Mapping the social values of ecosystem services to support better decision making

MSc Thesis

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Abstract

Social values of ecosystem services are the perceived benefits of natural ecosystems for the well-being of people. For sustainable land management, social values and preferences need to be integrated into land-use decision-making. Existing methods of social value capture commonly use participatory mapping and deliberative mapping. However, social media data has recently contributed to the gathering of spatial social value data. By reducing the time and cost of mapping, social media may be effective in social value mapping. However, the credibility of this data source has rarely been assessed for land planning.

This thesis critically analysed the results of social media-based mapping (passive Volunteered Geographic Information (VGI)) and deliberative mapping (expert-based evaluation) methods into providing credible social value data (recreation, aesthetics, and historical/cultural values) for recreation planning. We analysed the content of 4642 photographs uploaded to Flickr as passive VGI and the results of an online survey and face to face interview for expert-based evaluation.

This thesis found both the passive VGI and expert-based evaluation could identify all three types of relevant social values for ecosystem services (recreation, aesthetics, and historical/cultural).

Passive VGI can provide reasonably reliable information on the recreational preferences of people at the time that data is provided. Although social values identified in expert-based evaluation included useful information about current public preferences and a potential supply of recreation ecosystem services, it only captured a general view of the study area. Large areas of interest were provided by each of the experts participating in the online survey. Several landscape units were missed by passive VGI while expert-based dataset overrepresented a majority of landscape units.

The results of this research demonstrated that spatial social value data are limited when a single method is applied. Potential users of such data need to understand their limitations. Applying several mapping methods (PPGIS, expert-based evaluation, passive VGI, etc.) may create a more useful and credible social value dataset to appropriately support recreational planning.

Contents

List of Figures

List of Tables

GLOSSARY

PPGIS: Public Participation Geographic Information System

VGI: Volunteered Geographic Information

IPBES: Intergovernmental Platform on Biodiversity and Ecosystem Services

NCP: Nature’s Contributions to People

CICES: Common International Classification of Ecosystem Services

DOC: Department of Conservation

LINZ: Land Information New Zealand

GPS: Global Positioning System

NGO: Non-Governmental Organisation

NZLC: New Zealand Landscape Classification

Chapter 1: Introduction

1.1 Background

Including social values and preferences in land use decision making is vital to ensure sustainable land management decisions (Agbenyega et al., 2009; Chan et al., 2012). Land use decision making is dependent on high-quality and reliable information (Brown et al., 2015).

Ecosystem services analysis provides a useful framework for land-use decision-making (Burkhard & Maes, 2017; Daily et al., 2009; Förster et al., 2015). The Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), defined ecosystem services as “nature’s contributions to people” (NCP) (Díaz et al., 2018:270). This holistic view of ecosystem service represents interactions between people and nature as well as its contribution to achieve sustainable development and management goals. Ecosystem services are currently assessed using biophysical methods, monetary techniques (economic), and socio- cultural methods. Biophysical and monetary approaches have dominated ecosystem services studies (García-Llorente et al., 2011; Schröter et al., 2014; (Zoderer et al., 2016). There is less emphasis on social values assessment as a bridge linking people to decision-makers (Chan et al., 2012; Martín-López et al., 2012; Oteros-Rozas et al., 2018; van Riper et al., 2017). Embedding social value can strengthen an ecosystem services approach for land-use decision making (García-Llorente et al., 2012).

Social values can be identified and quantified in multiple ways. The social value assessment methods vary from non-monetary to monetary techniques (García-Llorente et al., 2012). Non-monetary approaches of social value assessment provide a useful data about demands and preferences of ecosystem services and potential conflicts between various stakeholders (Walz et al., 2016).

These approaches include quantitative methods (preference assessment, time-use and photo-elicitation), qualitative methods (narrative methods), combined quantitative and qualitative methods (social value mapping, participatory scenario planning and deliberative valuation) (Burkhard & Maes, 2017). Among these methods, mapping approaches support decision-makers by creating, assessing and categorising spatial data of social values (Nahuelhual et al., 2016). This social value assessment technique is important in making spatially influenced decisions in the real-world (Arkema et al., 2015; Hill & Aspinall, 2000; Kopackova et al., 2008; Lavorel et al., 2017).

Methods to map social values include participatory mapping, deliberative mapping, and social media-based mapping (Burkhard & Maes, 2017). Participatory mapping involves various stakeholders to identify and assess social values. Deliberative mapping uses knowledge of a group of people to create a map based on their consensus on social values in a certain area. Mapping method based on the social media data reveals location of people's preferences of ecosystem services on a map.

The integration of spatial social value data into a decision-making system requires a reliable mapping method with a clear conceptual and methodological framework (Burkhard & Maes, 2017; Gould et al., 2015; Kenter et al., 2014). In other words, the credibility of mapping outcomes is essential to support sustainable decision-making. Credibility assesses the quality of data to determine whether they are useful to real-world decision-makers (Baker, 2019).

Although social value mapping of ecosystem services has been considered in a lot of research (Brown & Brabyn, 2012; Gliozzo et al., 2016; Nahuelhual et al., 2016; Walz et al., 2019), the credibility of different mapping methods and produced outcomes is not well covered. The subjective nature of social value has limited applying authoritative criteria (spatial resolution, position, and attribute accuracy) to assess the credibility of mapping methods (Brown et al., 2019; Burkhard & Maes, 2017). The applicability of a method (time and cost) and the production of relevant outcomes for a specific target are important criteria in choosing the credible mapping method to create subjective spatial data (Burkhard & Maes, 2017), however, these metrics have rarely been applied to assess the credibility of some emerging mapping methods in this field such as using geo-tagged social media data.

1.2 Problem

Recreation has been an integral part of the culture and economy of New Zealand. The Department of Conservation of New Zealand (DOC) is working with the tourism industry and recreational groups to planning and monitoring of recreational businesses and activities in the natural areas. One of the main challenges DOC faced in sustainable recreational planning and managing is embedding the spatial data of community expectations and trends in this process (Chick & Laurence, 2016). To deal with this issue, DOC needs to identify and illustrate social values of cultural ecosystem services. DOC developed a mapping project in 2012 to identify the recreational use and value of New Zealand's coastal and marine environment. The spatial data created by this project gave a general overview of the recreational activity in the coastal study area, however, the applicability of the data for planning is still somewhat unclear (Chick & Laurence, 2016). Powell (2005) attempted to provide a geospatial database for recreation, cultural and historical heritage, and Māori cultural values in water bodies of New Zealand at a national scale. It indicated the difficulty and complexity to determine the importance of services at different scales (e.g. sub-catchment, catchment, entire river).

To support spatially oriented decisions in planning practices such as recreation planning, it is important to select a practical and adequate method or a mix of several methods (Kenter et al., 2014). The method of mapping social values varies based on the goals, data availability, and time and resource limitations. Mapping methods reveal diverse spatial social values, such as aesthetics, historical/cultural, conservation, etc. (Brown et al., 2019) and, therefore, the credibility of these approaches is best supported with a specific planning target, such as recreation planning. In the other words, clarifying the goals and objectives of social value mapping helps to choose a credible and appropriate approach.

Recently social media platforms have been used as a data source to reveal the social values of ecosystem services (Oteros-Rozas et al., 2018). Social media data provides a supply of valuable insights for recreation planners using geo-tagged photographs, comments, and other metadata (Keeler et al., 2015; Laura Nahuelhual et al., 2013; Richards & Friess, 2015). For instance, the uploaded photographs on social media are used as a surrogate for the real experience of people in a landscape (van Zanten et al., 2016). This method (called Passive Volunteer Geographic Information (VGI) in this research) employs geographic information which is passively provided by volunteers with reasonable time and cost. Geo-tagged photographs have been applied to determine the spatial and temporal dynamics of recreational activities (Girardin et al., 2008), the frequency of recreational trips (Kisilevich et al., 2010), the attractiveness of places (Mancini et al., 2018), hot spots and digital footprint of tourists (Heikinheimo et al., 2017; Orsi & Geneletti, 2013), behaviour of tourist, and aesthetics or recreation values in different scales of natural and urban environments (Sottini et al., 2019; Vu et al., 2015).

