root restricting layer depth is defined as the soil depth where root penetration is largely prevented due to physical or chemical properties (Sharp et al. 2020: 110).	CoCT (2022)
	Plant available water content	Raster dataset comprising plant available water content value for every cell (Sharp et al. 2020: 110). Plant available water content pertains to the portion of water which can be deposited into the soil for plants to utilise (Sharp et al. 2020: 110).	Hengl et al. (2017)
	Land use/land cover	Raster of LULC for each pixel.	Geoterraimage (2021)
	Watershed layer	Shapefile including one polygon for every watershed.	ArcGIS watershed delineation tool, derived from DEM
	Sub watersheds layer	Shapefile including one polygon for every subwatershed.	Same as the watershed layer.
	Biophysical table	CSV table containing values for each LULC.	Prepared using Excel.
	Z parameter	A floating-point value which ranges from 1 to 30 which relates to the periodic distribution of rainfall (Sharp et al. 2020: 111).	Sharp et al. (2020)

3.3 DATA PRE-PROCESSING

3.3.1 Preparing Spatial and Questionnaire Survey Data

All locations respondents listed with associated SVs were digitised in ArcGIS 10.7 (ArcGIS Desktop 2022) in the form of point features, together with value allocation data. The dataset also included seven environmental characteristics which could account for spatial variations in SVs intensity on the Cape Peninsula (Table 3.3). The datasets selected are relevant to the specific social and biophysical context of the study area.

Table 3.3 Description of environmental layers used in the SolVES analysis and the data source of each layer.

Environmental characteristic	Dataset description	Source
Elevation	Light Detection and Ranging (Lidar) Digital Elevation Model (DEM) of the Cape Peninsula in metres.	CoCT (2022)
Distance to Trails (DTT)	Horizontal straight-line distance of every point to a trail pathway in metres.	Derived in ArcGIS using Euclidean Distance Tool
Distance to Water (DTW)	Horizontal straight-line distance of every point to a water body in metres.	Derived as was done for DTT
Distance to Roads (DTR)	Horizontal straight-line distance of every point to a road in metres.	Derived as was done for DTT
Land Cover	Eight class categorial land cover data.	Geoterraimage (2021)
Slope	Percentage slope.	Derived from DEM
Vegetation type	Vegetation cover of dominant plant communities within the Cape Peninsula.	South African National Biodiversity Institute (2018)

SolVES also requires all the raster datasets to share a common coordinate reference system (Sherrouse & Clement 2015). All the datasets were projected to the WGS 1984 UTM Zone 34S coordinate system. The environmental characteristics were used to set parameters in SolVES. DTW, DTT, DTR, elevation, and slope were set as continuous data. Land cover and vegetation type were set to categorical data.

Analysis was carried out “By Survey Subgroups Across Social Value Types” (Figure 3.3). The “Public Use” and “Attitude Preference” settings were left out to analyse all the questionnaire data. The approximate scale of the map used in the questionnaire mapping exercise was 1:110 000. This was the scale of the aerial image map that was prepared in ArcGIS for the questionnaire. This was part of an aerial image of the CoCT. The SolVES manual recommends setting the output cell size to 1:1000 of the map scale, and a cell size of 110 m was subsequently chosen (Sherrouse & Semmens 2015). Thus, the SolVES analysis was conducted at a spatial resolution of 110m. The search radius determines the extent of the data that was used to calculate SolVES statistics, which is by default set to ten times the output cell size, to ensure data near the study area boundary are also included. Survey points were weighted by selecting "Yes" by the "Weight Survey Points" option. The "Threshold Features" option was chosen to lessen the visibility of high-profile structures in the heat maps.

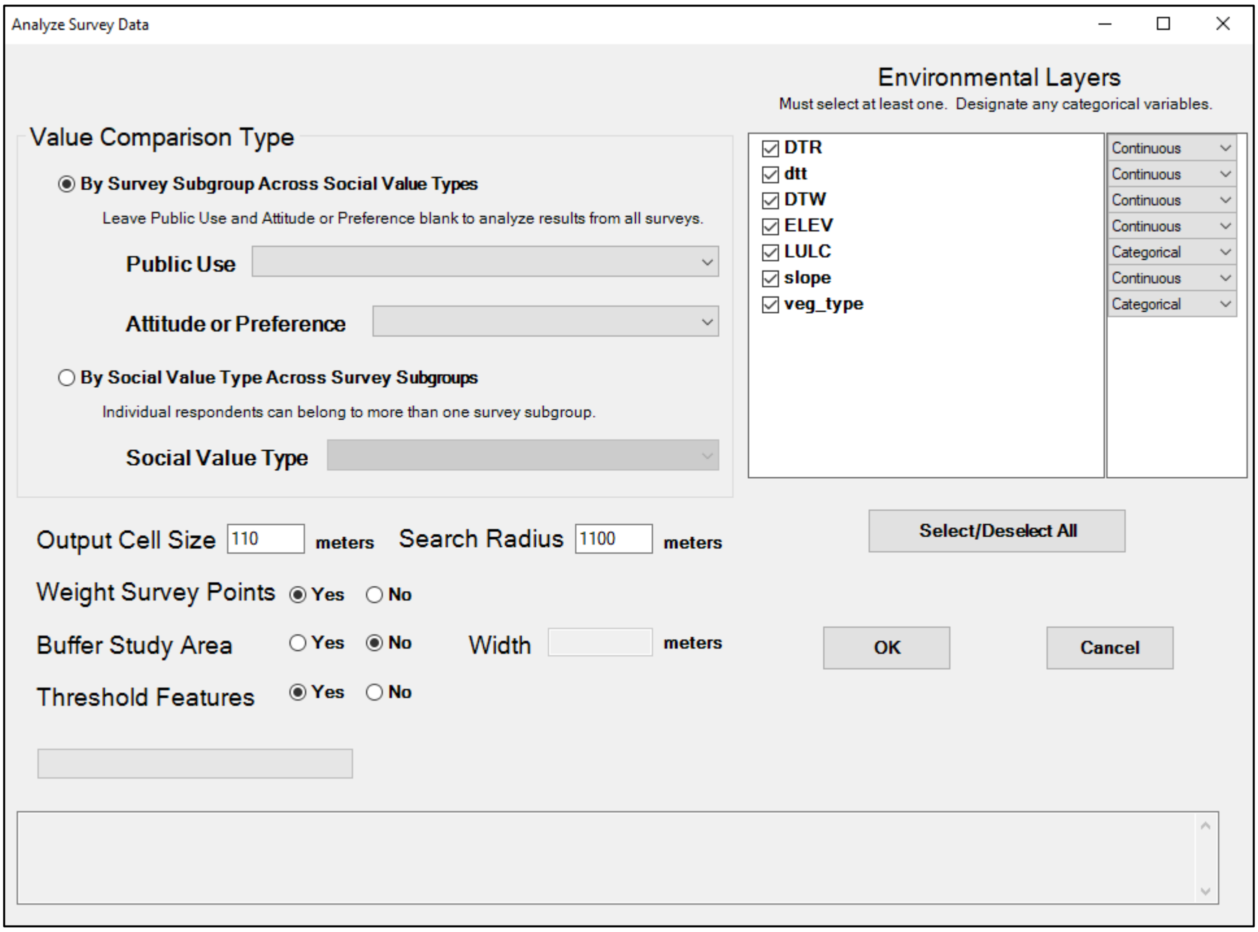


Figure 3. 3 Screenshot of the SolVES Analyse Survey Data Tool.

3.3.2 Input for InVEST models

3.3.2.1 Carbon Storage

Two types of input data were prepared for the InVEST Carbon storage model, including a LULC raster dataset and a CSV format table of carbon values for the four carbon pools and corresponding LULC types. A LULC map for the study area was produced as a required input for the InVEST carbon storage model, LULC data from Geoterraimage (2021) was used. The Geoterraimage (2021) LULC data is part of the South African National Land-Cover (SANLC) 2020 dataset which was produced from multi-seasonal Sentinel 2 20-metre satellite imagery. The LULC dataset consists of 73 land cover classes for various forests, shrubland, waterbodies, wetlands, bare surfaces, cultivated and urban area classes (Geoterraimage 2021). The LULC was then reclassed using ArcGIS into eight main LULC categories: forests, shrubland, grassland, water bodies, wetlands, bare areas, cultivated areas, and urban areas. Table 3.4 describes each of these LULC categories.

Table 3.4 LULC classifications used in the study area and a description of each category.

Land Cover	Description
Forests	Land mainly covered in trees (forests and woodlands).
Shrubland	Bush and shrub cover (Fynbos).
Grassland	Area mainly covered in herbaceous vegetation and natural grass.
Water bodies	Rivers, streams, lakes, reservoirs, and estuaries.
Wetlands	Regions in which the water table remains above the ground for a long time.
Barren areas	Beaches, bare rock surfaces, and sandy areas with no vegetation cover.
Cultivated areas	Land used for crops including croplands, orchards, and vineyards.
Urban areas	Residential, commercial, industrial, and built-up land.

Adapted from Anderson (1976)

Figure 3.4 provides a map of these LULC categories for the Cape Peninsula. This LULC data was also used to model Habitat Quality, Flood Risk Mitigation and Annual Water Yield. LULC data is frequently used as a proxy indicator for the existence of different ES within ES assessments (Sharp et al. 2020).

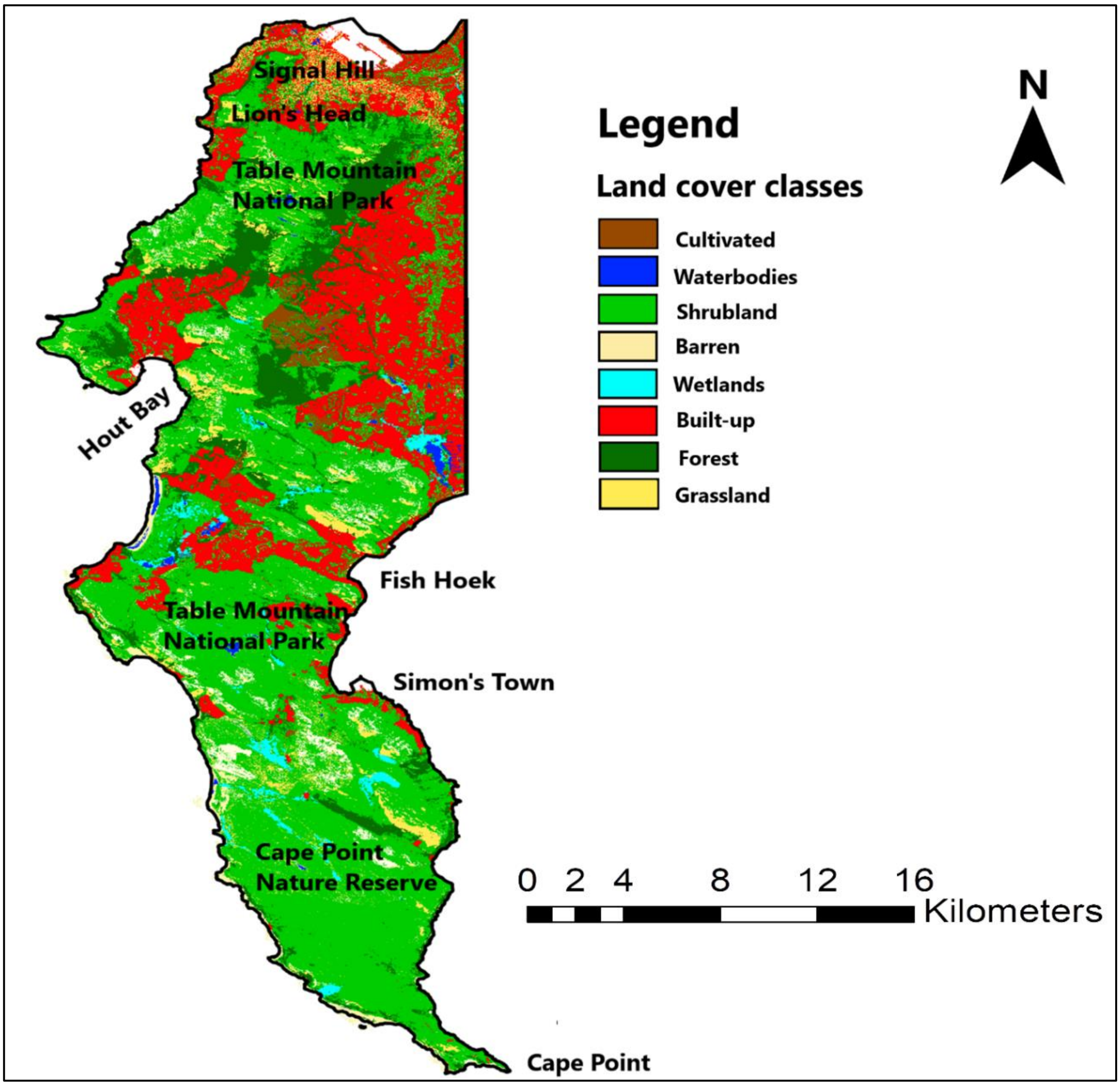


Figure 3. 4 The LULC map used to model BpSs in the study area.

The carbon storage model requires each LULC code (unique integer representing a LULC type, for example 1 for forest, 2 for shrubland) from its attribute table to correspond to the carbon data from the four carbon pools in a CSV table. A CSV table containing carbon pool parameter values was produced in Microsoft Excel (Table 3.5). The table included carbon values for each of the four carbon pools (aboveground biomass, belowground biomass, soil carbon and dead decaying wood matter) for each LULC type (Sharp et al. 2020: 73). Carbon pool values for the four carbon pools were obtained from the IPCC (2006) report. The IPCC (2006) report provides parameter values pertaining to the amount of carbon stock stored within the four carbon pools for agriculture, forestry, and other land uses. According to Sharp et al. (2020), the IPCC (2006) report offers very accurate, but general estimations of the amount of carbon stored in LULC categories. The LULC raster data and the CSV table with the carbon parameter values were incorporated to run with the InVEST 3.9 software (Sharp et al. 2020). The LULC data were projected to the WGS 1984 UTM Zone 34S coordinate system.

Table 3.5 Carbon storage (metric tons) for aboveground biomass (C_above), belowground biomass (C_below), soil carbon (C_soil) and dead organic matter (C_dead) carbon pools, for each LULC type (LULC_Name).

LULC code	LULC_Name	C_above	C_below	C_soil	C_dead
1	Forests	355.46	70	35	12
2	Shrubland	12.7	13	66.7	0.7
3	Grassland	29	23	128	4
4	Waterbodies	1	1	10	0
5	Wetlands	34.45	16.84	227.16	3.41
6	Cultivated areas	4.02	0.76	105.14	0
7	Urban areas	0.01	0	57.63	0
8	Barren areas	0.4	0.83	245	0

3.3.2.2 Habitat Quality

Six types of input data were prepared for the InVEST Habitat Quality model, including a raster LULC, a CSV table for threats data, threat raster datasets, a CSV table indicating the sensitivity of every habitat to every threat, an accessibility polygon, and a half saturation constant. LULC data for the habitat quality model was obtained from Geoterraimage (2021) comprising the eight reclassified LULC types. The LULC map is used to investigate the present condition of habitats within the study area. To determine which LULC types can be considered habitats within the model, each LULC type was assigned a habitat suitability score. In a Microsoft Excel CSV table, different habitat suitability scores were assigned to each LULC type, ranging from 0 to 1. Zero indicated low habitat suitability, and 1 indicated highest habitat suitability (Table 3.6). Habitat suitability scores were adapted based on Hack, Molewiky & Beißler (2020). Forests, shrublands, grasslands, waterbodies, and wetlands were assigned high habitat suitability scores, as they are relatively untouched from human transformation, while built-up areas, cultivated areas, and barren areas were assigned lower habitat suitability scores (Table 3.6).

Table 3.6 The habitat suitability scores (HABITAT) assigned to each LULC type within the study area.

LULC	NAME	HABITAT
1	Forests	1
2	Shrubland	1
3	Grassland	1
4	Waterbodies	0.8
5	Wetlands	0.7
6	Cultivated areas	0.5
7	Urban areas	0.15
8	Barren areas	0.2

Habitat quality pertains to the approximate vegetation extent within the study area and the level of threats towards these habitats such as agricultural lands, roads, railways, and built-up areas (higher impact level of threats result in lower habitat quality, while the inverse can be said about lower-level impacts of threats) (Sharp et al. 2020). Threats can be thought of as human-modified LULC types (for example, urban areas) that trigger habitat fragmentation, edge effects and degradation of adjacent habitats. This study considered five threats to habitat quality in the study area including paved and unpaved roads, railways, built-up areas, and cultivated areas. These are currently threatening biodiversity and ES within the Cape Peninsula according to Cowling et al. (1998), Elmqvist et al. (2013) and Okes & O'Riain (2017). These threats were first mapped using vector datasets of road and railway networks, agricultural areas, and urban areas obtained from the CoCT (2022), indicating the distribution of threats. This vector data was then converted into raster data with grid cell values of 0 and 1, where 0 indicated an absence of these threats and 1 a presence. Four factors are used to establish the impact of these threats on habitats. These include relative impact, maximum effective distance, level of accessibility to habitats, and relative sensitivity of each habitat concerning these threats. Firstly, the relative impact of a threat is indicated by the extent to which these five threats impact habitats. Some threats impact habitats more than others, for example, urban areas can cause double the amount of degradation to adjacent habitats compared to agricultural areas (Sharp et al. 2020). The threats are then assigned weight values from 0 to 1 on a CSV table, where 1 represents the highest impact, while 0 represents the lowest impact on habitat quality (Table 3.7).