Expert knowledge has commonly been used to identify people's preferences and trends about recreation services of ecosystems (Paudyal et al., 2015). This knowledge can be translated into a credible and rich source of spatial information. In the other words, the knowledge and real-world experience of local experts apply to delineate the social value of ecosystem services in a specific area (Jacobs et al., 2015). This method has been applied to map the supply and social value of recreation services (Kopperoinen et al., 2014; Mukherjee et al., 2014; Nahuelhual et al., 2016; Paracchini et al., 2014; Paudyal et al., 2015).

Both methods have been shown to create outcomes of social value maps to support recreational planning (Adnan, 2018; Langemeyer et al., 2018; Paracchini et al., 2014), however, little literature focuses on credibility assessment of passive VGI and expert-based data. For instance, geo-tagged data on social media has mostly been uploaded for tourist attractions. Whether this data can be used to provide sufficient social values at a regional scale still remains unknown. The literature has been dominated by studies identifying a single social value (predominatly aesthetics) for recreational planning (Richards & Friess, 2015; Tenerelli et al., 2016a; Van Berkel et al., 2018). Such a limited focus may limit the wider applicability of this data. Expert knowledge can provide spatial social value data at a larger scale (Langemeyer et al., 2018) but whether this approach also captures a diversity of features or views has not been well researched. Another possible concern is the under lack or overrepresentation of different landscape types or ecosystems.

As methods of social value mapping like passive VGI and expert-based evaluation increase in popularity and usage, credibility of these methods must assess before integrating outcomes in the planning system.

1.3 Research questions

This research will focus on the assessment of the credibility of two social value mapping methods to support recreation planning. This will be achieved by answering this research question:

How can the credibility of passive Volunteer Geographic Information (VGI) and expert-based knowledge be demonstrated as a data source for social value mapping in ecosystem services, using the South Wairarapa District as a case study?

To answer this question, this study aims to critically analyse the outcomes of mentioned methods by exploring the following objectives:

• What are the key types of social values identified using these methods?

• To what extent does the spatial distribution of social values vary using different methods?

• Are any landscape or ecosystem types missed or overrepresented in different methods of social value mapping?

• What are the advantages and disadvantages of the two different methods of social value mapping?

1.4 Thesis structure

This thesis consists of six chapters:

Chapter 1 provides the context of research and outlines research gaps, problems, questions, and objectives addressed by this research.

Chapter 2 explores the concepts of ecosystem services, social values, and why they are important. The chapter then considers different methods of social value mapping: passive

Volunteered Geographic Information (VGI), expert knowledge evaluation, and Public Participation GIS (PPGIS). Finally, this chapter explains the credibility assessment of social value mapping methods in the literature.

Chapter 3 outlines the case study and methodology applied for the two methods of social value mapping applied in this thesis. The processes used to analyse the gathered data are described.

Chapter 4 presents detailed results using both social values mapping methods, including thematic analysis of recreation, aesthetics, and cultural/historical values and address two first objectives of this thesis.

Chapters 5 discusses the results of research and answers two last objectives by addressing the advantages and disadvantages of the two social value mapping methods to support recreation planning and analysing credibility of the methods.

Chapter 6 concludes with the key findings of the research and provides avenues for future research.

Chapter 2: Literature Review

This chapter explores the concepts of ecosystem services and social values, with a focus on social value mapping. The chapter then focuses on passive Volunteered Geographic Information (VGI), expert knowledge evaluation, and Public Participation Geographic Information Systems (PPGIS) as different methods of social value mapping and then comments on the strengths and weaknesses of these methods. The chapter then explores credibility assessment of these methods for land planning and the challenges of communicating these social value mapping methods to support decision-makers and other end-users in recreational planning.

2.1 Ecosystem services

The modern interpretation of ecosystem services emerged in the late 1970s and was deeply influenced by economics (Braat & de Groot, 2012). Since then different definitions for ecosystem services have been formulated and published. Table 2.1 provides such definitions. In 2005, the ecosystem services reached a turning point with the Millennium Ecosystem Assessment.

Table2. 1. Key definitions for ecosystem services

The benefits human populations derive directly or indirectly from ecosystem function	Costanza et al., 1997: 253
The benefits people obtain from ecosystems	Millennium Ecosystem Assessmen, 2005:40
Components of nature, directly enjoyed, consumed or used to yield human benefit	Boyd & Banzhaf, 2007:619
Services are the aspects of ecosystems utilised (actively or passively) to produce human well-being.	Fisher et al. 2009:645
The direct and indirect contributions of ecosystems to human well-being.	The Economics of Ecosystems and Biodiversity Foundations (de Groot et al., 2010:12)
The contributions that ecosystems make to wellbeing	Common International Classification of Ecosystem Services (CICES), 2011: 2
Nature's contributions to people (NCP)	Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) (Díaz et al., 2018:270)

The Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), defined ecosystem services as "nature's contributions to people" (NCP) (Díaz et al., 2018:270). These contributions include both positive and negative aspects of living nature to the quality of life for people. NCP considers ecosystem services as a social concept and emphasises the importance of local and indigenous knowledge systems (Díaz et al., 2018; Pascual et al., 2017). In this thesis, we use the NCP definition for ecosystem services.

The interface between nature and people based on definition of ecosystem services well presented in "cascade model" (Fig1) (Haines-Young & Potschin, 2010). This model shows how ecosystem and human wellbeing are related each other.

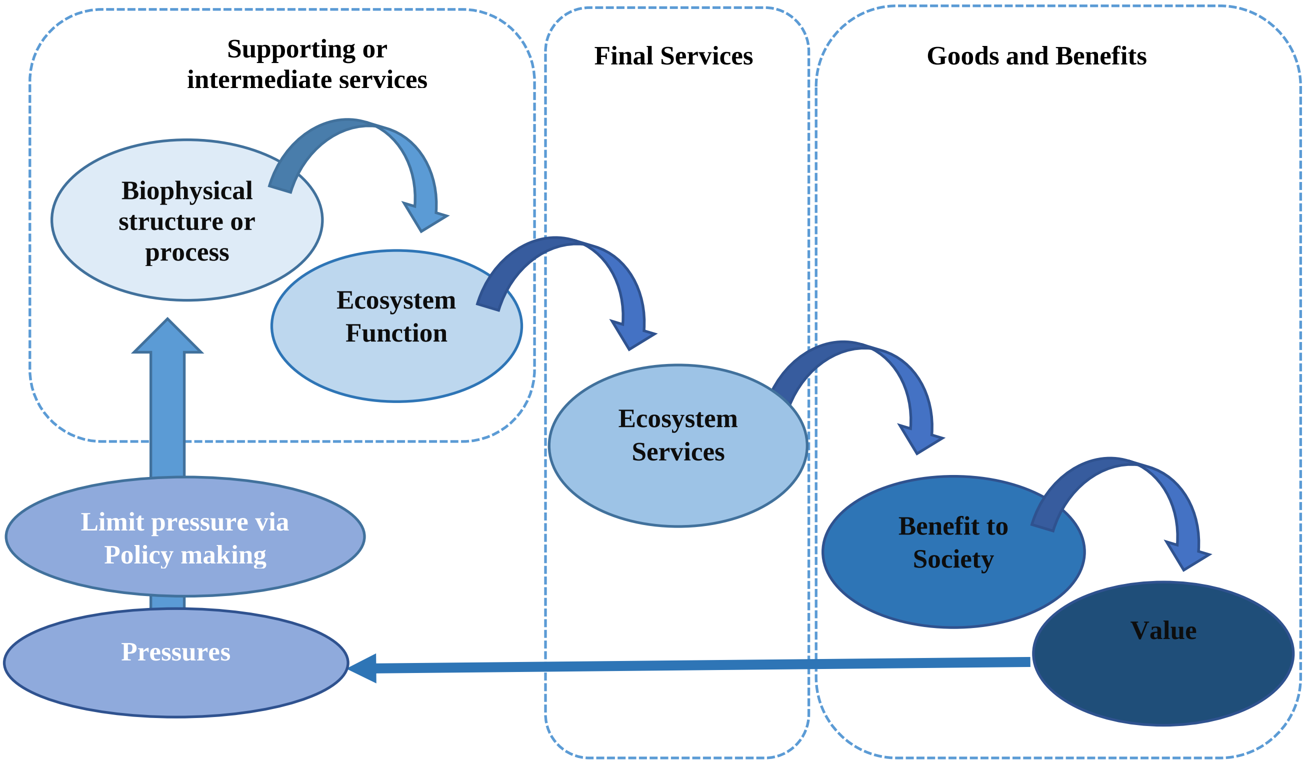


Figure 2. 1. The cascade model (Haines-Young & Potschin, 2010:578)

Biophysical structures and processes in this model show the characters of ecosystem. Ecosystem functions are the abilities of biophysical structure (intermediate services) to generate final ecosystem services (e.g. landcover to generate beautiful sceneries). These final services promote well-being of humans by providing benefits to society (e.g. landscape aesthetics experience or recreation). People value these benefits using quantitative (monetary) and qualitative (non-monetary) criteria. Pressure on ecosystems by human activities changes the ecosystem condition (its biophysical structure and processes) and affects the supply of ecosystem services. As a result, the social values or preferences for the benefits of ecosystems change, and this change persuades decision makers to intervene in the ecosystem in order to preserve sustainability.