Table 3.7 List of threats and each of their maximum effective distance (MAX_DIST), the relative impact of each threat (WEIGHT) and the distance decay function (DECAY).

THREAT NAME	MAX_DIST	WEIGHT	DECAY
Crops	1	0.5	Linear
Railroads	2	0.9	Linear
Roads (Paved)	2	1	Linear
Roads (Unpaved)	2	0.75	Linear
Urban areas	10	1	Exponential

Values of relative impact were obtained from relevant literature (Hack, Molewiky & Beißler 2020; Wu, Sun & Fan 2021). Secondly, the maximum effective distance of the threats indicated the maximum distance at which these threats can impact habitats in kilometres (km). In a Microsoft Excel CSV table, maximum effective distance values in km were assigned to each threat (Table 3.7). When the habitats fall within these distances, it is within the degradation zone of these threats. The model also assumes that the impact of threats decreases over distance. The threats can be listed as linear or exponential distance decay functions (Table 3.7), which explains how these threats decay across space. The impact of each exponential threat which originates from a grid cell toward a habitat cell is expressed as follows (Sharp et al. 2020: 26):

$$i_{rxy} = exp^{-\left(\frac{2.99}{d_{rmax}}\right)d_{xy}} \quad \text{Equation 3-1}$$

While linear threats are expressed as (Sharp et al. 2020: 26):

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}}\right) \quad \text{Equation 3-2}$$

where r is the impact of the threat;

d_{xy} represents the linear distance between cells x and y; and

d_{rmax} represents the maximum effective distance of the threat r's reach.

Values of relative maximum effective distance are based on Wu, Sun & Fan (2021) and Wang & Cheng (2022). These studies determined the maximum effective distance of threats with expert knowledge and with the use of empirical values and the level of accessibility is determined by the level of legal protection (such as protected areas) for habitats. The model assumes the higher legal protection the habitat has, the lower the impacts from threats will be. A polygon layer was used to indicate the level of accessibility, where areas with low accessibility (such as protected areas and nature reserves) were assigned values lower than 1. In contrast, areas with high accessibility (such as extract reserves) were assigned values of 1. Most of the Cape Peninsula's habitats are protected by the TMNP. GIS-protected area data was obtained from the Department of Forestry, Fisheries, and the Environment (2021), indicating protected areas within the Cape Peninsula. Lastly, the relative sensitivity of habitats indicated how susceptible the habitats are to threats. The relative sensitivity of each habitat was indicated using a CSV table containing LULC types considered habitats, and values indicating how sensitive these habitat types are towards specific threats (Table 3.8). These values can range from 0 to 1, where 0 denotes no sensitivity, and 1 indicates high sensitivity towards a specific threat (Sharp et al. 2020). Certain habitats are more impacted by threats than others (Sharp et al. 2020). For instance, grassland habitat is quite sensitive to urban area threats, although it is relatively less sensitive to road threats. Habitat sensitivity values were obtained from Ding et al. (2020) and Wang & Cheng (2022). When a specific habitat is highly sensitive towards a threat, it will face higher degradation from that threat. The half saturation constant is set to 0.5 by default and gives a degradation score based on the first model run. The model should be run a second time and should be set as half of the degradation score.

Table 3.8 The LULC habitats and their relative sensitivity to each threat.

Lucode	LULC Name	Crops	Roads (paved)	Roads (unpaved)	Railroads	Urban areas
1	Forests	0.8	0.5	0.4	0.8	0.85
2	Shrubland	0.72	0.78	0.71	0.6	0.69
3	Grassland	0.75	0.6	0.51	0.6	0.8
4	Waterbodies	0.76	0.72	0.64	0.51	0.72
5	Wetlands	0.8	0.84	0.74	0.64	0.8
6	Cultivated areas	-	0.4	0.2	0.2	0.6
7	Urban areas	0	0	0	0	0
8	Barren areas	0.29	0.7	0.6	0.2	0.61

The degradation score for the first run was 0.082257, and thus a value of 0.04111285 was chosen as the half-saturation constant for the second and final model run. The half saturation constant aids in displaying heterogeneity in quality throughout the landscape (Sharp et al. 2020). The model utilises the half-saturation constant to transform the degradation score into habitat quality scores (Sharp et al. 2020). The threat raster datasets, LULC data and relevant CSV tables for threat parameters and habitat suitability were all used to run the InVEST Habitat Quality Model. All the threat raster datasets were projected to the WGS 1984 UTM Zone 34S coordinate system.

3.3.2.3 Flood Risk Mitigation

Five types of input data were prepared for the InVEST Flood Risk Mitigation model, including LULC data, a watershed vector, a soils hydrological group raster, rainfall depth and a biophysical CSV table. LULC data was obtained from Geoterraimage (2021), consisting of the eight reclassified LULC types. The watershed vector for the study area was prepared using the watershed tool within ArcGIS (ESRI 2022d). The watershed tool used a DEM obtained from CoCT (2022) to delineate a watershed within the study area. This was a 10 m spatial resolution Lidar DEM which is freely available from CoCT (2022). The soil hydrological group raster was obtained from Ross et al. (2018a), which includes a global hydrological soil groups raster dataset with a spatial resolution of 250 m. The raster classifies soils into four different hydrological soil groups: A, B, C and D (Table 3.9) (Ross et al. 2018b). These hydrological soil groups are described in Table 3.9.

Table 3.9 Definition of hydrological soil groups.

Hydrological soil group	Description
Group A	Soils with a low runoff potential and high rate of water transmission, around <10 % clay and 90% sand (Ross et al. 2018b: 2).
Group B	Soils with a relatively low runoff potential and relative rate of water transmission, around 50-90% sand and 10-20% clay (Ross et al. 2018b: 2).
Group C	Soils with a high runoff potential, around <50% sand and 20-40% clay (Ross et al. 2018b: 2).
Group D	Soils having high runoff potential and low rate of water transmission, around 40% clay and <50% sand (Ross et al. 2018b: 2).

Adapted from Ross et al. (2018b)

According to Rosenzweig et al. (2019), a rainstorm occurrence is one rainfall event of 50 mm or higher: thus, a value of 50 mm was chosen for the rainfall depth. The model also requires a biophysical CSV table which contains Curve Numbers (CN) information relating to each LULC type and soil hydrologic group. The CSV table was produced using Microsoft Excel. CN for each LULC type and each hydrological soil group (A, B, C and D) are provided in Table 3.10. CN numbers are values with no physical dimension which pertain to observed approximations for the measurement of run-off depth following rainfall occurrences. These CN values depend on LULC, soil hydrological groups, and antecedent moisture conditions within a specific geographic location (Sharp et al. 2020). These CN values typically range from 0 to 100 indicating tremendous values of minimal and significant run-off production, respectively. CN values were obtained from the United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS) (2007), which provides CN values for various LULC categories. Water bodies and wetlands absorb incoming run-off generated from rainfall events instead of overflowing, therefore values for these LULC types are set to 1.

Table 3.10 Curve number values for each LULC type and hydrologic soil group. The Curve number values are suffixed with each soil hydrologic group A, B, C, and D.

Lucode	LULC name	CN_A	CN_B	CN_C	CN_D
1	Forests	36	60	73	79
2	Shrubland	35	56	70	77
3	Grassland	49	62	74	85
4	Waterbodies	1	1	1	1
5	Wetlands	1	1	1	1
6	Cultivated areas	67	78	85	89
7	Urban areas	51	68	79	84
8	Barren areas	77	86	91	94

The LULC data, watershed vector, subwatershed vector, the soil hydrological group raster dataset, the rainfall depth, and the biophysical properties were served as inputs to run the InVEST Flood Risk Mitigation model. All the datasets were projected to the WGS 1984 UTM Zone 34S coordinate system.

3.3.2.4 Annual Water Yield

Seven types of input data were prepared for the InVEST Annual Water Yield model, including LULC data, watershed and subwatershed vectors, an average annual precipitation raster, an annual reference evapotranspiration raster, a biophysical CSV table and a Z parameter. LULC data was obtained from Geoterraimage (2021). To generate an average annual precipitation raster, annual rainfall data in millimetres (mm) for rainfall stations within the Cape Peninsula was collected for the year 2020 from the South African Weather Service (SAWS). The average annual precipitation raster was then produced using the Kriging interpolation (ArcGIS for Desktop 2022) method in

ArcGIS 7.1, based on point locations of 12 rainfall stations and their annual precipitation amounts in mm. Kriging interpolation offers the best method for hydrological modelling compared to other geostatistical modelling techniques (Louvet et al. 2016). The watershed vector generated for the flood risk mitigation model was also used for the annual water yield model. The average annual evapotranspiration raster (in mm) was derived from the existing Moderate Resolution Imaging Spectroradiometer (MODIS) satellite evapotranspiration data obtained from NASA Oak Ridge Laboratory (ORNL) Distributed Archive Center (DAAC) (2018) and Running (2017). The root restricting layer depth raster was generated using soil depth data in mm from CoCT (2022). This dataset defines the depth of the soil available for plant root growth before reaching bedrock. A biophysical CSV table was generated using Microsoft Excel expressing the characteristics of LULC and soil cover, a plant evapotranspiration coefficient (Kc) and root depth (Table 3.11).

Table 3.11 The biophysical table expressing characteristics of soil cover and each LULC type and LULC code, a plant evapotranspiration coefficient (Kc), and root depth (mm).

Lucode	LULC name	root_depth	Kc	LULC_veg
1	Forests	3500	1	1
2	Shrubland	2500	1	1
3	Grassland	2000	0.865	1
4	Waterbodies	-1	1.05	0
5	Wetlands	-1	1.05	0
6	Cultivated areas	1000	1.1	1
7	Urban areas	-1	0.2	0
8	Barren areas	-1	1	0

Adapted from Sharp et al. (2020)

The root restricting layer depth indicates the maximum root depth of vegetated LULC classes, indicated in mm (Sharp et al. 2020: 107). This is where 95% of vegetated LULC classes' root biomass exists. Root depth values were obtained from Sharp et al. (2020). Sharp et al. (2020) provide the root depth of various vegetated LULC classes. The LULC classes that were not used (non-vegetated LULC classes such as urban areas), the value was set to -1 so the root depth field for these classes could be ignored. The plant evapotranspiration coefficient is utilised to quantify potential evapotranspiration with the use of plant biological attributes to alter the reference evapotranspiration, according to alfalfa (steadily growing, sufficiently watered surface of grass 15 cm in height). The coefficient consists of a value that goes from 0 to 1.5. Plant evapotranspiration coefficient values were obtained from Sharp et al. (2020).

The seasonal factor (Z parameter) can have values from 1 to 30 (Sharp et al. 2020). The average number of yearly rainfall events may be used to estimate the Z parameter, using the formula Z= 0.2*N, where N is the annual number of rainfall events (Moarrab et al. 2022: 7). The Cape Peninsula study area receives an average of 103 rain days per year (Weather Atlas 2022). Thus, the Z parameter was set to a value of 20. Plant available water content was approximated in line with the physical and chemical characteristics of the soil within the study area (Sharp et al. 2020: 107). Plant available water content was premised on Hengl et al. (2017), which provided an available soil water capacity raster dataset at a spatial resolution of 250 m. The annual reference evapotranspiration raster, LULC data, average annual precipitation raster, watershed and subwatershed vectors, a biophysical CSV table, and a Z parameter served to run with the InVEST Annual Water Yield model. All the datasets were projected to the WGS 1984 UTM Zone 34S. The InVEST model resamples all the input raster datasets to match the resolution of the LULC raster. Thus, the InVEST analysis was conducted at a 20 m resolution for the four BpS models.

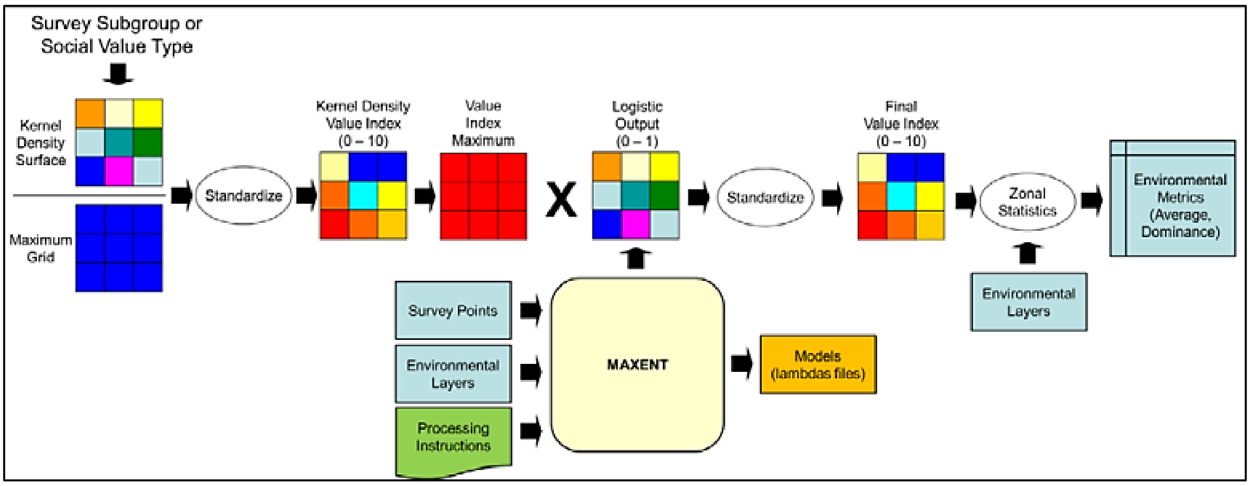
3.4 DATA ANALYSIS

3.4.1 SolVES Analysis

SolVES has a standardised 10-point value index, representing a spatially explicit indicator of SVs for ES (Sherrouse & Semmens 2015: 3; Van Riper et al. 2017). The value index enables a representation of the 11 SVs measures and their respective spatial distribution and intensity (Table 3.1) (Van Riper et al. 2017) SolVES produces the value index established with respondents' respective value allocations and the concentration of points listed from the mapping exercise (Bagstad et al. 2017). Numerous value maps for the study area consisting of a 10-point value index is then generated (Bagstad et al. 2016). To quantify the value index maps, the Maximum Entropy software (MaxEnt) generated logistic surface consisting of values between 0 and 1 (the probability of respondents designating value to an area) is multiplied with a maximum value index layer (Bagstad et al. 2016). The maximum value index layer consists of values between 1 and 10 (relative to the maximum density for every SV normalising a weighted kernel density surface) (Bagstad et al. 2017) (Figure 3.5).

SolVES also produces a relative clustering, dispersion, or randomness measure for all digitised points with Completely Spatially Random (CSR) testing (Sherrouse & Semmens 2015; Van Riper et al. 2017). CSR is quantified with average neighbourhood statistics (Sherrouse & Semmens 2015;

Van Riper et al. 2017). The R-value output of the hypothesis test expresses the ratio associated with the examined distance amongst points to the estimated distance between them (Sherrouse & Semmens 2015; Chen et al. 2020). The z-score quantifies the number of standard deviations that the data point is from the average (Sherrouse & Semmens 2015: 38). The R-value and z-score also determine whether point patterns are clustered (R-values lower than 1, large negative z-scores) or dispersed (R-values larger than 1, positive z-scores) (Sherrouse & Semmens 2015). SolVES then uses the digitised points which were weighted by preference point allocations for each SV indicator to produce weighted kernel density surfaces (Sherrouse & Semmens 2015). Each of these surfaces was standardised and normalised to establish the respective intensity of SVs (Figure 3.5) (Sherrouse & Semmens 2015).



Source: Sherrouse & Semmens (2015: 40)

Figure 3. 5 Summarised procedure flow of SV map production.

The seven environmental characteristics (elevation, DTT, DTW, DTR, land cover, slope, and vegetation type) were analysed using the freely available MaxEnt software (Phillips, Dudík & Schapire 2017). MaxEnt is integrated within SolVES which produces a logistic surface layer and assign a relative measure of regions of where designate SVs were listed according to point locations and inherent environmental characteristics of those locations (Figure 3.5) (Sherrouse & Semmens 2015; Van Riper et al. 2017). The logistic surface layer along with associated models produced by MaxEnt yield spatial estimations of SVs areas according to point data obtained from the participatory mapping exercise (Sherrouse & Semmens 2015). Specifically, this method produced maps predicting the locations where the 11 SVs would be assigned. Geographic zones outlined through integer zones (0 to 10) pertaining to the value index served to produce zonal statistics (majority value for categorical data, mean value for continuous data) that summarised the relationship between assigned SVs and the seven environmental characteristics of the Cape Peninsula (Sherrouse & Semmens 2015; Van Riper et al. 2017).

To determine the predictive power and the suitability of the MaxEnt models predicted for the questionnaire population, the digitised points were divided among training and test data. 25% of the points were retained as test points and the remaining 75% is used as the training points. An Area Under Curve (AUC) calculation within MaxEnt represented the total area for the training and test data from the questionnaire points (Sherrouse & Semmens 2015: 4). Training AUC expresses the model's goodness-of-fit of the study area, and the test AUC expresses the model's predictive capability (i.e., how well the models can be transferred to other regions where no survey data exists) (Sherrouse & Semmens 2015: 41). If AUC values are over 0.90, the model is considered good, if the values are 0.70 to 0.90 the model is useful, and if the values are under 0.70, the model is deemed poor (Sherrouse & Semmens 2015). Furthermore, Maxent additionally quantifies the contribution of each environmental characteristic (the total of the gain from incorporating every environmental layer within each iteration of the training process), as a percentage. The final output of the SolVES model is 11 raster datasets that map the Value Index, which calculates the comparative value for each SV type within the study area. The 11 SVs layers were also added together to generate a single summed SV map, to outline locations of low and high combined SVs.