Ecosystem services have been classified using several approaches to help better understanding what benefits humans obtain from the ecosystems. The Common International Classification of Ecosystem Services (CICES) categorised the ecosystem services in three major sections: provisioning, regulating, and cultural (Potschin & Haines-Young, 2011). Definitions of these sections of ecosystem services are shown in Table 2 based on CICES V5.1.

Table2. 2. Definition of three sections of ecosystem services categories in CICES V5.1
(Haines-Young & Potschin, 2018, p.10)

Section	Definition
Provisioning	"This Section covers all nutritional, non-nutritional material and energetic outputs from living systems as well as abiotic outputs (including water)."
Regulation and Maintenance	"All the ways in which living organisms can mediate or moderate the ambient environment that affects human health, safety or comfort, together with abiotic equivalents."
Cultural	"All the non-material, and normally non-rival and non-consumptive, outputs of ecosystems (biotic and abiotic) that affect physical and mental states of people."

To monitor ecosystems and support decision-making systems, there is a need to assess and quantify various sections of ecosystem services. Several methodologies are used for assessing ecosystem services categorised as economic, biophysical, and socio-cultural methods (Burkhard & Maes, 2017). The ecosystem services literature has been dominated by biophysical and economic methods, however, socio-cultural methods have been considered and developed in the last decade (Chan, Guerry, et al., 2012; Martín-López et al., 2012; Oteros-Rozas et al., 2018; van Riper et al., 2017).

Socio-cultural methods have the potential to address interactions between people and nature by revealing the social values of ecosystem services (Martín-López et al., 2014; Walz et al., 2019). Information of social values and people 'preferences contributes to support the decision-making systems particularly about land planning and management where the benefits of people conflict with the preservation of ecosystems (Förster et al., 2015; Iniesta-Arandia et al., 2014; Nieto-Romero et al., 2014; Walz et al., 2019). Integrating a framework of ecosystem services and social value assessment into land planning systems has already been done using spatial data at different scales (national to local scales) in several countries (Cortinovis & Geneletti, 2018; Nahuelhual et al., 2017; Ruskule et al., 2018; Tenerelli et al., 2016). Spatial planning systems in these countries have profited from various tools of ecosystem services assessment, such as maps. For example, Latvia and Sweden used ecosystem services maps in spatial planning to assess various opportunities and impacts on a marine ecosystem (Marine & Management, 2019; Veidemane et al., 2017). Ecosystem services mapping has great potential to support spatial planning by addressing conflicts (Karimi & Brown, 2017), identifying hotspot areas of ecosystem services (Cai et al., 2017), identifying mismatch between supply and demand (González-García et al., 2020), engaging stakeholders in the planning process (Brown & Weber, 2013), and delineating the trade-offs in ecosystem services supply (Gimpel et al., 2018).

Despite the importance and success in using spatial information of ecosystem services in planning systems, little research focuses on mapping cultural ecosystem services and related social values (Crossman et al., 2013; Gould et al., 2019). The difficulty and complexity of mapping intangible social values limited developing appropriate methods in this field (Martínez Pastur et al., 2016; Plieninger et al., 2015). Applying and developing adequate mapping methods to create timely, reasonable, detailed, and credible spatial data of social values and people's preferences of ecosystem services is crucial (Burkhard & Maes, 2017; Crossman et al., 2013).

2.2 Social values of ecosystem services

Social values of ecosystem services are perceived benefits of natural ecosystem for the well-being of people (Kenter et al., 2015; van Riper et al., 2017). Social values are considered "held values" or "assigned values" that represent to the extent the nature is useful and important to people and intrinsically motivate people to manage and protect the natural resources (Díaz et al., 2015). People can value specific landscape due to social relations, particular experiences, and cultural or historical roots (Scholte et al., 2015). Social value assessment is a beneficial tool in revealing the non-market value of ecosystem services (de Groot et al., 2010; Pascual et al., 2017).

2.3 Social value mapping

Spatial delineation of social value is important to support land planning and decision-making systems. Social value maps support decision-makers by providing the opportunity for visualising people's preferences in the real-world (Arkema et al., 2015; Hill & Aspinall, 2000; Kopackova et al., 2008; Lavorel et al., 2017).

A range of methods has been applied to social value mapping. However, complex processes required by some of these methods have limited the application of social value maps in spatial planning systems (Burkhard & Maes, 2017; J.O. Kenter et al., 2014). Given the diversity of social values of ecosystem services and the planning targets, different technologies have been employed for mapping and creating social value data (Brown et al., 2019; Nahuelhual et al., 2016). Social value mapping methods range from modelling preferences based on land-use to implicitly integrate social values using interactive GIS software (Sekerka & Stimel, 2012). Three common methods in this field are Public Participatory Geographic Information Systems (PPGIS), Passive Volunteered Geographic Information (VGI), and expert-based evaluation.

2.3.1 Public Participatory Geographic Information Systems (PPGIS)

To map social values, most studies (e.g. Brown et al., 2012, 2015; Gliozzo et al., 2016) use PPGIS due to its potential to adapt to different social contexts and help to demonstrate the public perception of land for planning applications. PPGIS engages communities (to collect local knowledge) using a GIS to describe values and preferences related to ecosystem services and provide the opportunity to prioritise different kinds of social values (Bagstad et al., 2017; Brown et al., 2012). PPGIS has the potential to create different management indicators and capture various kinds of social values, and also, its data collection process is relatively readable (Brown, 2006; Raymond et al., 2009). However, there are several difficulties including in gathering data in a larger area like regional scale (Zhang & Zhu, 2018), and it is a time-consuming process (Brown & Weber, 2011).

The advancement in the PPGIS surveys using Internet platforms (instead of paper-based surveys) provides digitalised spatial data in different scales as well as using various base maps. However, a sufficient response rate may not gathered in a reasonable cost (time and money) using Internet-based PPGIS (Brown et al., 2012).

2.3.2 Passive Volunteered Geographic Information (VGI)

Recently, VGI has been applied to social value mapping (Ghermandi & Sinclair, 2019; Gliozzo et al., 2016; Oteros-Rozas et al., 2018; Richards et al., 2018). The term Volunteered Geographic Information introduced by Goodchild (2007) and refers to the use of web-based technology in gathering crowd-sourced data provided by non-experts (active VGI). The crowd-sourced data is increasingly employed by researchers in environmental studies and management plans, although these data are not originally generated for the research purposes in some cases (Connors et al., 2012).

One of the emerging techniques for VGI is using passive geo-referenced data uploaded on social media (called passive VGI in this research) (Thatcher, 2013). For instance, researchers analyse the content of uploaded photographs as well as related metadata (such as posts, comments, etc.) to reveal the social values of ecosystem services. The extracted datasets of social media particularly photo-sharing platforms have been successfully used to represent human preferences for recreation activities to support decision-making processes over large areas (Adnan, 2018; Keeler et al., 2015; Richards et al., 2018; Wood et al., 2013). Content of uploaded photographs on social media are considered a proxy for people’s real-time preferences or people’s interactions with nature (Gliozzo et al., 2016). Users tend to share their photographs regarding specific sites that show how valuable nature and its services are to them (Oteros-Rozas et al., 2018). This continuous and direct flow of data is accessible with less cost, time, and labour (Antoniou, 2017; Soliman et al., 2017; Tenerelli et al., 2016; Yan et al., 2017). Passive VGI has been used by Casalegno et al. (2013), Gliozzo et al. (2016), and Tenerelli et al. (2016) to demonstrate benefits of cultural ecosystem services at a landscape level. The results identified the spatial distribution of people's preferences on the case study area which can be applied in land-use planning (Gliozzo et al., 2016; Tenerelli et al., 2016). Vu et al (2015) analysed behaviour of tourists and travel patterns in Hong Kong using geo-tagged photographs to support tourism planners. Others used crowd-sourced photographs to map tourist flows and visitation rate (Orsi & Geneletti, 2013; Sessions et al., 2016; Wood et al., 2013) and aesthetics and recreation values (Casalegno et al., 2013; Van Zanten et al., 2016). Tenkanen et al. (2017) found a good spatial and temporal correlation between observed visitation and geo-tagged photograph counts.

Using social media as a data source has no interviewer bias (Martínez Pastur et al., 2016), and not suffer from recollection bias unlike other survey methods (Dunkel, 2015; Vu et al., 2015). However, some criticisms about privacy and ethical issues exist where the users of social media are not aware of their uploaded data being used for research (Arts et al., 2015; Connors et al., 2012).

Ghermandi & Sinclair (2019) reviewed and analysed 169 papers using passive VGI data between 2011 and 2017. Gathering data from a single social media was common in majority of studies, and there was a considerable emphasis on Twitter and Flickr, although popular social media, such as Facebook and Instagram were limited because of data access restrictions. Studies had more emphasis on analysing a combination of text and metadata or photograph content and metadata, such as geo-tagged location, titles and tags.

Moreover, different platforms have a different ability to create data, and often reflect the specific interests of their users. This issue limits engaging various stakeholders to gather data. For instance, Instagram users are younger than users of other social media (Heikinheimo et al., 2017). Flickr contains more relevant images of cultural ecosystem services than Panoramio (Oteros-Rozas et al., 2018). Flickr photographs have more biodiversity content than Instagram, while, uploaded Instagram photographs include more people (Tenkanen et al., 2017).

The large amount of available spatial data is a great strength of social media (Martin & Schuurman, 2017), however, there is limited data on social media for the area with restricted access like farms (Jongman et al., 2015; Richards & Friess, 2015; Tenkanen et al., 2017; Zhou & Xu, 2017).

Shared photographs on social media can have a representativeness bias. For instance, some users of social media find hard to share photographs of specific recreation activities such as diving, surfing or rock climbing (Spalding et al., 2017; Tenerelli et al., 2016; Wood et al., 2013). As a result land based activities appear more popular than water-based ones (Howarth, 2014). Some studies focused on comparing the usability of different photograph sharing platforms in gathering data using passive VGI. Antoniou et al. (2010) evaluated the usability of Geograph, Flickr, Panaramia, and Picasa as sources for geographical information. The spatial distribution of geotagged photographs was examined based on the numbers of photographs in the determined tiles. The study found most platforms do not provide adequately spatially distributed data. For instance, in Flickr, 84.6% of the tiles did not contain a geo-tagged photograph, and photographs were clustered on urban areas and tourist attractions. In contrast, spatially explicit applications, such as Geograph, suggest using geography as the main object of photography (Antoniou et al, 2010). Photo sharing platforms differ in their capability to create relevant and credible spatial social value data.

Gliozzo et al. (2016) examined whether various photo-sharing platforms (Panoramic, Flickr, and Geograph) behave spatially similarly in urban and non-urban areas. The number of users sharing pictures are considered as a proxy for cultural attachment to a specific area. Flickr dominated the number of shared photographs (73%) and contributors (62%), however, uploaded data on Geograph covered the whole study area. Also, the nonurban areas detected cultural features (human-made or natural) in all platforms, but Flickr represented more human made cultural artifacts.

Social media availability is not guaranteed in the future. For example Panoramio stopped in November 2016. Sometimes, the criteria for accessing data is changed, for instance the Instagram API for mining data was updated twice in 2016 and 2018 and more restrictions on available data were applied.

Using geo-tagged data is frequently criticised because of the degree of positional inaccuracy (Kirilenko et al., 2015; Leibovici et al., 2017; Tenerelli et al., 2016b). Different photo-sharing platforms show different level of positional accuracy referring to essential prerequisite standards for example, Panoramio had lower geo-tagging error than Flickr (Zielstra & Hochmair, 2013). Several other reasons affect the spatial accuracy of geo-tagged data on social media, such as low accuracy in remote and mountain areas, poor mobile and GPS coverage, impact of weather conditions and manual geo-tagging (Chua et al., 2016; Heikinheimo et al., 2017; Oteros-Rozas et al., 2018; Richards & Friess, 2015). Using tags and titles of metadata also do not provide fine scale information and create bias in finding accurate location of data.

Flickr is one of the popular geotagged photo sharing platforms, and over 30 studies used uploaded photographs on Flickr to analyse people's perceptions of the environment (Ghermandi & Sinclair, 2019). The address of users in this platform and location of shared photographs used in travel cost method for economic valuation of a specific area for recreation (Ghermandi, 2018). Mancini et al. (2018) validated the use of shared photographs on Flickr to evaluate nature-based recreation at national and regional scales in Scotland. Their findings conformed that spatial and temporal patterns on Flickr are reliable comparing existing visitor statistics for planning and management of nature-based recreation to a 10Km scale resolution. They suggested that this data should be cautiously used in very fine scale recreation planning as the number of wildlife photographs for representing the volume of recreation is not reliable metrics at a resolution finer than 10 km.

2.3.3 Expert-based evaluation

The expert knowledge is considered a credible source in supporting environmentally related decisions (e.g. Huntington 2000, Millennium Ecosystem Assessmen 2005). Experts also are a credible data source for the interpretation of social values of ecosystem services for decision-makers (Burkhard & Maes, 2017; Campagne & Roche, 2018). Expert mapping improves the quality of outcomes because experts can apply local knowledge and real-world experience (not just individual preferences) to the process of mapping. Indeed, local experts ensure the validity and implementation of maps by clearly delineating demands, cultures, and knowledge of a specific area (Burkhard & Maes, 2017). Burkhard (2009) suggests a matrix model for ecosystem services assessment that has been adopted by different researchers. This method can delineate various aspects of biophysical supply as well as the economic and social demand of ecosystem services (Campagne & Roche, 2018). Some attributes of this model, such as flexibility and speed, make it applicable and efficient in different aspects of ecosystem services research particularly if the model integrates with an expert-based scoring technique (Burkhard et al., 2011; Jacobs et al., 2015). Recreation ecosystem services and values have been assessed by experts to provide spatial data over the last decade. Van Berkel et al. (2018) introduced a landscape aesthetic quality index to reveal outdoor activities at different spatial scales.

Burkhard et al. (2014) developed a matrix to create spatial information about services (flows) in use within the ecosystem and the temporal aspects of various ecosystem services supplies.

Some criticisms despite have emerged (Jacobs et al., 2015). The main methodological uncertainty refers to using experts' opinions without full attention to the scientific and empirical basis of these data (Hou et al., 2013). Brown et al. (2004) state also the experts in some cases consider their own opinions about places in the results. Another common concern for mapping by expert-based matrix is that it does not have capacity to spatially represent social values (Burkhard & Maes, 2017). This means any geospatial unit (landscape or ecosystem) that not represented during data collection (particularly over large areas) will be ignored.

The reliability of the measurement instrument and the validity of the model are important concerns when using expert-based knowledge. Jacobs et al. (2015) suggest using an alpha risk statistic to assess the reliability of an expert-based matrix model. Also, the validity of the matrix model can be assessed using qualitative and quantitative data. The Bayesian model (Haines-Young, 2011) and choice model (Jacobs et al., 2015) apply to validate the expert based matrix. Rabe et al. (2018) developed an online survey assessing user preferences to validate expert-based knowledge.

2.4 Credibility assessment of passive VGI

Access to credible social value data is important due to the connection of spatial land planning practices to actual decisions that have potential to affect the future of nature and human. For example, Whitehead et al. (2014) showed the significant influence of spatial social values to change conservation scenarios in a planning practice in Australia.