3.4.2 InVEST Modelling

3.4.2.1 Carbon Storage

Carbon storage was estimated using InVEST by connecting LULC data with the aggregated quantity of carbon stored in four carbon pools. The InVEST carbon storage model utilises a map of the LULC types, and the amount of carbon stored in carbon pools. The model then maps carbon storage densities according to the LULC raster. The carbon density of each LULC type is expressed as follows (Sharp et al. 2020):

$$C_i = C_{i(above)} + C_{i(below)} + C_{i(dead)} + C_{i(soil)} \quad \text{Equation 3-3}$$

where i is the LULC type;

$C_{i(above)}$ represents the carbon density of aboveground biomass in the ith LULC type (tons/ha);

$C_{i(below)}$ represents the carbon density of belowground biomass in the ith LULC type (tons/ha);

$C_{i(dead)}$ represents the carbon density of dead organic matter in the ith LULC type (tons/ha); and

$C_{i(soil)}$ represents the carbon density of soil in the ith LULC type (tons/ha).

The model then approximates the total amount of carbon stored within the study area. The total carbon storage within the study area is then calculated as (Sharp et al. 2020):

$$C_{total} = \sum_{i}^{n} C_i + A_i \quad \text{Equation 3-4}$$

where C_{total} represents the total amount of carbon storage within the study area;

n represents the number of LULC within the study area; and

A_i represents the area of each LULC type (ha).

The model then outlines raster outputs of carbon storage. Outputs of the Carbon Storage model are conveyed as Megagrams (Mg) of carbon per pixel.

3.4.2.2 Habitat Quality

Habitat Quality was modelled with forest areas, grasslands, shrublands, water bodies, and wetlands selected as habitats within the LULC raster. The model integrates the LULC raster and threat raster datasets and parameters to generate Habitat Quality maps. The model calculates the total threat according to the four factors of the relative impact of each threat, maximum effective distance, level of accessibility, and relative sensitivity of each habitat type to each threat within the study area (Sharp et al. 2020: 26).

The InVEST Habitat Quality model then calculates the total threat level as follows (Sharp et al. 2020: 27):

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Yr} \frac{W_R}{\sum_{r=1}^{R} W_r} \times r_y \times i_{rxy} \times B_x \times S_{jr} \quad \text{Equation 3-5}$$

where Dxj represents the total threat level;

r represents the threat;

y indexes every cell on the threat raster of r;

Y_r is the group of grid cells on the threat raster of r;

W_r is the weight of each threat;

i_{rxy} is the impact of each threat;

B_x is the level of accessibility within the grid cell x; and

S_{jr} is the sensitivity score of the habitat j towards threat r.

Habitat quality is subsequently converted from each cell's degradation score by utilising the half-saturation function. The higher a grid cell's degradation score, the lower the habitat quality. Habitat quality is then computed as follows (Sharp et al. 2020: 27):

$$Q_{xj} = H_j \left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right) \qquad \text{Equation 3-6}$$

where Q_{xj} represents the quality of habitat within cell x of habitat type j;

H_j is the habitat suitability score of the LULC type j

D_{XJ}^Z is the total threat level; and

z and k are the scaling parameters.

Based on the LULC types and the five threats, the Habitat Quality model produced a map with habitat quality values between 0 and 1, where 0 expresses the lowest quality habitat and 1 expresses the best quality habitat (Sharp et al. 2020).

3.4.2.3 Flood Risk Mitigation

Flood Risk Mitigation was computed according to the built-up area, soil characteristics and LULC types in the study area. Flood Risk Mitigation is calculated as the amount of flood retention and run-off production because of green spaces. For each pixel that consisted of a LULC type and soil attributes, run-off (in mm) was calculated with the Curve-Number method as follows (Sharp et al. 2020: 263):

$$Q_{p,i} = \frac{(P - \lambda S_{max,i})^2}{(P + (1-\lambda) S_{max,i})} \ if \ P > \lambda S_{max,i} \ otherwise \ Q_{p,i} = 0 \qquad \text{Equation 3-7}$$

In which

$$S_{max} = \frac{25400}{CN_i} - 254 \qquad \text{Equation 3-8}$$

where Q is the estimated run-off;

i represents each pixel;

P pertains to the design storm depth;

$S_{max,i}$ (Quantified in mm), represents the possible retention in mm;

$\lambda S_{max,i}$ represents the rainfall depth required to generate run-off; and

CN represents the Curve Number for each LULC type and soil attributes.

Run-off retention for each pixel is subsequently calculated as (Sharp et al. 2020: 264):

$$R_i = 1 - \frac{Q_{p,i}}{P}$$ Equation 3-9

where Ri represents run-off for each pixel.

Run-off retention volume for each pixel is then calculated as (Sharp et al. 2020: 264):

$$R\_m3_i = R_i \times P \times PixelArea \times 10^{-3}$$ Equation 3-10

where R_m3_i is the run-off retention for each pixel.

The model then produces a map of the run-off retention (the amount of water retained per pixel) volume in m^3. The resulting map is a raster with run-off retention values depicted as dark and light blue pixels. These values represent the amount of water retained by the landscape per pixel.

3.4.2.4 Annual Water Yield

Annual Water Yield pertains to how much water (mm) is contributed from different areas within the study area (Sharp et al. 2020). The ET segment of the annual water balance is estimated with average annual precipitation, plant available water content, a Budyko curve (Fu 1981; Zhang et al. 2004), and a seasonality factor (Z parameter) which expresses the distribution and volume of regular rainfall (Sharp et al. 2020: 105). It calculates the amount of run-off water for each pixel as precipitation minus water that is lost because of evapotranspiration. The evapotranspiration is calculated differently for vegetated and non-vegetated LULC types. The model subsequently aggregates and provides the average water yield to the subwatershed level.

Annual Water Yield was then calculated for every pixel as follows (Sharp et al. 2020: 106):

$$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right) \times P(x)$$ Equation 3-11

where Y represents the annual water yield for each pixel;

x represents each pixel;

$AET(x)$ represents the actual evapotranspiration for each pixel x; and

P represents the annual precipitation within pixel x.

Concerning vegetated LULC types, the evapotranspiration segment of the water balance, is derived with the Budyko curve as follows (Sharp et al. 2020: 106):

$$\frac{AET(x)}{P(x)} = 1 + \frac{PET(x)}{P(x)} - [1 + \left(\frac{PET(x)}{P(x)}\right)^{w}]^{1/w}$$ Equation 3-12

in which

$$PET(x) = K_c(l_x) \cdot ET_0(x)$$ Equation 3-13

where $w(x)$ represents the plant-available water coefficient;

$PET(x)$ represents the potential evapotranspiration;

$(K_c)(l_c)$ pertains to the plant evapotranspiration coefficient associated to the LULC type l_x within pixel x; and

$ET_0(x)$ represents the reference evapotranspiration within pixel x.

The plant-available water coefficient $w(x)$ represents a dimensionless value which distinguishes physical climatic-soil conditions and is calculated as follows (Sharp et al. 2020: 106):

$$w(x) = Z\frac{AWC(x)}{P(x)} + 1.25$$ Equation 3-14

where Z represents the Zhang parameter;

$AWC(x)$ represents the volumetric (mm) plant available water content; and

1.25 represents the lowest value of $w(x)$, and is considered as the value for bare soil (when root depth is 0).

$AWC(x)$ defines how much water which can be stored and discharged within the soil for a plant to consume (Sharp et al. 2020: 107). It is calculated when the plant available water capacity is multiplied by the minimum root restrict layer depth and vegetation rooting depth (Sharp et al. 2020: 107):

$$AWC(x) = Min(Rest.layer.depth, root.depth) \cdot PAWC$$ Equation 3-15

where $Rest.layer.depth$ is the root restrict layer depth;

$root.depth$ represents the vegetation rooting depth; and

$PAWC$ represents the plant available water capacity.

Vegetation rooting depth typically pertains to the depth, “at which 95% of a vegetation type’s root biomass occur” (Sharp et al. 2020: 107). Plant available water capacity refers to, “the difference between field capacity and wilting point” (Sharp et al. 2020: 107).

Concerning non-vegetated LULC types, actual evapotranspiration is calculated precisely from the reference evapotranspiration as follows (Sharp et al. 2020: 107):

$$AET(x) = Min(K_c)(l_c) \cdot ET_0(x), P(x)) \qquad \text{Equation 3-16}$$

where $ET_0(X)$ represents the reference evapotranspiration; and

$(K_c)(l_c)$ represents the evaporation element for every LULC type.

The model output finally expresses the mean and total annual water yield per pixel in mm. The resulting map is a raster with annual water yield values depicted as dark and light blue pixels. These values represent how much water runs off on the landscape annually per pixel.

3.4.3 Hotspot Analysis

In this study, hotspot analysis extends to contemporary hotspot mapping methods of social and biophysical variables (Bagstad et al. 2016; Smart et al. 2021). The Getis-Ord Gi* statistic was used to delineate SVs and BpS hotspots, coldspots, and overlapping areas within ArcGIS (Getis & Ord 2010; ESRI 2021a). The Getis-Ord Gi* will indicate local spatial autocorrelation between summed SVs and BpSs values. The Getis-Ord Gi* tool at the α= 0.05 significance level (i.e., 95% confidence level) determines statistically significant spatial clustering of high values (hotspots) and low values (coldspots) (ESRI 2021a: 1). This study sought to determine clustering in SVs and BpSs within the Cape Peninsula study area. The Getis-Ord Gi* statistic computes p-values and z-scores which determine clustering of high data values (low p-value and high z-score) and low data values (low p-value and low negative z-score) (ESRI 2021a: 1). The z-score expresses the statistical significance of hotspots outlined through the Gi* statistic (ESRI 2021a: 1). At the 0.05 significance level, the z-score must be smaller than -1.96 or larger than 1.96 to be designated statistically significant (Figure 3.6) (ESRI 2021a :1: Zhu et al. 2010). Therefore, in this study, grid cells containing a z-score larger than 1.96 were outlined as hotspots of SVs and BpS values at the 0.05 significance level, which mapped hotspots of SVs and BpSs.

The Getis-Ord Gi* statistic is calculated as follows (ESRI 2021a: 1):

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2}{n-1}}}$$ Equation 3-17

In which

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$ Equation 3-18

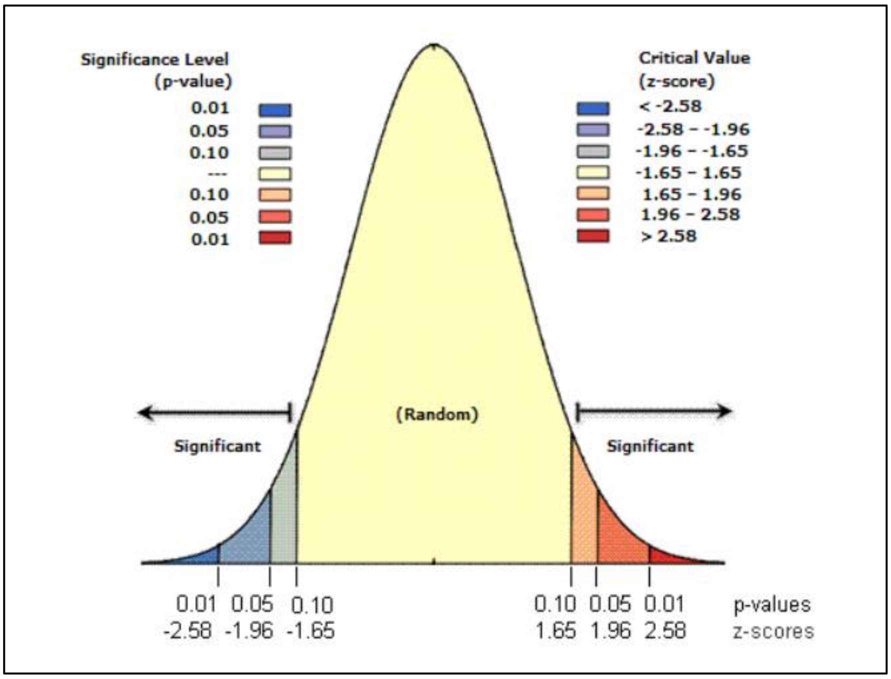
$$S = \sqrt{\frac{\sum_{j=1}^{n} x_i^2}{n} - (\overline{X})^2}$$ Equation 3-19

where w_j Represents the attribute value for the feature j;

$w_{i,j}$ Represents the spatial weight between feature i and j; and

n Is equivalent to the overall number of features.

Clusters of low values pertain to grid cell values with a z-score smaller than -1.96, which outlined coldspots of SVs and BpSs (Zhu et al. 2010).



Source: (ESRI 2021a: 1)

Figure 3. 6 P-value and z-scores for 90%, 95% and 99% confidence levels. The blue represents coldspots delineated and the red represents hotspots delineated.

One advantage the Getis-Ord Gi* statistic possesses compared to other hotspot delineation approaches, such as Local Moran's I (Anselin 1995), is that it can, "distinguish between hotspots/coldspots of clustered high value and clustered low value clusters" (Bagstad et al. 2016:

13). This enables a possible comparison between SVs and BpSs hotspots and coldspots, and different suitable management implications can be suggested for these areas. The results will be a raster dataset which indicates local BpSs and SVs hotspots and coldspots. The 11 SVs and four BpS layers were equally weighted by normalising each layer to values between 0 and 1. The normalised 11 SVs and four BpS models were then summed using the Weighted Sum tool in ArcGIS (ESRI 2022b), to produce cumulative SV and BpS layers. The hotspot analysis was then performed on the cumulative SV and BpS layers using ArcGIS 10.7.

3.4.4 Regression Analysis

Following Bagstad et al. (2016), a regression analysis was conducted to compare spatially explicit SVs and BpSs. Regression analysis assesses the relationships between two or more feature characteristics (Scott & Janikas 2010). To measure the relationship between SVs and ES values, three univariate models were produced contrasting SVs (dependent variable, Table 3.1) and BpS models (independent variable, Table 3.2). The life-sustaining value (respondent value for sustainable services such as renewing air, soil and water) was contrasted with BpS models of (1) carbon storage, and (2) water yield. The questionnaire's definition of the life-sustaining value is generally similar to descriptions of regulating ES (Bagstad et al. 2016). As a result, the life-sustaining value was contrasted to modelled ES of clean air (carbon storage) and water (water yield). The biological diversity value was contrasted with (3) habitat quality. Habitat quality is not exactly similar to the questionnaire's definition of biological diversity, although the InVEST habitat quality definition comes the closest to biological diversity.

The Ordinary Least Squares (OLS) linear regression analysis tool within ArcGIS 10.7 was used. The regression analysis is calculated as follows (ESRI 2021b: 1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \qquad \text{Equation 3-20}$$

where Y is the dependent variable;

β is the regression coefficient, expressing the significance and type of relationships the dependent variable has to the independent/exploratory variables;

X is the Independent/Explanatory variables; and

ε is the divergence of the point from the regression line (random error term).

The OLS tool produces a global model of relationships between a group of data variables (Scott & Janikas 2010). A global model produces a single equation to express the relationship between dependent and independent variables (Scott & Janikas 2010). The OLS tool models a dependent variable regarding its relationships to a group of explanatory variables (ESRI 2021b). Every independent variable consists of a regression coefficient. The model fit can be evaluated concerning six rules: (1) the coefficients contain the anticipated signs; (2) there is no redundancy among the independent variables; (3) the coefficients have statistically significant values; (4) the residuals (model under/over predictions) are distributed ordinarily; (5) the adjusted R-square value is strong; and (6) the residuals are not spatially autocorrelated (Table 3.12) (ESRI 2021b).

Table 3.12 The six rules of the OLS tool and a description of each.

OLS rules	Explanation of rules
1.	The sign (+/-) linked with each coefficient outlines if a relationship is positive or negative. A positive coefficient suggests that the relationship is positive. A negative coefficient suggests that the relationship is negative.
2.	Redundancy with independent variables is outlined with a VIF (variance inflation factor) value. If any of the variables have a VIF value above 7.5, it entails that one or several variables have an identical relationship and should be removed from the model.
3.	Probability and Robust probability determine whether the coefficient is statistically significant. An asterisk beside the probability expresses whether the coefficient is statistically significant. Smaller probabilities have larger significance than larger probabilities.
4.	Residuals (model over/under predictions) from a good model fit will have a random spatial pattern (no clustering of over/under predictions). The Jarque-Bera test quantifies if the regression model residuals are ordinally distributed. This test should ideally not be statistically significant otherwise the model is biased. This could indicate that one or more important independent variables are missing.
5.	Adjusted R squared values go from 0 to 1.0 which indicates how much of the dependent variables' variation is described by the model. This evaluates model performance. Ideal values would be 0.5 and higher.
6.	Lastly, to determine whether residuals are not spatially autocorrelated (clustering of over and under predictions), the Spatial Autocorrelation tool within ArcGIS can be used. This tool outlines whether residuals display a random spatial pattern. A random spatial pattern of residuals and no clustering or dispersion indicates a correctly specified model. The model is not reliable if residuals are spatially clustered.