Several studies (Brown et al., 2017; Moreri et al., 2018; Severinsen et al., 2019) evaluate the credibility of objective data using different mapping approaches (such as VGI and PPGIS), although the subjective data, such as social values, are almost neglected (Brown et al., 2019). Most studies focus on assessing the credibility of data provided by crowd-sourced data collection methods, such as the active VGI and PPGIS, less attention is given to assess the credibility of passive VGI for social value mapping. This is because of the complicated nature of defining authoritative criteria for assessing credibility of social value data (Greg Brown et al., 2019)

Two concepts most commonly used to assess the credibility of crowd sourced data are; the attributes of participants and spatial accuracy (Spielman, 2014). The credibility of participants is important to explore the credibility of created data. Flanagin & Metzger (2008) used people's motivations and attitudes as the criteria to address the quality and source reliability of data (Flanagin & Metzger, 2008). Mapping effort and data usability are also used as metrics to assess the credibility of participants using PPGIS (Brown et al., 2012). Mapping effort is the respondents' motivations to engage in the PPGIS survey and data usability refers to what extent of captured data are useful. Brown et al. (2012) showed volunteers were more interested in mapping compared to online participants in a survey in Australia. A lack of motivation to participate negatively impacts on the quality of spatial data (Spielman, 2014). PPGIS and active VGI, to some extent, can explore the motivations of volunteers and participants as they consciously create the spatial data and they are aware of the purpose of data creation. But the motivation of contributors in passive VGI is not clear. A concern when assessing the attributes of contributors in crowd-sourced data collection methods is the lack of sufficient demographic information of the contributors (unrecorded or inaccessible) (Basiri et al., 2019).

For the spatial data accuracy, the most important metrics for credibility assessment are positional accuracy data and completeness of the data. Positional accuracy refers to how exact the coordinate value of an object is in comparison to the reality on the ground (Haklay, 2010). The positional accuracy of people's preferences and local knowledge about objective features (e.g. native species or wildlife habitat) can be examined by biophysical landscape features or other spatial data as a benchmark (Brown et al., 2015; Haklay, 2010). Haklay (2010) addressed 80% - 86% positional accuracy in Open Street Mapping (OSM) effort using VGI (Haklay, 2010). Wood et al. (2013) found significant correlations between the crowd-sourced information and gathered empirical data about visitation rates at national parks (Wood et al., 2013).

Assessing positional accuracy of spatial data of subjective social values is more difficult (Brown et al., 2015). For instance, the data quality of recreational or aesthetic values cannot be assessed by their positional accuracy because these are specific preferences by the public about recreational ecosystem services and can be assigned to any desired location.

Completeness in spatial data refers to the relationship between gathered data and the entirety of such data in the real world or to what extent the coverage of data is comprehensive (Brown et al., 2015; Haklay, 2010). Decision makers must be able to determine which areas are well covered and which are missed. To assess the completeness of data, the comprehensive data coverage area must be defined. Lechner et al. (2015) developed an assessment of completeness of biological/conservation values provided by PPGIS. They explored the extent to which biological/conservation values provided by PPGIS participants overlaid with areas of high conservation importance. The result was a sufficient completeness of gathered data for adequate conservation planning to tackle conflicts between stakeholders.

Assessment of completeness of data addresses the usefulness of gathered data for a specific target of planning (Brown et al., 2015). For instance, when the end-users of collected data are recreational planners, completeness can mean the extent outcomes of social value maps reveal locations of people's preferences for various recreational values (e.g. recreation, aesthetics, and cultural/historical) in different ecosystems or landscapes. Expert-based spatial data has been considered as a credible source and has traditionally been used to support decision making and land planning process. Cowling & Pressey (2003) assessed the similar results between expert based assessment and algorithm-based approach where experts reveal areas with high biological values for locals. They showed the importance of expert knowledge in terms of creating spatial social value data to integrate into planning systems (Cowling & Pressey, 2003). Currently, the emerging social value mapping methods such as passive VGI needs to assess of usefulness for a specific target comparing expert-based data (Brown et al., 2015). Comparing results between public created spatial data and expert created spatial data to achieve the end users' target is the common method to assess the credibility of crowd-sourced data collection methods. Brown (2004) used spatial similarity and coincidence as a metric to compare biological marine values (Brown et al.'s results show a moderate degree of spatial similarity (25–43%) between these two different methods. The outcomes of PPGIS revealed the importance of biological area to people whereas the expert-based method could not value the selected areas. Also, experts identified areas that had been visited continuously for work or research targets. Experts identify places from their subjective field of research, however people represent their general perceptions about places (Brown et al., 2004). This is considered a serious limitation to use expert-driven maps (Bojórquez-Tapia et al., 2003; Brown et al., 2004) as the main goal of social value mapping effort using expert knowledge is to explore the people's preferences about benefits of ecosystem services rather than the experts personal opinions. Rabe et al. (2018) compare the results of an expert model in recreational planning against the preferences of potential users. The results represented different values in some areas although a clear consensus exists between both data sources. This study proposed to use a combination of both approaches to best define scenarios for recreational planning.

Credible social value data using passive VGI needs a well-designed mapping system with fewer biases. However, due to the subjective nature of social value data, applying the same credibility criteria as for other spatial data is difficult. Selecting the appropriate platform as a data source and evaluating the gathered data to ensure their completeness are the most important metrics to measure credibility assessment of passive VGI data.

2.5 Summary

Spatial planning requires credible data of social values to reveal people's preferences about different benefits of ecosystem services. Three mapping methods are largely used to reveal assigned social values to ecosystem services particularly cultural ecosystem services; PPGIS, expert knowledge evaluation, and passive VGI. PPGIS identifies the preferences of various stakeholders of ecosystem services in specific locations. Passive VGI considers the number of taking and sharing photographs on social media platforms as a proxy for social values of ecosystem. Expert knowledge is traditionally used as a proxy for the people preferences about areas.

There are considerable efforts to develop the theoretical context or appropriate methodological framework for social value mapping, although the credibility of these methods particularly passive VGI, is underassessed.

Some credibility assessment metrics used with PPGIS and active VGI data may apply for evaluating passive VGI and expert-based datasets. For example, the completeness must be considered according to the usability of spatial data for specific targets. This helps to assess the credibility of social value data created by passive VGI and expert-based evaluation for recreational planning. Given this metric, credibility in this context refers to the extent to which extracted spatial data represents various types of social values and their distribution in different landscape units to support recreational planning.

Chapter 3: Methodology

Socially valuing cultural services is a complex issue and difficult to spatially represent due to the subjectivity of people's social values. This research is a deductive study in which two different methods of social value mapping (passive VGI and expert-based evaluation) are assessed to explore their credibility in supporting recreational planning. Chapter 3 explores how to identify and map the social values by content analysis of the uploaded photographs on the Flickr in the passive VGI. Also, the online survey and the face to face interviews conducted to gather expert-based knowledge are detailed. This thesis was granted ethics approval by Victoria University of Wellington's human ethics committee (reference number: 0000028965). We adopted the definition of social values provided by Brown et al. (2014) and Brown & Brabyn (2012) to align with the characteristics of our case study area. Recreation value referred to places that provided outdoor recreation services. Aesthetics value assigns to an area contains attractive scenery. Historical/cultural value includes identity, history, and culture of people. Table 3.1 provides the definition of expected social values of cultural ecosystem services for recreational planning based on current literature in three categories; aesthetic, recreation, and historical/cultural.

Table 3. 1. Expected social values to support recreational planning in New Zealand

Social value	definition
Recreation	This value refers to places that people enjoy spending their leisure time participating in outdoor recreation activities with family, friends, or by themselves (e.g. walking, camping, fishing, swimming, bird watching, etc.).
Aesthetic	This value refers to places with attractive scenery including sights, smells, and sounds.
Cultural/Historical	This value refers to places with historical and cultural values including traditions, tikanga, and mātauranga Māori.

To spatially demonstration of social values, this study used two methods: passive Volunteered Geographic Information (passive VGI) and expert-based evaluation. Mapping methods were selected that were practicable given existing data, time, constrains source and Covid-19 limitations. Figure 3.1 illustrates the workflow of social value mapping methods in this study.

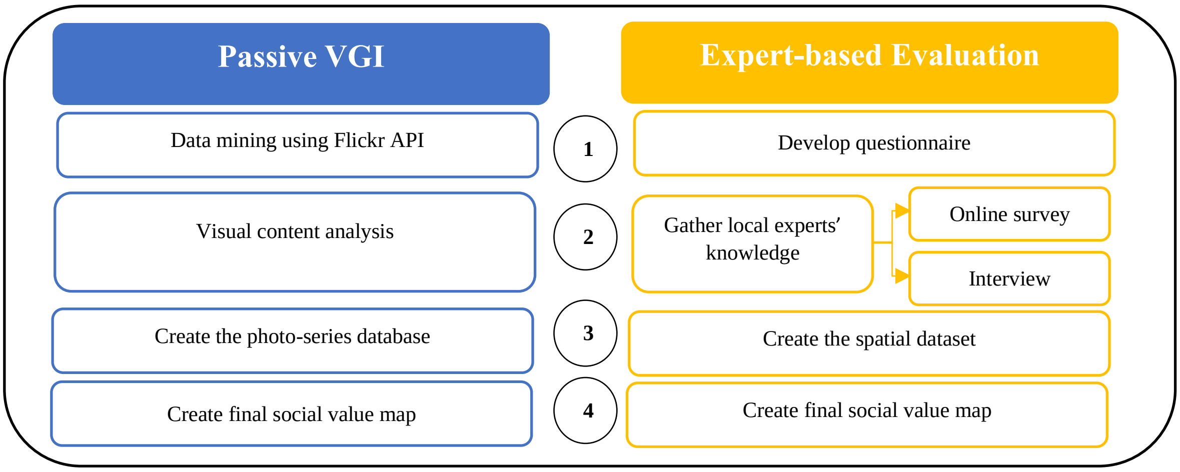


Figure 3. 1. Workflow of social value mapping in this thesis

3.2 Study area

This research will create a passive VGI and an expert-based maps for the South Wairarapa district. This area is located in the North Island of New Zealand and is a part of Wairarapa bioregion. The South Wairarapa district has an area of 2485 km^2 which includes the flood plain of the Ruamahanga River in the north and Lake Ferry, Cape Palliser, and coastal areas in the south (Figure 3.2). This area represents a combination of different landscapes (for example, mountain, hill, coastal, etc.), as well as various stakeholder groups (for example, tourists, farmers etc.).

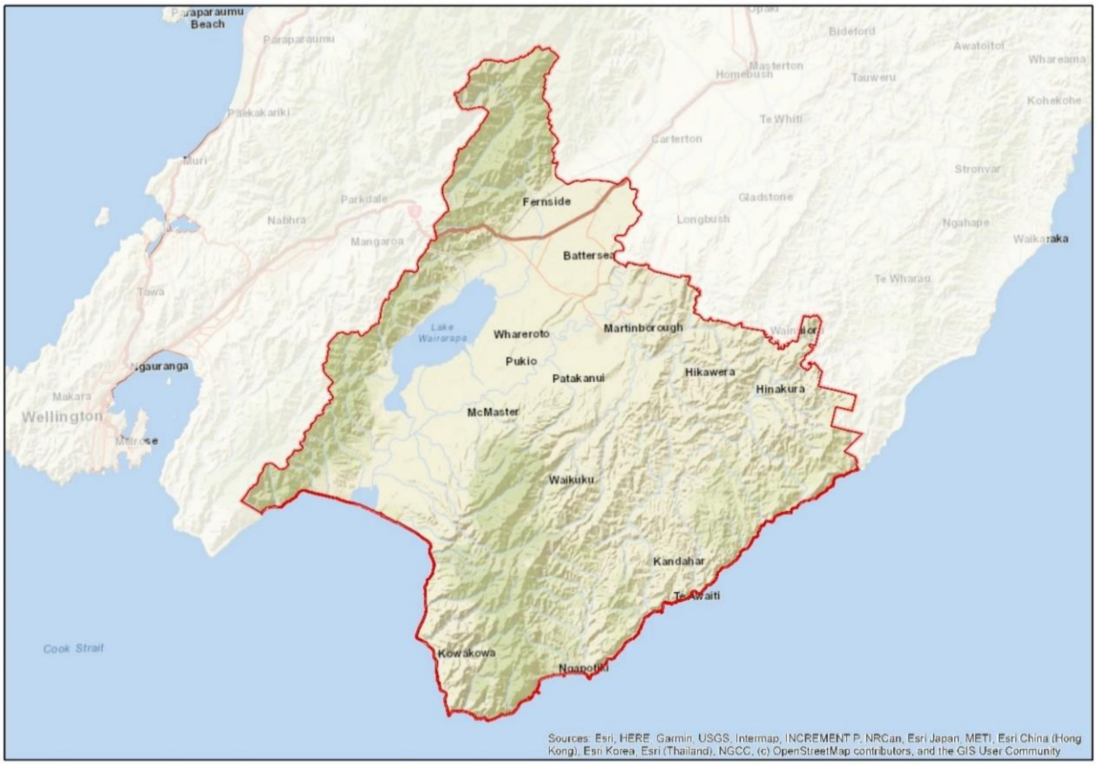


Figure 3. 2. South Wairarapa District

3.3. Social value mapping using Passive VGI

In passive VGI, uploaded photographs are considered as user preferences of the ecosystem services. This study uses Flickr as the data source to map social value using passive VGI in the following steps.

3.3.1. Data mining using Flickr API

Most studies (Chen et al., 2020; Gliozzo et al., 2016; Han et al., 2020; Oteros-Rozas et al., 2018) in crowdsourced mapping directly retrieve the data from the social media, either using the sites' Application Programming Interfaces (APIs) or by manual download. Reliance on the APIs' structured interfaces is the de facto standard approach for social media data retrieval, as opposed to techniques based for instance on web data scraping (Gliozzo et al., 2016).

We used a Python code provided on Git Hub (https://github.com/tgrippa/flickr_api_scripts) that was created to gather uploaded photographs on Flickr in the city centre of Brussels in 2018. We modified this python code to apply the Flickr API in the South Wairarapa district (the modified code is available in Appendix A). The South Wairarapa district boundary was downloaded from the Land Information New Zealand (LINZ) open database.

The publicly available photos were downloaded as point features within the polygon containing the study area between 2004 -2019. Table 3.2 shows a sample of downloaded data. The extracted data includes coordinate address, owner user id, and photographs' Flickr URL of 4642 photographs. The coordinate addresses have given as latitude and longitude in WGS84 Spatial Reference System (SRS) used by default in Global Positioning System (GPS) receivers.

Table 3. 2.Extracted data from Flickr

FID	Shape *	id	latitude	longitude	accuracy	owner	farm	server	secret	URL_static	URL_websit
434	Point ZM	2821236042	-41.608768	175.273475	16	13885025@N05	4	3140	e220cca9d5	https://farm4.staticflickr.com/3140/2821236042_e220cca9d5.jpg	https://www.flickr.com/photos/13885025@N05/2821236042
404	Point ZM	24015616169	-41.609687	175.273727	16	26654815@N08	2	1598	e5af209da2	https://farm2.staticflickr.com/1598/24015616169_e5af209da2.jpg	https://www.flickr.com/photos/26654815@N08/24015616169
3	Point ZM	32559791703	-41.613239	175.289847	16	43421354@N04	4	3750	1659f5582f	https://farm4.staticflickr.com/3750/32559791703_1659f5582f.jpg	https://www.flickr.com/photos/43421354@N04/32559791703
4	Point ZM	33374118045	-41.613239	175.289847	16	43421354@N04	3	2859	7f12ff7533	https://farm3.staticflickr.com/2859/33374118045_7f12ff7533.jpg	https://www.flickr.com/photos/43421354@N04/33374118045
5	Point ZM	32559790213	-41.613239	175.289847	16	43421354@N04	1	639	e3df896398	https://farm1.staticflickr.com/639/32559790213_e3df896398.jpg	https://www.flickr.com/photos/43421354@N04/32559790213
7	Point ZM	7629413480	-41.613239	175.289847	16	43421354@N04	9	8425	e25a706506	https://farm9.staticflickr.com/8425/7629413480_e25a706506.jpg	https://www.flickr.com/photos/43421354@N04/7629413480
8	Point ZM	7629411904	-41.613239	175.289847	16	43421354@N04	9	8027	7ab13f13ac	https://farm9.staticflickr.com/8027/7629411904_7ab13f13ac.jpg	https://www.flickr.com/photos/43421354@N04/7629411904
15	Point ZM	4485399487	-41.612979	175.292315	16	33633351@N00	5	4014	901bebcfd0	https://farm5.staticflickr.com/4014/4485399487_901bebcfd0.jpg	https://www.flickr.com/photos/33633351@N00/4485399487
75	Point ZM	3894991729	-41.612575	175.288698	16	11696418@N00	3	2593	b9bbea68cb	https://farm3.staticflickr.com/2593/3894991729_b9bbea68cb.jpg	https://www.flickr.com/photos/11696418@N00/3894991729
242	Point ZM	9577773191	-41.611903	175.29013	16	100721922@N07	8	7406	46f8e3cc79	https://farm8.staticflickr.com/7406/9577773191_46f8e3cc79.jpg	https://www.flickr.com/photos/100721922@N07/9577773191
243	Point ZM	9577773119	-41.611903	175.29013	16	100721922@N07	8	7395	7c6dfb916f	https://farm8.staticflickr.com/7395/9577773119_7c6dfb916f.jpg	https://www.flickr.com/photos/100721922@N07/9577773119
244	Point ZM	9580559778	-41.611903	175.29013	16	100721922@N07	4	3824	99cfe85d11	https://farm4.staticflickr.com/3824/9580559778_99cfe85d11.jpg	https://www.flickr.com/photos/100721922@N07/9580559778
248	Point ZM	9580552638	-41.611903	175.29013	16	100721922@N07	6	5331	a8c1b33e54	https://farm6.staticflickr.com/5331/9580552638_a8c1b33e54.jpg	https://www.flickr.com/photos/100721922@N07/9580552638
249	Point ZM	9580552568	-41.611903	175.29013	16	100721922@N07	8	7383	3b8a4df006	https://farm8.staticflickr.com/7383/9580552568_3b8a4df006.jpg	https://www.flickr.com/photos/100721922@N07/9580552568
250	Point ZM	9577765809	-41.611903	175.29013	16	100721922@N07	6	5530	269382a8ee	https://farm6.staticflickr.com/5530/9577765809_269382a8ee.jpg	https://www.flickr.com/photos/100721922@N07/9577765809
313	Point ZM	20537507220	-41.611512	175.287336	16	40578127@N00	1	780	138b53c065	https://farm1.staticflickr.com/780/20537507220_138b53c065.jpg	https://www.flickr.com/photos/40578127@N00/20537507220