Adapted from ESRI (2021b)

The dependent variable used in the regression analysis was digitised point locations listed by questionnaire respondents for the life-sustaining and biological diversity value types. These point locations were overlaid with the corresponding independent variable BpS layers of carbon storage, habitat quality, and annual water yield. Based on Bagstad et al. (2016: 8), the amount of preference points designated by every respondent to an SV type was divided by the number of points they listed for the SV type. For example, if a respondent designated 50 preference points to the biological diversity value, and recorded two points from the map, each point was assigned a value of 25. The corresponding BpS values at those point locations were then extracted using ArcGIS's "Extract values by points" tool (ESRI 2022a). This was to determine the strength of the relationships between questionnaire life-sustaining and biological diversity value types and BpS models of carbon storage, habitat quality and annual water yield. Jarque-Bera values were statistically significant for all three relationships. Thus, a Box-Cox power transformation was applied to transform the dependent variable for each model (Sakia 1992; Bagstad et al. 2016). The Box-Cox transformed tool subsequently decreased Jarque-Bera values for the three relationship models.

The Moran's I tool within ArcGIS (ESRI 2022c) was used to determine whether model residuals were not spatially autocorrelated. The tool uses an I index to determine whether there is spatial autocorrelation among a group of features. A Moran's I index value of -1 indicates a dispersed spatial pattern (ESRI 2022c). Values of 0 indicate a random spatial pattern (ESRI 2022c). And a value of +1 indicates spatial clustering (spatial autocorrelation) (ESRI 2022c). The tool also calculates a z-score to determine statistical significance (i.e., whether there is spatial clustering). At $\alpha = 0.05$, statistical significance is indicated with a z-score of lower than -1.96 and larger than 1.96 (ESRI 2022c). Spatial autocorrelation of model residuals determines the reliability of OLS results, where model residuals that are spatially autocorrelated are not reliable (ESRI 2022c). Model residuals that are not spatially autocorrelated indicate reliable OLS results.

The regression analysis then determined whether the questionnaire population recognised important areas of ES provision (Bagstad et al. 2016).

CHAPTER 4: RESULTS

This chapter provides the results of this study based on the questionnaire survey data, social values (SVs), biophysically modelled services (BpSs), hotspot and regression analysis of SVs and BpSs. The questionnaire survey results are provided first, then the spatial distribution of SVs. This is followed by the spatial distribution of BpSs, ecosystem services hotspot and regression analysis.

4.1 QUESTIONNAIRE SURVEY

The results of the questionnaire survey demographics are outlined in Figure 4.1. A total of 47 responses were collected through the online questionnaire survey. Most respondents had a tertiary qualification with 30% listing a master's degree. This was followed by 23% with an honour's degree, 17% possessing an undergraduate degree or a diploma, 7% with a PhD degree and 6% with a matric certificate and lower (see Figure 4.1a). Regarding the gender divide, 55% of respondents were female while 45% were male (Figure 4.1b). Most of the respondents reside in the Southern Suburbs of Cape Town (64%), followed by the City Bowl (18%), Blaauwberg and the Peninsula (7% each), and the Atlantic Seaboard at (4%) (Figure 4.1c). For this study, occupations were grouped into the following sectors: some of the respondents had jobs in the environment and agriculture sector: business, consulting and management; education; media; IT; healthcare; engineering and manufacturing; sales; accounting and banking; and law (Figure 4.1d). The respondents' largest job sector were business, consulting, and management (19%), followed by the environment and agriculture sector, media, and education (11%) (Figure 4.1d). Next are engineering and manufacturing, and healthcare (8% each) (Figure 4.1d). Accountancy, banking and finance, law, and sales each made up 4% of the respondents (Figure 4.1d). Retired and unemployed respondents each comprised 4% of the respondents (Figure 4.1d). The income groups of the respondents were somewhat evenly represented. About 22% of the respondents are within the high monthly income category (R30 000-R40 000 per month), and 15% earned over R60 000 (Figure 4.1e). Those earning between R10 000 and R20 000 and R20 000 and R30 000 also each represented 15%. Respondents earning between R0 and R10 000, R40 000 to R50 000, and R50 000 to R60 000 represented the lowest of the respondents at 11% each (Figure 4.1e). The age demographics indicated that most of the respondents were between 46 and 55 years old (36%), the least were between 18 and 25 (7%), and 65 years and above (7%) (Figure 4.1f). Those aged between 56 and 65 represented 25%. Respondents aged from 26 to 35 and 36 to 45 years each represented 11% (Figure 4.1f).

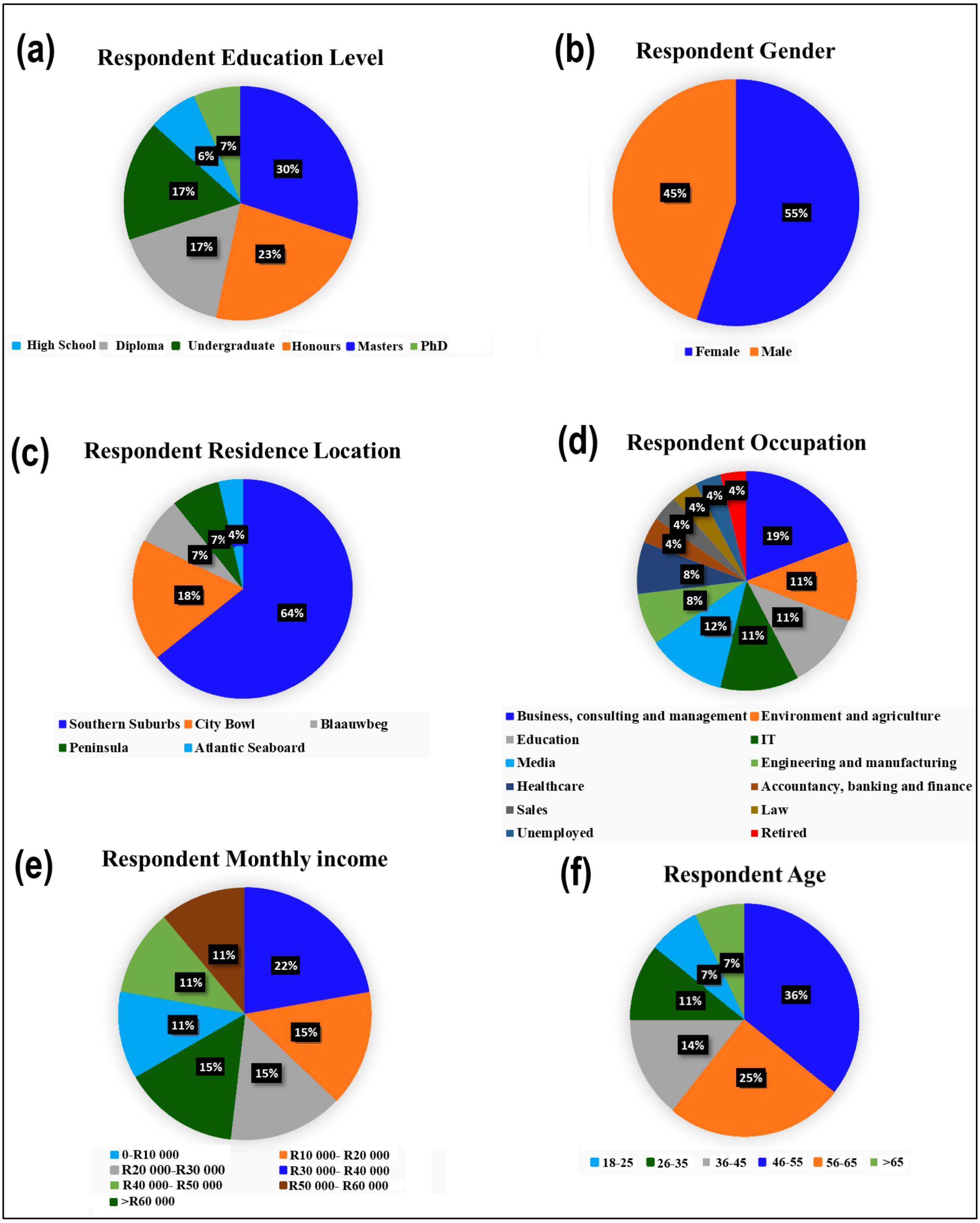


Figure 4. 1 Demographics of the questionnaire respondents. The pie graphs depict the respondent demographics for (a) education level, (b) gender, (c) residence location, (d) job occupation, (e) level of monthly income, and (f) age.

To summarise, most of the questionnaire respondents were fairly educated with 30% possessing a master's degree. About 55% of the respondents are female and 45% are male. The majority of the respondents reside in the Southern Suburbs of Cape Town (64%). The largest job sector of the respondents was within business, consulting, and management, followed by environment and agriculture, and then education. The income groups of the respondents were somewhat equally represented, although 22% are within a high monthly income category of R30 000 to R40 000 per month. The questionnaire population was generally older and most of the respondents (36%) were between 46 and 55 years of age.

4.2 SPATIAL DISTRIBUTIONS OF SOCIAL VALUES

Table 4.1 lists SolVES statistics of R-values and z-scores, the number of times relative SVs were listed by questionnaire respondents, and the maximum value index expresses the relative importance of each SV. A total of 237 points were recorded by the respondents in the questionnaire mapping exercise including 11 of the 12 SVs. SV types recorded include aesthetic, biological diversity, cultural, economic, future, historic, intrinsic, learning, life-sustaining, recreation, and therapeutic values. No spiritual values were registered by the respondents. Biological diversity, future, and recreation values were relatively clustered (R-values nearer to 0 than 1, negative z-score). These SVs had high counts and/or high preference within the Cape Peninsula. Aesthetic, cultural, and therapeutic values were relatively dispersed (R-value larger than 1). Cultural values had the highest R-value (R-Value= 2.05071) while recreation had the lowest R-value (R-value= 0.50501). The cultural value also had the highest z-score (Z-score= 4.494085), while recreation had the lowest z-score (Z-score= -7.086332).

Table 4.1 SolVES statistics of R-values and z-scores, which are indicators of spatial clustering. Count expresses the number of times relative SVs were listed by questionnaire respondents. Maximum value index expresses the relative importance of each SV, with 10 indicating the highest relative importance, and 0 indicating the lowest relative importance.

Social Value Type	Count	R-value	Z-score	Maximum Value Index
Aesthetic	24	1.101531	0.951554	8
Biological diversity	54	0.542242	-6.435224	10
Cultural	5	2.05071	4.494085	5
Economic	10	0.935934	-0.38758	5
Future	18	0.371774	-5.098979	7
Historic	6	0.611	-1.821469	5
Intrinsic	6	0.621335	-1.774442	5
Learning	19	0.776419	-1.864414	6
Life-sustaining	18	0.982932	-0.138534	6
Recreation	56	0.50501	-7.086332	10
Spiritual	0	-	-	-
Therapeutic	21	1.16518	1.448098	6

A maximum value index between 5 and 10 was recorded for all the SVs. Biological diversity and recreation recorded the highest value index (Value Index = 10), and then aesthetic values (Value Index = 8), and future values (Value Index = 7). This indicates the highest relative importance these values represented for the respondents. Cultural, economic, historic, and intrinsic values received the lowest maximum value index (Value Index = 5), indicating the lowest relative importance of these values to the respondents. Table 4.2 lists SolVES MaxEnt training and test AUC statistics. All 11 SVs yielded a training value of over 0.9, indicating models with a good suitability fit (training AUC). While the future, learning and therapeutic values had a test AUC over 0.8, indicating useful predictability of the models, the remainder of the eight SVs recorded test AUC values of over 0.9 (indicating good predictability of the models).

Table 4.2 SolVES Maxent training and test AUC statistics, indicating the model fit (training AUC) and predictability (test AUC) of the model.

Social Value Type	Training AUC	Test AUC
Aesthetic	0.95	0.95
Biological Diversity	0.97	0.97
Cultural	0.97	0.97
Economic	0.96	0.9
Future	0.94	0.82
Historic	0.98	0.96
Intrinsic	0.93	0.93
Learning	0.96	0.85
Life-sustaining	0.96	0.98
Recreation	0.95	0.93
Spiritual	-	-
Therapeutic	0.92	0.83

Figure 4.2 depicts maps of the spatial distribution of SVs and relative value indices. Aesthetic values are relatively clustered around Table Mountain, and the Newlands Forest. Biological diversity and recreation values were highly valued at Table Mountain, the Kirstenbosch Gardens, the Newlands Forest, the Tokai Forest, and the Silvermine Nature Reserve. Cultural values occurred over the smallest spatial gradient and had no large areas of spatial clustering. Economic values were somewhat clustered around the Kirstenbosch Gardens, the Newlands Forest, and the Tokai Forest. Future values were highly clustered around Table Mountain and Devil’s Peak, the Orange Kloof Nature Reserve, and the Silvermine Nature Reserve. Future values were also somewhat clustered around the areas of Simon’s Town, Elsie’s Peak, Boulders Beach, and Cape Point. Historic values were mainly clustered around Kirstenbosch and the Tokai Forest. Intrinsic and therapeutic values generally occurred over a larger spatial distribution compared to the other nine SVs, with particular clustering occurring around the areas of Table Mountain, Lion’s head, the Kirstenbosch Gardens, the Newlands Forest, the Tokai Forest, and the Silvermine Nature

Reserve. Learning values were particularly clustered around Table Mountain, the Newlands Forest, Kirstenbosch, and the Tokai Forest. Life-sustaining values were clustered around Table Mountain, the Newlands Forest, the Kirstenbosch Gardens, and the Tokai Forest. Figure 4.3 depicts the sum of all 11 SVs maps as a single summed SV map. High-value indices were located around Table Mountain, the Kirstenbosch Gardens, the Newlands Forest, the Tokai Forest, the Orange Kloof Nature Reserve, and the Silvermine Nature Reserve.

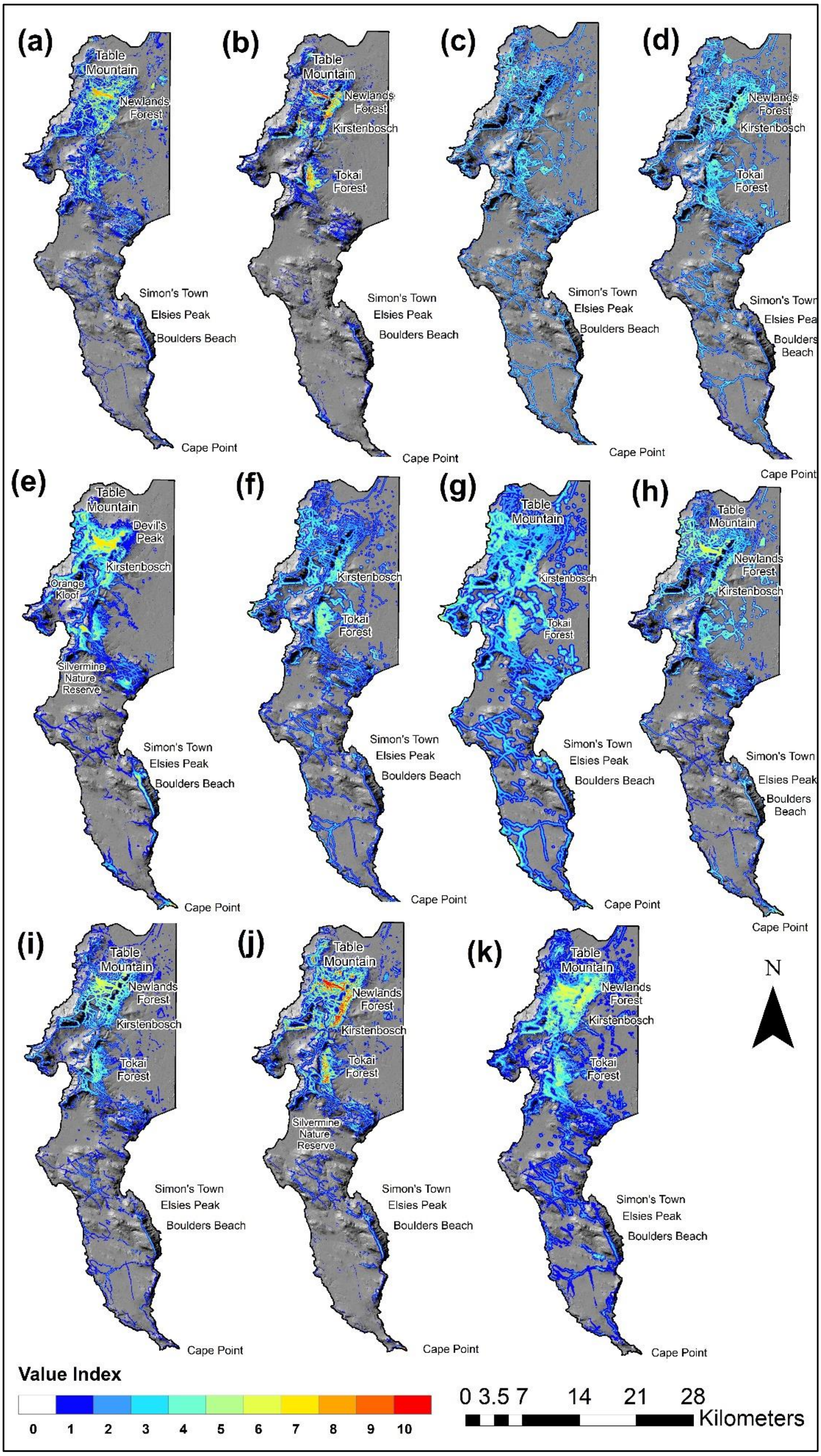


Figure 4. 2 Spatial distributions in (a) Aesthetic, (b) Biological diversity, (c) Cultural, (d) Economic, (e) Future, (f) Historic, (g) Intrinsic, (h) Learning, (i) Life-sustaining, (j) Recreation, and (k) Therapeutic values for the Cape Peninsula study area. The relative spatial distribution of the value index for the 11 SVs ranges from no value (grey) to low value (blue) and high value (red).

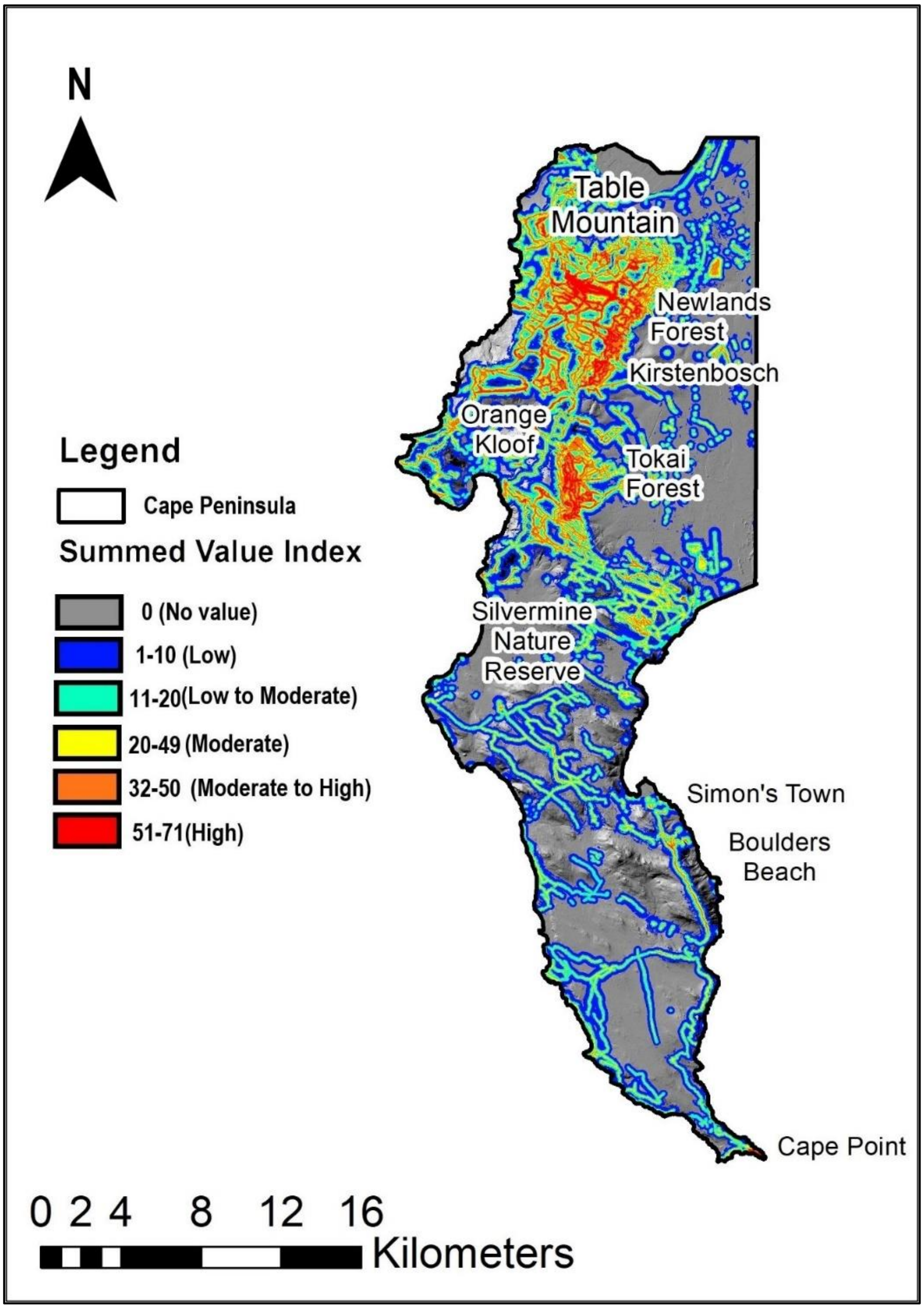


Figure 4. 3 The summed SVs map. Grey areas consist of no value. Blue areas consist of the lowest summed value index. Red areas consist of the highest summed value index.

Results for relative contribution for each SV are given in Table 4.3. The percent contribution for each environmental characteristic reflects the relative importance of the characteristic within SolVES for each SV. Distance to Trails (DTT) yielded the highest percent contribution for nine out the 11 SVs, namely aesthetic (47.26%), biological diversity (31.05%), cultural (91.52%), economic (88.02%), historic (62.02%), intrinsic (69.68%), learning (64.73%), life-sustaining (43.43%), and recreation (44.74%) values. Distance to roads (DTR) and Slope recorded a very low percent contribution to all 11 SV types. DTR recorded a percentage contribution of 7.89% for aesthetic, 6.50% for biological diversity, 0% for cultural and economic values, 0.36% for future, 2.68% for historic, 1.42% for intrinsic, 1.95% for learning, 0.23% for life-sustaining, and 1.49%

for recreation. DTR recorded a 0% percent contribution for cultural, economic, and therapeutic values. Slope recorded a percent contribution of 3.36% for aesthetic, 0.36% for biological diversity, 3.53% for life sustaining, and 3.54% for recreation. Concerning slope, it recorded a 0% percent contribution for cultural, economic, future, historic, intrinsic, learning, and therapeutic values.

Table 4.3 Relative contribution (expressed as a percent) of each environmental characteristic to modelling the 11 SVs.

Social Value Type	DTR	DTT	DTW	Elevation	LULC type	Slope	Vegetation type
Aesthetic	7.89	47.26	5.84	26.06	6.34	3.36	3.21
Biological diversity	6.50	31.05	24.48	12.68	19.18	0.36	5.73
Cultural	0	91.52	0	0	3.46	0	5.01
Economic	0	88.02	6.17	0.50	0	0	5.28
Future	0.36	24.50	7.30	51.96	6.52	0	9.33
Historic	2.68	62.02	0	0	18.48	0	16.80
Intrinsic	1.42	69.68	0	0	0.92	0	27.96
Learning	1.95	64.73	2.44	15.91	0.95	0	13.99
Life-sustaining	0.23	43.43	0.18	39.60	10.73	3.53	2.28
Recreation	1.49	44.74	4.88	29.85	8.02	3.54	7.44
Therapeutic	0	27.44	3.78	30.12	29.75	0	8.89

The other environmental characteristics including Distance to Water (DTW), elevation, LULC type, and vegetation type also had a generally low percent contribution towards the 11 SVs (Table 4.3).

Elevation recorded a fairly high percent contribution towards the future value (51.96%), and a moderately high percent contribution towards life-sustaining (39.60%), recreation (29.85%) and therapeutic (30.12%) values. Elevation also recorded a percentage of 26.06% for the aesthetic value, 12.68% for biological diversity, 0.50% for the economic value, and 15.91% for the learning value. Elevation recorded a 0% percentage contribution for cultural, historic, and intrinsic values. When it comes to DTW, it recorded a 5.84% percent contribution for the aesthetic, 24.48% for biological diversity, 6.17% for economic, 7.30% for the future, 2.44% for the learning, 0.18% for the life-sustaining, 4.88% for the recreation, and 3.78% for therapeutic values. DTW recorded a 0% percent contribution for cultural, historic, and intrinsic values. LULC type recorded a percent contribution of 6.34% for aesthetic, 19.18% for biological diversity, 3.46% for cultural, 0% for economic, 6.52% for future, 18.48% for historic, 0.92% for intrinsic, 0.95% for learning, 10.73% for life-sustaining, 8.02% for recreation, and 29.75% for therapeutic values. Concerning vegetation type, it recorded a percent contribution of 3.21% for aesthetic, 5.73% for biological diversity, 5.01% for cultural, 5.28% for economic, 9.33% for future, 16.80% for historic, 27.96% for intrinsic, 13.99% for learning, 2.28% for life-sustaining, 7.44% for recreation, and 8.89% for therapeutic values.

Overall, the results for the spatial distribution of SVs indicated that most of the SVs were clustered around Lion’s Head, Table Mountain, Devil’s Peak, the Newlands Forest, the Kirstenbosch Gardens, the Tokai Forest, the Silvermine Nature Reserve and Cape Point. Cultural values meanwhile, had no apparent clustering. The most valued areas were Table Mountain, the Newlands Forest, the Kirstenbosch Gardens, the Tokai Forest, the Orange Kloof Nature Reserve, and the Silvermine Nature Reserve. The respondents preferred aesthetic, biological diversity and recreation values were preferred the most. Respondents moderately valued future, learning, life-sustaining, and therapeutic values. Respondents valued cultural, economic, historic, intrinsic and spiritual values the least.

4.3 SPATIAL DISTRIBUTIONS OF BIOPHYSICALLY MODELLED SERVICES

Results of the spatial distribution of BpSs are shown in Figure 4.4. Maximum carbon stock of 16.80 t/ha was recorded within the Cape Peninsula. Areas that store large amounts of carbon are indicated in dark green, while those areas that store low amounts of carbon are indicated in light green. Most of the carbon stock appears to be stored within the forested areas in the Cape Peninsula, including the Newlands Forest, the Cecilia Forest, the Tokai Forest, and the Orange Kloof Nature Reserve. Carbon stock is also high in certain areas of the Cape Point Nature Reserve (in the South of the Cape Peninsula), which consists of wetlands and small forested areas. Fair amounts of carbon are also stored in the rest of the TMNP mainly consisting of shrubland. As shown in Figure 4.4a, carbon stocks are fairly low around the built-up areas of Cape Town lowlands and the Peninsula suburbs, with little to no vegetation within these areas.

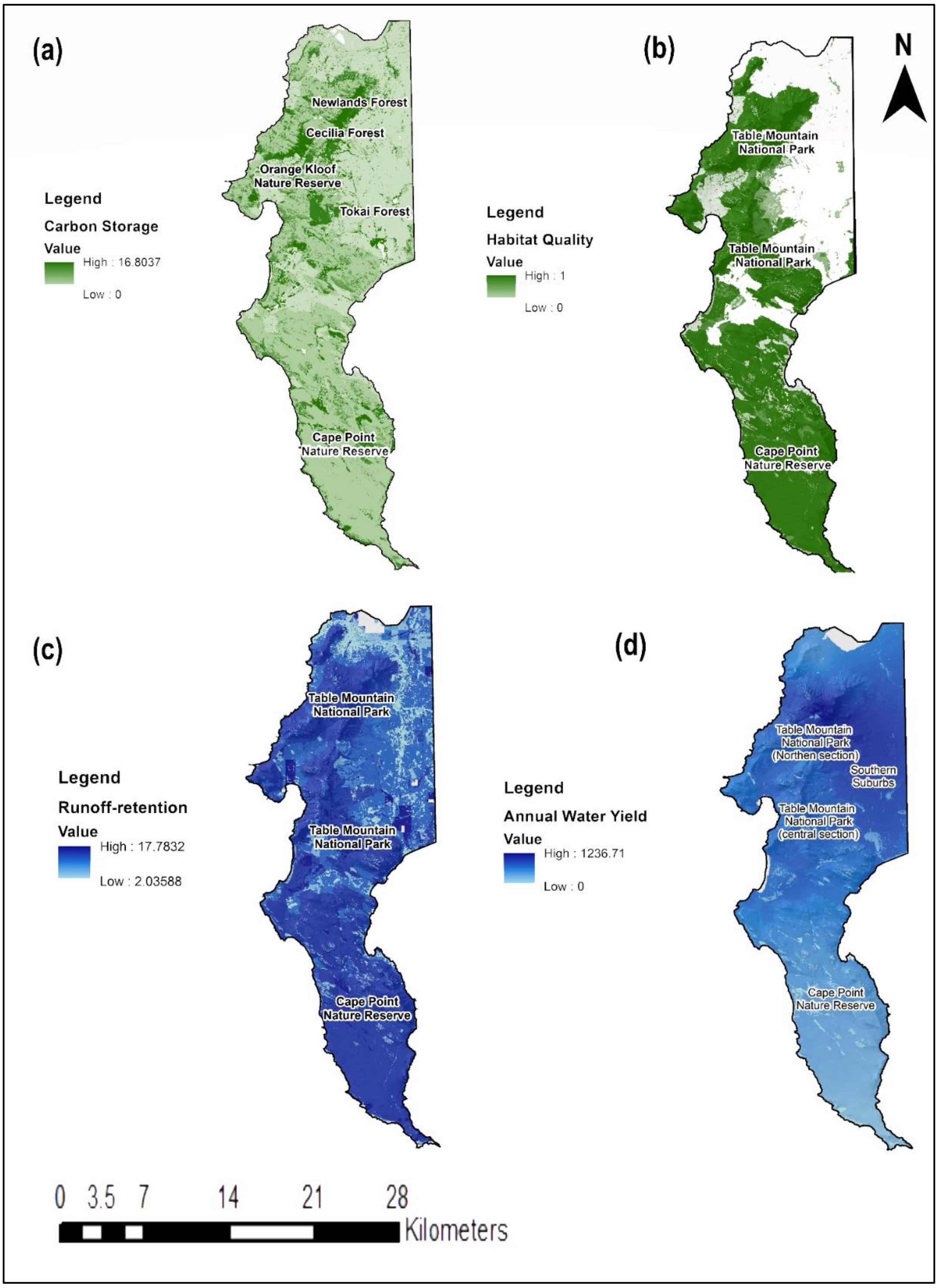


Figure 4. 4 Spatial distributions in (a) Carbon Storage, (b) Habitat Quality, (c) Flood Risk Mitigation, and (d) Annual Water Yield.

Concerning habitat quality results, they are depicted in Figure 4.4 b. While most of the area in the vicinity of the Cape Peninsula recorded high habitat quality values, built-up areas of the Lowlands of Cape Town and the residential suburbs adjacent to the TMNP yielded the lowest habitat quality values.

Figure 4.4c depicts the Flood Risk Mitigation model results, indicating rainfall run-off retention volume in m³. Run-off retention values ranging from 17.78 m³ to 2.035 m³ were recorded for the study area. Areas of high run-off retention are shown in dark blue, while areas with lower run-off retention are indicated in lighter shades of blue. Run-off retention (Flood Risk Mitigation) is high among the vegetated areas of the TMNP, and the wetland areas within the Cape Point Nature Reserve. These areas retain large amounts of run-off generated from rainfall events. Run-off retention is low around the Cape Town city centre, in the middle of the Cape Flats, and within the Peninsula suburbs of Noordhoek and Fish Hoek. These areas receive large amounts of run-off generated from rainfall events.

Annual Water Yield model results are presented in Figure 4.4 d. The maximum annual water yield for the Cape Peninsula study area is 1236.71 mm. Areas with high water yield are dark blue, while areas with lower water yield are light blue. High water yield values are observable around the northern parts of the TMNP, and parts of the Southern Suburbs. Water yield values are low in the central parts of the TMNP. Low water yield values can also be seen around the Cape Point Nature Reserve.

To summarise, carbon storage was high along the forested areas within the Cape Peninsula. Carbon stock was also fairly high within the wetland areas of the Cape Point Nature Reserve. Habitat Quality was high within most areas of the TMNP. Flood risk mitigation was high among the vegetated areas of the TMNP, and the wetland areas of the Cape Point Nature Reserve. Annual Water Yield was high around the northern section of the TMNP, and parts of the Southern Suburb.

4.4 ECOSYSTEM SERVICE HOTSPOTS/COLDSPOTS

Results of the BpS and SVs hotspots analysis are presented in Figure 4.5. The map depicts statistically significant clusters of high and low BpSs and SVs values at the $\alpha = 0.05$ significance level. Hotspots of BpSs and SVs values are shown in red, while hotspots of BpSs and coldspots of SVs are indicated in green. The hotspots of SVs and coldspots of BpSs are indicated in yellow. Coldspots of BpSs and SVs are indicated in blue.

Hotspots of SVs and BpSs occurred mainly around the Newlands Forest, the Kirstenbosch Gardens, the Orange Kloof Nature Reserve, and the Tokai Forest. Hotspots of SVs and coldspots of BpSs are predominantly distributed around Table Mountain, and in the vicinity of Simon’s Town and Boulders Beach. Hotspots of BpSs and coldspots of SVs mostly occur around Hout Bay and small areas of Noordhoek. Coldspots of SVs and BpSs are largely distributed around the Cape Peninsula. Table 4.4 lists the percent area which each hotspot and coldspot areas occupy of the study area.

Table 4.4 The percent extent to which each of the SVs and BpS hotspots and coldspots occupies the study area.

Table 4.4 BpS and SVs hotspot area within the Cape Peninsula.

Hotspot type	Percent area of the Cape Peninsula
BpS hotspot and SVs hotspot	7
BpS hotspot and SVs coldspot	8
BpS coldspot and SVs hotspot	11
BpS coldspot and SVs coldspot	74

When looking at the percent area occupied by each hotspot and coldspot combination, BpSs and SVs coldspots occupy the largest area of the Cape Peninsula at 74%, followed by BpS coldspots and SVs hotspots (11%), BpSs hotspots and SVs coldspots (8%). BpSs and SVs hotspots occupy the smallest area of the Cape Peninsula at only 7%.