3.3.2. Visual content analysis

The density of photographs in a location corresponds closely to its popularity with visitors (Wood et al., 2013), but does not necessarily relate to public interest in that area. The presence of a photograph does not tell us why people visited a location. Content analysis of social media photographs has demonstrated to be an adequate model to reveal cultural ecosystem services and their benefits and values at multiple spatial scales (Martínez Pastur et al., 2016; Richards & Friess, 2015). A photograph's content can demonstrate why and how people place a value on the benefits of nature in a specific area (Dorwart et al., 2010) and helps to understand what aspects of environment are of most interest to people (Richards & Friess, 2015).

This section describes the methods used to analyse the semantic content of the geo-tagged photographs used in this research. The most common method of visual analysis of photographs is manual analysis where assessors categorise the content of photographs based on the identified classes. Despite the time-consuming nature of manual analysing, this method can provide better results as it is difficult to code subjective photograph content for social value mapping.

Based on former studies on content analysis of photographs (Kennedy et al., 2007; Martínez Pastur et al., 2016; Oteros-Rozas et al., 2018; Van Zanten et al., 2016), the following rules were applied to filter the photographs before content analysis was applied.

- All photographs are outdoors and outside of urban areas. As mapping the ecosystem services and social values focuses on nature, only outdoors and non- urban areas photographs are included.
- Repeated photographs provided by the same user of the same location and landscape were removed. Some users upload a large number of photographs in comparison to others. If we include all photographs, then these users would unnecessarily bias the locations mapped (Kennedy et al., 2007).
- Photographs with unrelated subjects were removed from the database. For example, photographs of people's belongings (such as cars), people where there is no connection to nature or recreation activities, interiors of houses, signs and logos not related to the nature, etc. (Figure 3.3).

Figure 3. 3. Sample of removed photographs with unrelated subjects (Source: Author)

- If people are in the photograph and doing activities that can refer to ecosystem services (such as recreational activities or enjoying landscapes), those photographs remained in the dataset (Figure 3.4).

Figure 3. 4. Example of selected photographs with people (Source: Author)

- Photographs of a building or hut (in non-urban areas) were kept in the dataset if they reflected the recreation or cultural/historical context, such as church or wine sellers on the farms (Figure 3.5).

Figure 3. 5. Example of selected photographs with building (Source: Author)

- Photograph content was labelled using a fixed set of categories.

Photographs were then categorised into three social value classes: Recreation, Aesthetics, and Historical/cultural (see table 3.3).

Table 3. 3. Criteria to content analysis of photographs

Social value	**Accepted content of Photographs**
Recreation (Figure 3.6)	experiential use and enjoyment of: wildlife represented by photographs of wildlife physical activities including sport and recreational activities such as tramping, walking, boating, canoeing, rafting, tubing, kayaking, horse trekking, picnicking, quad-biking, cycling, camping, fishing, hunting, and swimming, photography
Aesthetics (Figure 3.7)	photographs of natural landscapes and seascapes
Cultural/Historical (Figure 3.8)	representation of farming such as sheep shearing representation of lifestyle related to agriculture such as grape picking representation of historical landscapes and sites such as lighthouse representation of cultural activities such as a wine festival on a farm, representation of cultural sites such as a church, graveyard or historical houses

Figures 3.6, 3.7, and 3.8 show examples of photographs in each category. Due to the limitations of ethics approval, authors' photographs are shown rather than categorised photographs used in the analysis. These photographs are indicative and some were taken outside the study area.

Figure 3. 6. Selected photographs with recreation value (Source: Author)

Figure 3. 7. Selected photographs with aesthetics value (Source: Author)

Figure 3. 8. Selected photographs with historical/cultural value (Source: Author)

As researcher bias may happen during a manual photograph content analysis (Martínez Pastur et al., 2016; Oteros-Rozas et al., 2018), a consistency assessment was conducted. A random subsample of photographs (30 photographs) were independently analysed by 5 people and a level of agreement was assessed among assessors using statistical methods (Cohen's kappa value in SPSS) (Oteros-Rozas et al., 2018). Comparison of results produced a kappa value of 0.591 for recreation, 0.533 for aesthetics, and 0.783 for historical/cultural which suggested moderate and substantial agreement among assessors. After testing, all photographs were analysed by the researcher.

3.3.3. Create the passive VGI dataset

2551 social value points were captured in the passive VGI dataset (Figure 3.9). This dataset includes coordinate address of photograph, owner user id, and photographs' Flickr URL as well as an assigned social value (Table 3.4).

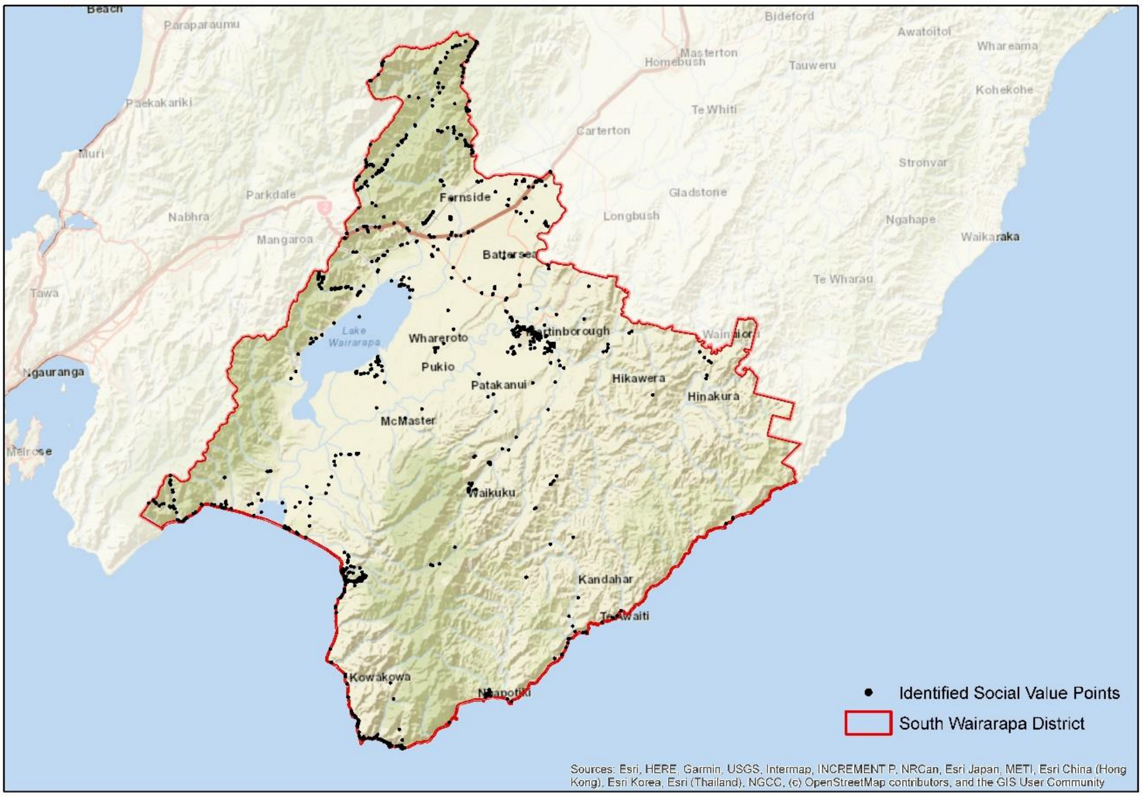


Figure 3. 9. Spatial distribution of identified social values in the passive VGI dataset