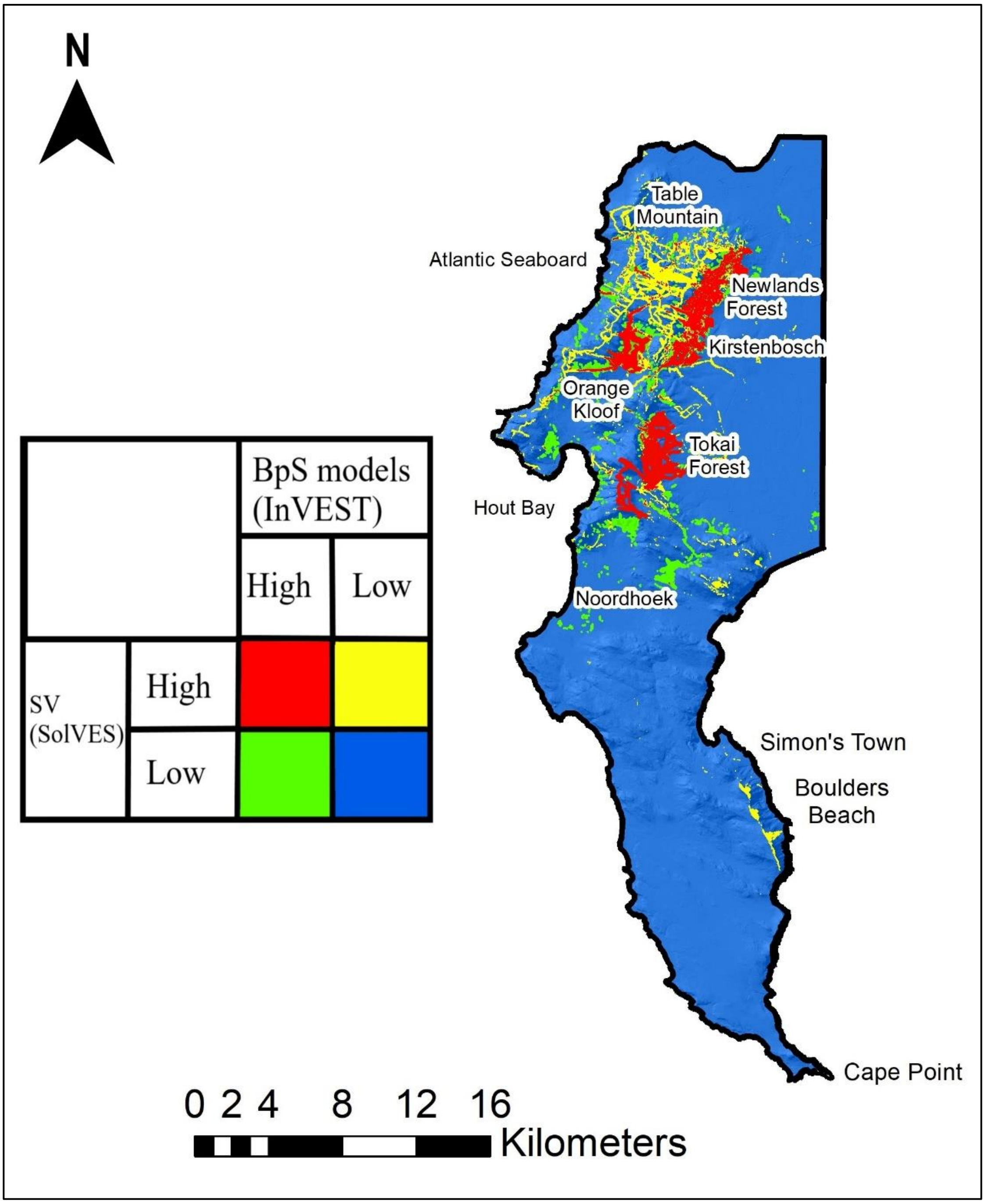


Figure 4. 5 The spatial distribution of BpS and SVs hotspots and coldspots. Hotspots and coldspots are illustrated with a 2×2 colour matrix.

Overall, hotspots of SVs and BpSs occurred mainly around the Newlands Forest, the Kirstenbosch Gardens, the Orange Kloof Nature Reserve, and the Tokai Forest. Hotspots of SVs and coldspots of BpSs were mainly distributed around Table Mountain, Simon's Town, and Boulders Beach. Hotspots of BpSs and coldspots of SVs mostly occurred within Hout Bay, and small areas of Noordhoek. Coldspots of BpSs and SVs are largely distributed within the Cape Peninsula.

4.5 REGRESSION ANALYSIS

Table 4.5 provides the results of the OLS regression analysis. A negative correlation between the Life-sustaining value and carbon storage is recorded. A regression coefficient value of -0.604856 is recorded for life-sustaining value and carbon storage. This signals that as the values for carbon storage increase, value allocations for the life-sustaining value type decrease. On the other hand, the life-sustaining value and annual water yield recorded a positive correlation of 0.0168885. This means that when the value allocations for life-sustaining value increase, values for annual water yield also increase. The biological diversity value was positively correlated to the BpS of Habitat quality (a coefficient value of 3.365014 was recorded). This means that when the value allocations for biological diversity increase, values for habitat quality also increase.

Table 4.5 OLS regression results.

Dependent variable and independent variable	Coefficient	Probability	Robust probability	Adjusted R^2 value	Moran's I Index	Moran's I z-score	Koenker Statistic	Jarque-Bera statistic
Life-sustaining and carbon storage	-0.604858	0.479794	0.198357	0.061614	-0.479570	-0.977456	3.340122	22.754241
Life-sustaining and annual water yield	0.0168885	0.249138	0.247105	0.0143024	-0.493633	-1.019050	3.494865	13.329268
Biological diversity and habitat quality	3.365014	0.542521	0.386841	-0.011917	-0.087195	-0.690894	436.523302	0.012067

Note: * indicates statistical significance

The adjusted R-squared value for life-sustaining and carbon storage were low at 0.061614, indicating a very weak relationship. This means that carbon storage only explained 6.16% of the life-sustaining value. The Adjusted R-squared value for life-sustaining and annual water yield was also low at 0.016885, also indicating a very weak relationship. Therefore, annual water yield only explained 1.69% of the life-sustaining value. The adjusted R-squared value for biological diversity and habitat quality was -0.011917, indicating a very weak relationship. This means the habitat quality only explains 1.12% of the biological diversity value.

The Probability and Robust probability values for all three relationships coefficients were not statistically significant. All three relationships did not yield a VIF value. The OLS tool only generates a VIF value when the independent variables are two or more. Carbon storage and annual water yield were modelled separately according to the life-sustaining value. Habitat quality was the only independent variable for the biological diversity dependent variable. All three relationship model residuals had non-statistically significant Jarque-Bera values. Concerning the Koenker Statistic, all three relationships had non-statistically significant koenker statistic values. This indicates that the relationship between the SVs and BpSs were consistent within the study area (i.e., the processes within the geographic study area are stationary).

Concerning the Moran's I index, the index value for the life sustaining and carbon storage model residuals was -0.479570. The Moran's I index value for the life-sustaining and annual water yield model residuals was -0.493633. The Moran's I z-score value for the life-sustaining and carbon storage was -0.977456. The Moran's I z-score value for the life-sustaining and annual water yield was -1.019050. The Moran's Index value for the biological diversity and habitat quality model was -0.087195. The z-score for biological diversity and habitat quality was -0.690894. The spatially random Moran's Index values (values of 0) and non-statistically significant z-scores (less than -1.96 and larger than 1.96) indicate model's residuals recorded a spatially random pattern for all three relationships (i.e., there was no spatial autocorrelation among the three model residuals). In other words, the OLS results for the three models are reliable according to the random dispersion of the model residuals. Although the OLS documentation states that points with less than 30 features produce unreliable results (ESRI2021b). The life-sustaining value used as the dependent variable only had 18 points. Thus, OLS results for the life sustaining and carbon storage, and life sustaining annual water yield relationships are overall unreliable.

To summarise, carbon storage and annual water yield negatively correlated with the life-sustaining value. Annual water yield recorded a positive correlation with the life-sustaining value. Habitat quality was positively correlated with biological diversity. Carbon storage registered a non-significant R-squared value of 0.061614 with the life-sustaining value. This indicates a very weak relationship between carbon storage and the life-sustaining value. Annual water yield also yielded a non-significant R-squared value of 0.0143024 with the life-sustaining value, indicating a very weak relationship. Habitat quality also recorded a non-significant R-squared value of -0.011917, highlighting a very weak relationship between habitat quality and biological diversity. Probability and Robust probability values were not statistically significant for the life-sustaining value, carbon storage and water yield. Probability and Robust probability values for biological diversity habitat quality were also not statistically significant. Concerning the Koenker Statistic, all three relationships had non-statistically significant Koenker statistic values. All three relationships recorded non-statistically significant Jarque-Bera values. All three relationship model residuals recorded a random spatial pattern. Although OLS results for the life-sustaining and carbon storage and life-sustaining annual water yield relationships are unreliable.

CHAPTER 5: DISCUSSION

This chapter provides a discussion of the results of this study. The results are interpreted and put in perspective of existing knowledge. Questionnaire survey results are discussed first, followed by the spatial distributions of social values (SVs), biophysically modelled services (BpSs), and hotspots and regression analysis.

5.1 QUESTIONNAIRE SURVEY RESULTS

To explain the social context of SV allocations, this part of the discussion considers the questionnaire survey demographics. This is based on section four of the questionnaire survey highlighted in Chapter 3. The study found that questionnaire respondents were generally more educated, consisted of more females, most resided in the Southern Suburbs of Cape Town, and were mainly older persons. Income groups were somewhat evenly represented, although a few respondents earned over R30 000 a month. The large participation of these Southern Suburbs participants could be attributed to Southern Suburbs residents comprising a large portion of the Facebook groups where the questionnaire was distributed.

The questionnaire survey population is a very particular group of recreational users of the Cape Peninsula. The sample population is small, and as pointed out by Pertrakis et al. (2020), it can yield a bias in participation within the demographic variables (Pertrakis et al. 2020). This finding aligns with other Public Participatory Geographic Information Systems (PPGIS) studies within Canada, Australia, and the USA which concluded that PPGIS respondents were mostly older, male, more well educated, and high-income earners (Beverly et al. 2008; Brown & Reed 2009; Raymond & Brown 2011). In contrast, there were more female participants than males in this study and income groups are somewhat equally represented. However, this is not always the case with small sample populations. Donaldson et al. (2016) recorded a much larger sample (n=3247) questionnaire survey that looked at the demographics of visitors to Table Mountain National Park (TMNP). Their study recorded that most respondents were also generally older and high-income earners. The study was conducted within the TMNP. The survey was administered through on-site surveys at various sites within the TMNP.

Socio-demographic variables like age, formal education and gender can affect the number and types of cultural ES that questionnaire survey respondents prefer (Brown & Fagerholm 2015; Semmens, Sherrouse & Ancona 2019; Zhou et al. 2020; Ma, Chen & Zeng 2021). Also, the environmental characteristics of the study area can influence SV allocations (Zhou et al. 2020). However, Zhou et al. (2020) highlight that demographics are a direct driving factor, while environmental characteristics are an indirect driver. This is because the SolVES results are mainly generated from a questionnaire survey (Sherrouse & Semmens 2015; Zhou et al. 2020).

Where PPGIS respondents reside in relation to the study area, it can influence the allocation of where the respondents map the values, also referred to as spatial discounting (Brown 2016). Spatial discounting describes the tendency of people to be near to what they favour and further away from what they dislike or fear (Brown, Reed & Raymond 2020). Place values also relate to a person's place attachment for one's house. For example, Brown & Reed (2002) found that place values were clustered around communities where people live. As a result, people which are more familiar with the geographic study area can generally provide more accurate PPGIS data including mapped values (Brown & Reed 2002).

Concerning income, it can influence the desired activities of respondents (Dade et al. 2020; Petrakis et al. 2020). According to Dade et al. (2020), high income and highly educated residents are usually more frequent park visitors, and as a result, benefit from a wide range of cultural ES. Age also plays a role in users' activities (Dade et al. 2020). Younger users often utilise parks for fitness activities while older people often tend to use parks for nature appreciation and leisure (Dade et al. 2020: 2). This study's SV allocations and their locations could be characteristic of the respondents. Other factors also influence respondents' SV allocations. SV preferences can vary according to the general topography, landscape characteristics and infrastructure (Ma, Chen, & Zeng 2021). In addition, spatial variations of SVs can also be contingent on people's environmental worldviews (such as biocentrism and anthropocentrism) (Van Riper & Kyle 2014). People with certain worldviews do tend to map different values (Van Riper & Kyle 2014). This study did not consider environmental worldviews.

5.2 SOCIAL VALUE MAPS

SV maps were generated using SolVES based on the questionnaire survey section three responses. The 11 SVs maps generated and relative Value Indices revealed several trends. Overall, high perceived SVs were mainly clustered around Table Mountain, the Newlands Forest, the Kirstenbosch Gardens, Tokai Forest, Silvermine Nature Reserve, and Cape Point. These are high-use sites within the Cape Peninsula and are thus popular and well-recognised sites for users (Ferreira 2011; Donaldson et al. 2016; Brill, Anderson, & O'Farrell 2022). SolVES studies have also found high index value clustering around mountainous areas, forests, nature reserves, botanical gardens, and national parks similar to this study (Sherrouse, Clement & Semmens 2011; Van Riper et al. 2017; Chen et al. 2020), although the spatial distribution of the value index is not always the same for all SolVES studies (Lin et al. 2017b). Other SolVES studies have also indicated high-value index clustering for watershed areas, wetlands, fishponds, and man-made features (such as bridges and religious structures) (Lin et al. 2017b; Petrakis et al. 2020; Zhou et al. 2020). This indicates that respondents value certain ecological areas more than others. High-value index clustering did not occur within the study area's wetland areas and manmade features. These areas were thus not as important to this study's respondents compared to respondents in other SolVES studies.

These sites also generally have good access for the public (Brill, Anderson, & O'Farrell 2022; Ferreira 2011). Their popularity and ease of access are likely major driving factors for the high SV ratings (Lin et al. 2017b; Petrakis et al. 2020). The spatial distribution of SVs was much lower in the southern parts of the Cape Peninsula and the Cape Point Nature Reserve, besides the Boulders Beach and Cape Point areas. This could indicate that the respondents do not use these areas frequently (Petrakis et al. 2020). Petrakis et al. (2020) highlighted that highly valued areas do not necessarily mean that these areas are more important than others. Instead, this is probably attributed to their current recognition. Thus, it is also likely that the respondents do not acknowledge the southern areas of the Cape Peninsula. However, these southern areas also do not have as many attraction sites as the northern section of the Cape Peninsula (Brill, Anderson & O' Farrell 2022). Thus, it could be more likely that there are fewer sites to value in comparison to the northern section. Brill, Anderson & O' Farrell (2022) noted that the northern and central sections of the Cape Peninsula have more access points to features compared to the southern section. Therefore, this could explain why these areas are favoured based on their accessibility.

When examining trends of the 11 SV types, aesthetic, biological diversity, and recreation values were preferred the most by respondents and had the highest Value Indices. This finding aligns with other SolVES studies conducted in the USA (Sherrouse, Semmens, & Clement 2014), Australia (Van Riper et al. 2017) and China (Ma, Chen & Zeng 2021). This is most probably due to the Cape Peninsula being favoured for its scenic beauty, high biodiversity, and recreational activities such as hiking (Brill, Anderson, & O'Farrell P 2022). These values are thus popular on a global scale, although these aesthetic, biological diversity and recreation values are not always valued the most, as demonstrated by other SolVES studies (Zhang et al. 2019; Chen et al. 2020; Zhou et al. 2020). Subsequently, it could be that the respondents recognised and/or favoured these values more than others.

Future, learning, life-sustaining, and therapeutic values were moderately valued with fair clustering and Value Indices. The respondents valued cultural, economic, historic, intrinsic, and spiritual values the least. These values had low value indices and clustering. These values generally tend to be the least popular in other studies as well (Van Riper et al. 2017; Bogdan et al. 2019;

Johnson et al. 2019; Petrakis et al. 2020). According to Chen et al. (2020), this could be due to these values' intangibility and effability. Also likely, that the sample of respondents do not recognise these values. Cultural, economic, historic, intrinsic, and spiritual values were more prevalent in other SolVES studies in China (Zhang et al. 2019; Zhou et al. 2020). This possibly indicates that the allocation and recognition of SV types depend on the study area location and questionnaire population (Zhou et al. 2020).

The environmental characteristics used to explain the physical context of SV allocations for the Cape Peninsula were elevation, slope, vegetation type, LULC, and distance to roads, trails, and water. Distance to Trails (DTT) was the largest contributing environmental characteristic for most of the SVs. This signals that the respondents highly valued SVs close to trail pathways. This is highly likely due to the respondents being mainly recreational users, presumably making regular use of the Cape Peninsula's hiking trail pathways. Trail pathways could thus be a significant driving factor in where respondents listed locations in the mapping exercise (Petrakis et al. 2020). These trail pathways also provide access to most of the Cape Peninsula's ecological areas. Accessibility to areas is an essential driver of an area's high value (Lin et al. 2017b; Brill, Anderson, & O'Farrell P 2022). Based on this finding, spatial planning that increases trail pathways can therefore strongly foster SVs (Chen et al. 2020). Such environmental characteristics can thus be considered important indirect drivers of SVs distributions (Van Riper et al. 2017). Elevation, slope, vegetation type, LULC, and distance to roads and water generally recorded a very low percent contribution to modelling the 11 SVs. These environmental characteristics were thus not substantial driving factors of the spatial variations of SVs compared to DTT. Water bodies occupy a very small area of the Cape Peninsula's land cover (Geoterraimage 2021). Elevation and slope are highly variable within the Cape Peninsula (Cowling, MacDonald & Simmons 1995). As a result, SV allocations were generally not situated in specific areas of low or high elevation, and steep or shallow slopes. These factors could explain their generally low contribution to SVs modelling. That is, respondents are more inclined to trail pathways compared to certain types of land cover and vegetation types, elevation, and water and roads (Zhou et al. 2020).

In contrast, other SolVES studies have found higher percent contributions of elevation, slope, vegetation type, LULC, and distance to roads and variables to modelling SVs (Van Riper et al. 2017; Bogdan et al. 2019; Petrakis et al. 2020). However, these studies most likely have completely different environmental study site characteristics and spatial distributions of SVs. Petrakis et al. (2020) investigated SVs preferences within the Sonoita Creek watershed, Arizona. SVs preferences were determined using a mail survey with residents residing in the watershed. They found that SVs were generally highly valued along the area's water bodies (specifically tributaries). Bogdan et al. (2019) investigated SVs in a high-mountain area within Southern Carpathians, Romania. SVs preferences were determined through an onsite survey of tourists. They revealed that distance to peaks, buildings, main rivers, and elevation significantly contributed to modelling SVs. Van Riper et al. (2017) investigated perceived biological diversity values for Santa Cruz Island, California. SVs were determined with an on-site survey of visitors to Santa Cruz Island. They revealed that biological diversity was highly valued closer to infrastructure, viewshed and marine protected areas. The contribution of environmental characteristics could thus depend on the study area characteristics in question (Zhou et al. 2019). Thus, Lin et al. (2017b) highlighted that the spatial distribution of SVs is highly context specific. This inhibits the potential for value transfer (transferring survey data to areas where survey data is not available) to other areas that do not have similar socio-demographic and physical environmental characteristics (Semmens, Sherrouse & Ancona 2019).

5.3 SPATIAL DISTRIBUTION OF BPS

Four spatial distributions of BpSs were modelled with InVEST based on geospatial data. These include spatial distributions of carbon storage, habitat quality, flood risk mitigation, and annual water yield. Areas of high carbon storage within the Cape Peninsula are forested areas mainly consisting of Afromontane, Western Cape Milkwood, and Western Cape Talus Forest species (Poulsen & Hoffman 2015). This result is consistent with other InVEST studies recording forested areas storing the highest amount of carbon (Irman & Din 2021; Piyathilake et al. 2021). Carbon stock was also high in certain Cape Point Nature Reserve areas, consisting of wetlands and small forested areas. Forests store more carbon than most ecosystems (Sharp et al. 2020). However, forests make up a small area of the Cape Peninsula (Poulsen & Hoffman 2015). According to Sharp et al. (2020), forest restoration should be promoted where possible, as this can lead to storing large amounts of carbon. This is especially important when considering climate change, as carbon storage plays a large role in the regulation of climate (MEA 2005).

Most of the Cape Peninsula has a high habitat quality, which is well-protected in the TMNP. Thus, these areas also do not experience anthropogenic transformation into agricultural and urban areas. Other InVEST habitat quality studies also found habitat quality was the highest within vegetated and protected areas (Sharma et al. 2018; Wang & Cheng 2021; Ding et al. 2021). The protected area status of the landscape is then important in ensuring high habitat quality (Sharma et al. 2018). Most of the urban areas in the Cape Peninsula have a very low habitat quality score. This is also consistent with the aforementioned InVEST habitat quality studies (Sharma et al. 2018; Wang & Cheng 2021; Ding et al. 2021). These built-up areas pose a high threat to the Cape Peninsula's biodiversity (Cowling, MacDonald & Simmons 1995). These built-up areas have low habitat suitability and generally do not fall within protected areas. Meanwhile, areas within the TMNP have high habitat suitability based on vegetated LULC types. Habitats on the Table Mountain chain are also located further away from threat sources. Habitat quality is a function of vegetation extent, low level of threats, and the level of legal protection from disturbances (Sharp et al. 2020). Most of the low-lying areas of the Cape Peninsula consist of urban developments, and thus have a lower habitat quality and higher threat level (Okes & O'Riain 2017).

Flood Risk Mitigation was high along vegetated areas of the TMNP and low within the urban areas of the Cape Peninsula. These vegetated areas thus retain larger amounts of run-off water-generated rainfall events compared to urban areas. The broader CoCT area including the Cape Peninsula does occasionally experience flooding, particularly informal settlements (Jordhus-Lier et al. 2019). The impermeability of cities makes these areas particularly vulnerable to flooding. Due to poor planning, some of these settlements are in floodplain areas (Jordhus-Lier et al. 2019). To mitigate the risk of flooding within these areas, Flood Risk Mitigation can be improved by increasing urban blue and green infrastructure (Kadaverugu, Rao & Viswanadh 2020). This consists of vegetation and water bodies that absorb water during flooding events (Kadaverugu, Rao & Viswanadh 2020). Kadaverugu, Rao & Viswanadh (2020) and Quagliolo, Comino & Pezzoli (2021) also revealed high flood risk mitigation within vegetated areas. Kadaverugu, Rao & Viswanadh (2020) also recorded high flood risk mitigation within open spaces (playgrounds and grass patches). However, this study did not consider open space as a LULC category.

While Annual Water Yield was high within the northern section of the TMNP and parts of the southern suburbs, it was generally low within the southern parts of the Cape Peninsula. This could be due to highly variable rainfall patterns within the Cape Peninsula (Shroyer, Kilian, & Jackelman 2000). Other InVEST annual water yield studies also revealed correlations between high rainfall and water yield (Wei et al. 2021). Rainfall is generally very high in the areas of Table Mountain and the Southern Suburbs (Shroyer, Kilian, & Jackelman 2000). At the same time, rainfall is much lower in the south of the Peninsula (Shroyer, Kilian, & Jackelman 2000). Rainfall does contribute largely to the amount of water yield (Sharp et al. 2020). This explains the high water yield within the northern section of the TMNP and the adjacent southern suburbs and the low water yield in the south of the TMNP.

Based on a visual assessment, the distribution of the four BpSs is also generally low within the urban areas of the Cape Peninsula. The finding is also consistent with other InVEST studies (Hack, Molewiky & Beißler 2020; Kadaverugu, Rao & Viswanadh 2020; Imran & Din 2021). This emphasises the fact that the spatial distribution of ES has yet to comprehensively inform urban planning for more resilient and green cities (Ahern, Cilliers & Niemelä 2014; Cortinovis & Geneletti 2018; La Rosa 2019).

5.4 HOTSPOT ANALYSIS

SVs and BpSs hotspots and coldspots were generated with the use of the Getis-Ord Gi* statistic based on the spatial distribution of SolVES modelled SVs and InVEST modelled BpSs. BpSs and SVs hotspots were located along the Newlands Forest, the Kirstenbosch Gardens, the Orange Kloof Nature Reserve, and the Tokai Forest. These areas thus had an overlap of high SV and BpS values. These are mainly within forested areas. Forests provide a high amount of ES from a biophysical and socio-cultural perspective (Acharya, Maraseni & Cockfield 2019; Cuni-Sanchez et al. 2019; Beckmann-Wübbelt et al. 2020).

Bagstad et al. (2016) and Smart et al. (2021) similarly found BpSs and SVs hotspots within forested areas. Although, in contrast, Smart et al. (2021) also found hotspots within farmland, marshes, and wetlands. Bagstad et al. (2016) broadly found that SVs and BpSs largely occur in wilderness areas, although they included a larger number of BpSs in their hotspot analysis, likely resulting in a different and larger spatial distribution of BpS hotspots. Bagstad et al. (2016) also had a much larger study area at the landscape scale (9,011km^2). While this research's study area was comparably smaller at 470 km^2, Smart et al. (2021) had a study area size of 220 km^2, at the local scale. ES relationships can vary according to the scale of the analysis (Lee & Lautenbach 2016).

Hotspots of BpS and coldspots of SVs mainly occurred around Hout Bay and small areas of Noordhoek. This indicates a disconnect between SVs and BpSs (i.e., SVs and BpSs values do not co-occur in these areas). These areas' SVs coldspots could be attributed to low popularity and acknowledgement compared to other sites such as Table Mountain and the Kirstenbosch Gardens. This indicates possible trade-offs since the respondents do not value these areas, while these areas have high BpS value (Castro et al. 2014). The respondents generally had a larger SVs preference within the northern sections of the Cape Peninsula, while these BpS hotspots and SVs coldspots areas are in the Central Peninsula. Another reason could be access roads and transport available to these areas for visitors and users. Distance to roads did not significantly contribute to modelling the 11 SVs. Other studies note that road access is an important feature that fosters SVs (Smart et al. 2021; Brill, Anderson, & O'Farrell 2022). Smart et al. (2021) found that respondents highlighted that accessibility and lack of public transport impeded their enjoyment of parks. The northern sections of the Cape Peninsula are generally easily accessible and close to the southern suburbs and the Cape Town city centre (Brill, Anderson, & O'Farrell 2022), while Noordhoek and the surrounding areas are on the far western side of Table Mountain and is thus further away compared to the northern section. Smart et al. (2021) found that SVs were located close to current residential and commercial developments while BpSs were in remote areas.

BpS and SVs coldspots occupy the largest area of the Cape Peninsula, followed by BpS coldspots and SVs hotspots, BpS hotspots and SVs coldspots, and BpS and SVs hotspots occupy the smallest area. That is, there is a limited overlap of SVs hotspots and BpSs hotspots. Bagstad et al. (2016) and Smart et al. (2021) also found small SVs and BpSs hotspots within their study site. This could possibly be attributed to the Getis-Ord Gi* approach used to map SVs and BpS hotspots. However, Lin et al. (2017b) used a quantile-based approach (i.e., the top 10, 20, and 30% of values) using the conservation software zonation. They also recorded limited overlap of SVs and BpSs hotspots, with SVs and BpSs coldspots occupying the largest proportion of the study area. Concerning the limited overlap of SVs and BpSs hotspots, Smart et al. (2021) highlighted the importance of stakeholder engagement to map SVs so they can be considered equally to BpS for decision-making. This generally limited overlap of BpSs and SVs emphasises the importance for better cooperation between community planning and conservation (Smart et al. 2021). This adds to the growing body of literature indicating that SVs ought to be mapped alongside BpSs, instead of evaluating BpSs in isolation (Cowling et al. 2008; Bagstad et al. 2016, Lin et al. 2017b, Smart et al. 2021). According to these results of the hotspots analysis, the study also provides possible implications for future landscape management. Figure 5.1 provides examples of potential management implications for areas of SVs and BpSs hotspots, SVs hotspots and BpSs coldspots, BpSs hotspots and SVs coldspots, and BpSs and SVs coldspots.

		Biophysically modelled ecosystem services (mapped using InVEST)	
		Hot	Cold
Social values (mapped using SolVES)	Hot	Good potential for stakeholder engagement in conservation planning. Ensure conservation of important ecological and landscape charateristics. Or. Possible conflict between management and visitor uses (if SV and BpS are not complementary).	Investigate reasons for low BpS and possible areas of conflict. Consider restoration if areas are degraded. These are areas where biophyiscal modelling solely is insuffcient to map value.
	Cold	Public awareness programmes needed to increase support for management (such as the working for water programme (Turpie, Marais & Blignaut 2008)).	Investigate reasons for low SV. Feasible areas for development if other essential natural and cultural resources are absent.

Adapted from Bagstad et al. (2016) and Korpilo et al. (2018).

Figure 5. 1 Examples of possible management implications for the SVs and BpS hotspot analysis.

Hotspots of SVs and BpS coldspot values are predominantly distributed around Table Mountain, as well as in the vicinity of Simon's Town and Boulders Beach. These areas mainly consist of bare surfaces of rock and sand (Cowling, MacDonald & Simmons 1995). Bare surfaces generally produce less ES compared to other types of LULC such as forests and shrubland (Huang et al. 2019; Sadat, Zoghi & Malekmohammadi 2020). Decision-making based on ES valuation should ideally not only be based on BpS assessments in such areas. BpS modelling alone cannot adequately capture SVs, as highlighted in the literature review. The Tokai Forest has been associated with conflicts over ES management because certain users' SVs in this area did not correspond to biodiversity priorities. Their SVs rather corresponded to alien invasive vegetation namely pine trees, which negatively impacts ES (Elmqvist et al. 2013; Ernston 2013). Therefore, it is important to consider that this area possibly has conflicting SVs co-occurring with BpS. These values should not be neglected to avoid future conflict over conservation measures. That is, tradeoffs can possibly exist even where SVs and BpS co-occur, when SVs are not complementary with BpS. Such areas require comprehensive stakeholder engagement to ensure management prescriptions for ES are understood and accepted (Rüdisser, Leitinger & Schirpke 2020).

Managing ES trade-offs within the TMNP is significantly more difficult when stakeholder SVs are associated with alien invasive species (van Wilgen 2012; Ernston 2013). However, this study did not examine the correlation between SVs and alien invasives which will require further data and analysis.

Most of the Cape Peninsula was outlined as BpSs and SVs coldspots. This can be due to high-value clusters of BpSs and SVs generally occupying a small area of the Cape Peninsula. Coldspots of BpSs and SVs occupying the majority of the study area have also been recorded in other ES hotspots analysis studies (Bagstad et al. 2016; Smart et al. 2021). However, a lot of these coldspot areas within the TMNP are nonetheless essential from a biodiversity perspective (Helme & Trinder-Smith 2006). The TMNP also includes many cultural and historical resources (Helme & Trinder-Smith 2006). Thus, these areas should not be regarded as devoid of value. Instead, these areas of significant biodiversity and cultural resources did not come up as high value hotspots. Resource extraction and urban development are also prohibited within the TMNP protected area (SANParks 2016). Bagstad et al. (2016) also noted that coldspot management strategies can include raising awareness of these areas relating to their value. According to Bagstad et al. (2016), landscape managers should not assume coldspots do not have value.

For practical implications of these hotspot analysis findings for ES management and planning of the Cape Peninsula, such information can be incorporated within the TMNP management plan. South African National Parks (SANParks) manages the TMNP within the Cape Peninsula. The TMNP management plan for 2015 to 2025 sets out plans for ecologically sustainable development to ensure conservation objectives of the TMNP protected area are met (SANParks 2016). The TMNP management plan includes ES as a conservation priority, as part of the plan's high-level biodiversity objective (SANParks 2016). The ES programme within this objective seeks to ,"identify interactions of key concern to the park, develop management activities, whether it is to act or monitor, and to implement these for continued management of diversity in the park" (SANParks 2016: 70). This ES programme, however, does not have set priorities for mapping ES trade-offs and synergies to inform planning and decision-making within the TMNP (SANParks 2016). The priority to map and assess ES synergies and trade-offs can subsequently be incorporated into their broader ES programme. This can help to increase ES synergies and mitigate trade-offs within the Cape Peninsula, to promote better overall ES conservation and management (Qiu & Turner 2013; Castro et al. 2014; Bagstad et al. 2016; Karimi, Yazdandad & Fagerholm 2020). This study's method of mapping SVs and BpS hotspots and coldspots could then also form part of their broader ES programme. Stakeholder engagement is also a large priority within the management plan to inform planning and projects. However, it does not include stakeholder engagement within the ES programme nor maps their SVs for ES.

One approach to possibly include stakeholder SVs in decision-making could be by including such PPGIS questionnaire research within their survey research objectives. The priority to conduct SVs mapping questionnaire surveys could thus fall into their "Conduct appropriate research to understand and address visitor and recreational users' expectations" Sub-objective (SANParks 2016: 94). This forms part of their responsible tourism programme and specifically the service quality objective therein. This can ensure the inclusion of users of the Cape Peninsula and their SVs preferences to inform planning and projects, and to subsequently carry out more socially acceptable conservation planning to prevent trade-offs in the form of stakeholder concerns. The management plan also prioritises promoting awareness to people and communities to ensure the conservation of the Cape Peninsula (SANParks 2016). Awareness programs can thus be conducted for ecological areas within BpSs hotspots and SVs coldspots and BpSs and SVs coldspots to ensure stakeholders recognise the value of these areas and thus management thereof.

5.5 REGRESSION ANALYSIS

Biological diversity and habitat quality recorded a very weak relationship (r^2=-0.011917). Based on this OLS result, the respondents did not recognise important areas of habitat quality. The biological diversity value was positively correlated to the BpS of habitat quality, although it inadequately explained the distribution of habitat quality. The non-statistically significant probability and robust probability values, non-statistically significant Koenker and Jarque-Bera values no spatial autocorrelation of model residuals indicated a good model fit and reliable results (ESRI 2021b).

The finding of a very weak relationship between biological diversity and habitat quality aligns with past studies highlighting the difficulty for respondents to map complex ES types (Brown et al. 2011; Brown, Montag & Lyon 2012; Bagstad et al. 2016). The MEA (2005) defines habitat quality as a supporting service. Brown & Fagerholm (2015) highlighted that regulating and supporting ES are generally the least recognised amongst the public. Further, Bagstad et al. (2016) stated that recreational users' and public comprehension of biodiversity and ecological conditions are typically inadequate and inaccurate. This could also explain respondents' lack of recognition of habitat quality in this study. In contrast, Alessa, Kliskey & Brown (2008) found a moderately significant relationship between respondent perceptions of biological diversity and areas of high ecological value (based on net primary productivity, also a supporting ES). Ruiz-Frau, Edwards-Jones & Kaiser (2011) noted that technical respondents (such as academics and representatives of environmental groups) tend to map supporting and regulating ES more often. Thus, Alessa, Kliskey & Brown (2008) possibly had more technical respondents participating in their survey, although they did not record the socio-demographics of the respondents.

As highlighted in the literature review, it is essential to improve communications about ES, particularly for ES that are poorly recognised or poorly understood (Rüdisser, Leitinger & Schirpke 2020). This ensures measures to protect ES are applied and accepted by the public and stakeholders (Rüdisser, Leitinger & Schirpke 2020). A better understanding of these service types can result in higher social value and acknowledgement for such ES (Menzel & Teng 2010.). Since the TMNP management plan prioritises promoting awareness to people and communities, SANParks could subsequently initiate awareness programmes on such complex ES types to promote better understanding and acknowledgement thereof.

CHAPTER 6: CONCLUSION

This chapter offers the synthesis of the study. The aims and objectives of the study are revisited to uncover the extent to which they were accomplished. The overall findings of the study are then summarised. Recommendations for future research and the limitations of this study are also given. Concluding remarks for the study are then offered.

6.1 REVISITING THE AIM AND OBJECTIVES

The study aimed to investigate the link between social values and ecosystem services for recreational users of the Cape Peninsula. In addition, the spatial distribution between social values and ES was modelled. To achieve the overall aim of the study, four objectives were set: 1) review literature to determine the current state of research on ES determination; 2) investigate the types and spatial distribution of social values linked to ecosystems in the Cape Peninsula using a participatory mapping excessive; 3) evaluate and quantify the spatial distribution of modelled services in the Cape Peninsula; and 4) investigate the relationship of social values and distribution of biophysically modelled services within the Cape Peninsula.

For Objective 1, a literature overview was done to reveal current trends of ES research. This literature review highlighted well-researched areas of ES and ES assessments, and areas that were lacking and under-researched. More specifically, the literature revealed comprehensively used methods of ES assessment and valuation, and methods which are still underrepresented and recently emerging in the literature. Non-monetary approaches for assessing ES are lacking compared to monetary approaches. Cultural ES and corresponding SVs also remain underrepresented in many ES assessments.

Regarding Objective 2, a questionnaire survey was conducted targeting select recreational groups on Facebook. Questionnaire respondents listed their preferred types of SVs and their location using a map of the Cape Peninsula. The listed locations were digitised in ArcGIS and mapped with SolVES to provide the spatial distribution of 11 SVs within the Cape Peninsula. The results for the spatial distribution of SVs revealed that most of the SVs were clustered around Lion’s Head, Table Mountain, Devil’s Peak, the Newlands Forest, the Kirstenbosch Gardens, the Tokai Forest, the Silvermine Nature Reserve and Cape Point. Cultural values meanwhile had no apparent clustering. Areas that were valued the most overall were Table Mountain, the Newlands Forest, the Kirstenbosch Gardens, the Tokai Forest, the Silvermine Nature Reserve, and Cape Point. The respondents preferred aesthetic, biological diversity and recreation values the most. Future, learning, life-sustaining, and therapeutic values were moderately valued. The least valued were cultural, economic, historic, intrinsic, and spiritual values.

Objective 3 was achieved by obtaining several geospatial biophysical data as required inputs of the BpSs of Carbon Storage, Habitat Quality, Flood Risk Mitigation and Annual Water Yield. This input data was then prepared with ArcGIS before being modelled with InVEST. InVEST then produced and quantified the spatial distribution of these four BpSs within the Cape. Overall, carbon storage was high along the forested areas within the Cape Peninsula. Carbon stock was also reasonably high within the wetland areas of the Cape Point Nature Reserve. Habitat Quality was high within most areas of the TMNP. Flood risk mitigation was high among the vegetated areas of the TMNP, and the wetland areas of the Cape Point Nature Reserve. Annual Water Yield was high around the northern section of the Cape Peninsula, and parts of the Southern Suburbs.

Concerning Objective 4, it was achieved using the Getis-Ord Gi* hotspots analysis tool, which outlined the clustering of SVs and BpSs hotspots and coldspots. The Ordinary Least Squares regression tool analysed the relationship between biological diversity and the corresponding BpS model of Habitat Quality. This was based on the digitised points of biological diversity and life-sustaining values and their value allocations, and the values of Carbon Storage, Habitat Quality and Annual Water Yield at these point locations. With regards to the hotspots analysis results overall, hotspots of SVs and BpSs occurred mainly around the Newlands Forest, the Kirstenbosch Gardens, the Orange Kloof Nature Reserve, and the Tokai Forest. Hotspots of SVs and coldspots of BpSs were mainly distributed around Table Mountain, Simon's Town, and Boulders Beach. Hotspots of BpSs and coldspots of SVs mostly occurred within Hout Bay, and small areas of Noordhoek. Coldspots of BpSs and SVs are primarily distributed within the Cape Peninsula.

Concerning the overall OLS results, carbon storage and annual water yield negatively correlated with the life-sustaining value Annual water yield recorded a positive correlation with the life-sustaining value. Habitat quality was positively correlated with biological diversity. Carbon storage registered a non-significant R-squared value of 0.061614 with the life sustaining value. Annual water yield also yielded a non-significant R-squared value of 0.0143024 with the life. Habitat quality also recorded a non-significant R-squared value of 0.011917. Probability and Robust probability values were not statistically significant for the life sustaining value, carbon storage and water yield. Biological diversity and habitat quality Probability and Robust probability values were also not statistically significant. All three relationships recorded non-statistically significant Jarque-Bera values. All three relationships had non-statistically significant koenker statistic values All three relationship's model residuals recorded a random spatial pattern. OLS results for the life sustaining and carbon storage, and life sustaining annual water yield relationships are overall unreliable.

6.2 LIMITATIONS OF THE STUDY

The questionnaire survey sample was small and focused on a particular group of users, which could bias the spatial information collected from the questionnaire (Brown & Fagerholm 2015). The SVs preferences of the questionnaire population most likely do not represent the general values of all users and visitors to the Cape Peninsula in general. Tourists also comprise a large Cape Peninsula user group (Donaldson et al. 2016). However, only residents of the CoCT participated in the questionnaire survey. Some users are also not on social media, so they could not participate in this study's online questionnaire. This would require an on-site PPGIS questionnaire survey to capture their SVs preferences. The values from other user groups and visitors of the Cape Peninsula could be completely different (Chen et al. 2019). Public participation processes can fail to be effective in planning and decision-making if they receive limited participation (i.e. not including a large sample of the target population) (Brown, Kelly & Whitall 2013). As a result, this can lead to bias in the SVs data generated by SolVES, based on the questionnaire population demographics and the number of questionnaire participants. To improve the accuracy and participation of sampling, future studies should include a longer survey timeframe, on-site surveys, and multiple samples to prevent subjectivity (Brown G & Kyttä M 2014; Brown & Fagerholm 2015; Zhao et al. 2019). Given the small sample size limitation, the SolVES results for the study area should thus be interpreted with caution (Bagstad et al. 2017).

The study nevertheless asserts that the spatial distributions of SVs in this study provides a good baseline example of how SVs can be considered alongside BpSs in an integrative ES assessment for the Cape Peninsula. It also provides a good example of how preferences of SVs can vary and cluster throughout the landscape. There have also been no SolVES studies conducted on the Cape Peninsula before.

Secondly, this study used InVEST to map BpSs in the study area since it has been primarily applied across research applications (Posner et al. 2016). However, InVEST largely relies on LULC data to model BpSs within the chosen study area (Sharp et al. 2020), and good quality InVEST model output data largely depends on good quality LULC data (Sharp et al. 2020). This study used LULC from Geoterraimage (2021), which had an overall accuracy of 85,47%. The residual errors of the data are possibly unevenly distributed throughout the LULC data in some areas. Thus, errors could be found in the InVEST BpSs models based on the LULC data used. Each of the input datasets for the four BpS models also had various spatial resolutions compared to the LULC raster. The InVEST user guide also notes that the four BpS modelling tools of Carbon Storage, Habitat Quality, Flood Risk Mitigation and Annual Water Yield have limitations and simplifications of their own (Sharp et al. 2020). Maps of Carbon Storage were generated using global carbon pool data. This means that there can be a level of uncertainty in the four BpS maps generated. The InVEST output data can be calibrated to create more accurate models (Sharp et al. 2020), although this requires field surveys in the study area which is often infeasible for large areas (Vihervaara et al. 2018). The InVEST models nevertheless provide a good baseline scenario of the spatial distributions of BpS (Sharp et al. 2020).

Possible errors within the InVEST model can also result in small errors in the hotspot or regression analysis (Bagstad et al.2016). One limitation of this study's OLS regression analysis is that points with less than 30 point features produce unreliable results (ESRI2021b). The life-sustaining value only had 18 point features. Thus, the OLS results for the life-sustaining and carbon storage, and life-sustaining and annual water yield relationships, are overall unreliable.

6.3 RECOMMENDATIONS FOR FUTURE WORK

This study did not use a probability sampling approach to select respondents. Respondents were targeted recreational groups on Facebook. This is due to difficulties in making physical contact because of the COVID-19 pandemic. The sample size of the study was also small. Consequently, it is unfeasible to generalise the findings of the study on the linkages between social values and ES services for all the users of the Cape Peninsula. Future studies should use a probabilistic sampling strategy that yields a representative sample of the sample population for the Cape Peninsula. The survey can also include face-to-face interviews and focus groups over and above online surveys. There are also benefits to using an on-site survey together with an online one to effectively increase participation rates (Brown 2017). Brown & Fagerholm (2015) also suggests the use of quota sampling to obtain increased population representativeness. The questionnaire survey of this study was only open for a limited period of four months. Future questionnaire survey studies could be conducted over a longer period to provide good temporal information (Brown 2017). This can also reduce bias by season (Brown 2017).

Conflict over the removal of alien invasive species and ES management has previously occurred within the Cape Peninsula (Ernston 2013; Elmqvist et al. 2013). However, this study did not consider the distribution of alien invasives underlying SVs distributions, which is challenging to map and requires further analysis (Ismail, Mutang & Peerbhay 2016; Royimani et al. 2019). Future studies should also investigate whether SVs preferences are correlated with the spatial distribution of alien invasive vegetation such as pines. SVs preferences for alien invasives could potentially highlight possible trade-offs with the removal of these species. Removing alien invasive species is a part of many ecological strategies and management as they pose a large threat to ES, indigenous vegetation, and water security (Rai & Singh 2020). However, these strategies are frequently met with conflict when the public has SVs for them (van Wilgen 2012; Elmqvist et al. 2013; Ernston 2013; Tebboth et al. 2020). This can help identify possible trade-offs that appear as stakeholder conflict early in the decision-making process for alien invasives removal. Numerous SolVES studies have investigated underlying environmental variables such as land cover, elevation, and distance to features that sought to explain the physical context of SVs (Sherrouse, Clement & Semmens 2011; Van Riper et al. 2017; Petrakis et al. 2020), although limited SolVES studies have used the spatial distribution of alien invasive species as an environmental variable to explain SV allocations. Thus, this provides an interesting opportunity for future SolVES studies investigating trade-offs among SVs and ES.

This study generated hotspots and coldspots of SVs and BpSs based on InVEST and SolVES models using the Getis-Ord GI* statistic. Different hotspot-generating methods of ES have been compared in a few studies (Schröter & Remme 2016; Bagstad et al. 2017). Very few studies have compared ES hotspots generated from different ES modelling tools. Future studies can compare hotspot extents generated based on various ES modelling tools. This can help in determining optimal ES modelling tools for generating ES hotspots. Future ES hotspot comparative studies should also compare different study scales including local, regional, and national scales. The influence of scale in ES modelling has not received much research attention (Bagstad et al. 2016). ES relationships occurring at numerous scales are crucial in decision-making (Lee & Lautenbach 2016). Deriving a better understanding of scale for ES modelling can also help determine which hotspot delineation methods are best suited for these various scales.

6.4 CONCLUDING REMARKS

Based on overall results with the aims and objectives of this study, essential relationships between SVs and BpSs were found within the Cape Peninsula. Hotspots SVs and BpS occurred mainly around the Newlands Forest, the Kirstenbosch Gardens, the Orange Kloof Nature Reserve, and the Tokai Forest. Hotspots of SVs and coldspots of BpSs were primarily distributed around Table Mountain, Simon’s Town, Boulders Beach, and Cape Point. Hotspots of BpSs and coldspots of SVs mainly occurred within Hout Bay, and small areas of Noordhoek. Coldspots of BpSs and SVs were largely distributed within the Cape Peninsula. Possibly trade-offs exist within BpSs and SV hotspot areas where SVs and BpSs are not compatible (in this case the Tokai Forest), and where there is a disconnect between SVs and BpSs (i.e., BpSs hotspots and SVs coldspots) within Noordhoek and Hout Bay. Future ES landscape management for the Cape Peninsula can consider the possible examples of management implications highlighted for each of these spatially explicit SVs and BpS hotspot and coldspot combinations. Considering these implications of SES-based hotspots for planning and decision-making can increase synergies and mitigate trade-offs among ES within the Cape Peninsula. This also allows SVs to be equally considered alongside more easily quantified BpSs in decision-making. Such methods can promote overall sustainable and inclusive conservation by considering more integrated ES assessments. This study's OLS results recorded a weak relationship between biological diversity and habitat quality. This indicated a possible lack of recognition and trade-off for habitat quality within the Cape Peninsula. Awareness programmes should be promoted to educate the public on the Cape Peninsula's ES to acknowledge habitat quality and other important BpS.

To conclude, this study highlighted that SVs information is important for ES assessments, especially in the context of ES-based approaches for conservation and management. The study also further highlighted the potential of using biophysical and SVs methods together instead of in isolated ES assessments. The study's findings provide useful examples to identify synergies and trade-offs among SVs and BpSs within the Cape Peninsula, and to integrate SVs into mainstream ES assessments. These findings are based on the social-ecological hotspot mapping and regression analysis of ES. These implications based on these findings can also be incorporated within management plans for the Cape Peninsula and decision-makers such as SANParks. The recommendations for future research should be considered to improve future ES assessments of SVs and BpSs.

Word count: 35 804

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APPENDICES

Appendix A Ethical clearance approval letter

APPENDIX A

Ethical clearance approval letter

UNIVERSITEIT
STELLENBOSCH
UNIVERSITY

CONFIRMATION OF RESEARCH ETHICS APPROVAL

REC: Social, Behavioural and Education Research (SBER) - Initial Application Form

27 April 2022

Project number: 23264

Project Title: Investigating the impact of social values on ecosystem services on the Cape Peninsula in South Africa using geospatial techniques.

Dear Mr CW Tonkin

Identified supervisor(s) and/or co-investigator(s):

Dr S Williams, Dr ZE Mashimbye

Your response to stipulations submitted on 04/03/2022 10:07 was reviewed and approved by the Social, Behavioural and Education Research Ethics Committee (REC: SBE).

Your research ethics approval is valid for the following period:

Protocol approval date (Humanities)	Protocol expiration date (Humanities)
18 February 2022	17 February 2025

GENERAL COMMENTS PERTAINING TO THIS PROJECT:

INVESTIGATOR RESPONSIBILITIES

1. Please take note of the General Investigator Responsibilities attached to this letter. You may commence with your research after complying fully with these guidelines.

2. Your approval is based on the information you provided in your online research ethics application form. If you are required to make amendments to or deviate from the proposal approved by the REC, please contact the REC: SBE office for advice: applyethics@sun.ac.za

3. Always use this project ID number (23264) in all communications with the REC: SBE concerning your project.

4. Please note that the REC has the prerogative and authority to ask further questions, seek additional information, and monitor the conduct of your research and the consent process, where required.

RENEWAL OF RESEARCH BEYOND THE EXPIRATION DATE

You are required to submit a progress report to the REC: SBE before the project approval period expires if renewal of ethics approval is required.

If you have completed your research, you are required to submit a final report to the REC: SBE to close the active REC record for this project.

Project documents approved by the REC:

Document Type	File Name	Date	Version
Proof of permission	Screenshot_20210909_224200_com.android.gallery3d	09/09/2021	
Recruitment material	Recruitment message_21015678	14/09/2021	1
Research Protocol/Proposal	ResearchProposal_21015678 (2)	05/01/2022	2
Default	Cape Peninsula Speleological Society (Caving)	05/01/2022	1
Default	Cape Town Outdoor hiking club	05/01/2022	1
Default	Friends of Table Mountain	05/01/2022	1
Default	Newlands Forest Conservation Group	05/01/2022	1
Default	TEMPLATE FOR RESPONSE LETTER	05/01/2022	1

Default	Privacyresults	18/02/2022	1
Default	Cape Peninsula Speleological Society (Caving)	18/02/2022	2
Default	Newlands Forest Conservation Group	18/02/2022	2
Data collection tool	Questionnaire_21015678(2)	22/02/2022	2
Informed Consent Form	Informed consent form	22/02/2022	2
Default	RESPONSE LETTER_21015678	22/02/2022	2

If you have any questions or need further help, please contact the REC office at applyethics@sun.ac.za

Sincerely,

Mrs Clarissa Robertson (cgraham@sun.ac.za)

Secretariat: Social, Behavioral and Education Research Ethics Committee (REC: SBE)

National Health Research Ethics Committee (NHREC) registration number: REC-050411-032.
The Social, Behavioural and Education Research Ethics Committee complies with the SA National Health Act No.61 2003 as it pertains to health research. In addition, this committee abides by the ethical norms and principles for research established by the Declaration of Helsinki (2013) and the Department of Health Guidelines for Ethical Research: Principles Structures and Processes (2nd Ed.) 2015. Annually a number of projects may be selected randomly for an external audit.