Table 3. 4. Passive VGI dataset

latitude	longitude	owner	URL_static	Social_Val
-41.232167	175.491166	64939175@N00	https://farm8.staticflickr.com/7387/9331733472_a1993e3e6e.jpg	Recreation
-41.231281	175.487797	88123052@N00	https://farm6.staticflickr.com/5665/30611991385_10a7277202.jpg	Aesthetics - Recreation
-41.224498	175.492447	88827093@N00	https://farm1.staticflickr.com/803/41056643161_0ab61133b9.jpg	Historical/Cutural
-41.222912	175.469054	81377865@N00	https://farm9.staticflickr.com/8356/8290729491_38699c4933.jpg	Aesthetics
-41.222908	175.469177	81377865@N00	https://farm9.staticflickr.com/8079/8291805004_4bc46c98a2.jpg	Aesthetics
-41.22289	175.469098	81377865@N00	https://farm9.staticflickr.com/8494/8290751161_7525a59fb7.jpg	Recreation - Historical/Cutural
-41.222869	175.468872	81377865@N00	https://farm9.staticflickr.com/8224/8291805730_4700fb01cf.jpg	Aesthetics - Recreation
-41.222831	175.469131	81377865@N00	https://farm9.staticflickr.com/8492/8290750271_d4bbb069b8.jpg	Aesthetics - Recreation
-41.221488	175.468246	81377865@N00	https://farm9.staticflickr.com/8497/8291805830_ab6de4e373.jpg	Historical/Cutural

3.3.4. Statistical analysis

We used Esri's ArcMAP (Version 10.8) to explore the spatial distribution of social value abundance and the importance for three types of identified values; recreation, aesthetics, and historical/cultural. In this section, we describe how data was aggregated into spatial units and then analysed for social value abundance and importance.

3.3.4.1. Spatial units

Planners need to identify homogenous areas to support development or management. While passive VGI provided information on the spatial distribution of recreation, aesthetics, and cultural/historical values of ecosystem services, it also illustrated a speckled effect that might not be useful to planners. Decision makers need to aggregate social value data into practical spatial units, to support better insights into the managerial and structural functioning of peoples' preferences for recreational planning.

We selected a hexagonal grid cell for the spatial aggregation. A hexagon grid cell makes a precise insight and contributes a granular and uniform analysis of spatial data(Adamczyk & Tiede, 2017; Karasov et al., 2020). Hexagons share a real border with every neighbour units while other geometric shapes such as squares and triangles only share a single point with some units. Furthermore, any point inside a hexagon is closer to the centre than other geometric shapes(Adamczyk & Tiede, 2017; Tammi et al., 2017). Hermes, et al. (2018), Langemeyer et al. (2018), and Schröter & Remme (2016) proposed 100 hectare cell size and (Cui et al., 2019; Estima & Painho, 2013; Zen et al., 2019) used 250 hectare cell size in recreational planning. Then, we calculated the spatial autocorrelation (Global Moran's I) of passive VGI data with both100-hectare and 250-hectare hexagon grids in ArcMap to select an appropriate cell size with sufficient detail for this research. The passive VGI data of each identified social value was separately aggregated into 100- and 250-hectare hexagonal grid cells. There is a high degree of correlation between the number of identified social values and 100-hectare hexagon grid in all three types of values: recreation, aesthetics, and historical/cultural. This hexagon grid included 2636 cells.

3.3.4.2. Social value abundance

We used Yin & He (2014) process of calculating a social value abundance index layer to explore the presence/absence of data. We used a binary model with a value of one given to spatial units containing social value and zero for those all with no value.

3.3.4.3. Social value importance

Areas with a high number of social values contributed passive VGI may be used in planning to represent high preferences of ecosystem services in a specific area. A social value importance index layer was calculated using quantiles to classify the grid pixels based on the number of identified social values into five levels of importance; very low, low, medium, high, and very high. As expected with quantile classification, each catagory contained an equal number of social values (Burkhard & Maes, 2017).

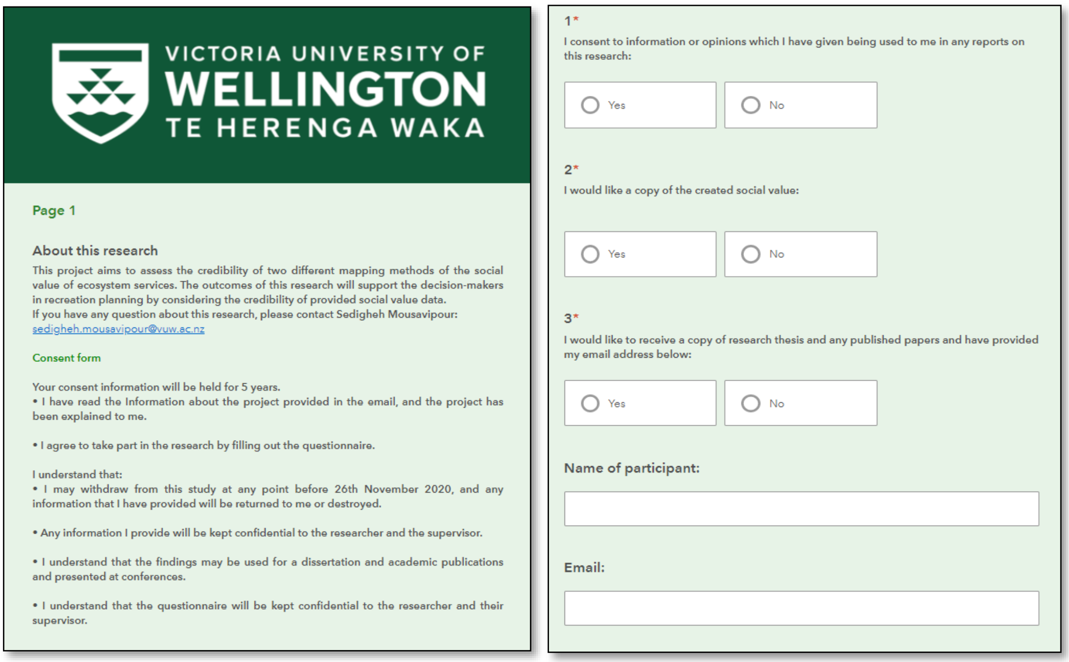
3.4. Social value mapping using expert-based evaluation

Expert-based evaluation can extract social values using local expert's knowledge. This method establishes a straightforward and structured procedure for social value mapping. An online survey was used to capture expert-based social values. This method was chosen due to logistical constraints as a result of the COVID-19 pandemic. To supplement our findings, we used also a single structured interview.

3.4.1. Survey design

The survey was made as simple and short as possible to encourage a high response. Esri's ArcGIS Survey123 web designer and Survey123 connect (version 3.11) were used as a platform for this online survey. The online survey had three main sections:

1. A consent form (See Figure 3.10).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Page 1

About this research

This project aims to assess the credibility of two different mapping methods of the social value of ecosystem services. The outcomes of this research will support the decision-makers in recreation planning by considering the credibility of provided social value data.
If you have any question about this research, please contact Sedigheh Mousavipour: sedigheh.mousavipour@vuw.ac.nz

Consent form

Your consent information will be held for 5 years.
• I have read the Information about the project provided in the email, and the project has been explained to me.

• I agree to take part in the research by filling out the questionnaire.

I understand that:
• I may withdraw from this study at any point before 26th November 2020, and any information that I have provided will be returned to me or destroyed.

• Any information I provide will be kept confidential to the researcher and the supervisor.

• I understand that the findings may be used for a dissertation and academic publications and presented at conferences.

• I understand that the questionnaire will be kept confidential to the researcher and their supervisor.

1*
I consent to information or opinions which I have given being used to me in any reports on this research:
Yes No

2*
I would like a copy of the created social value:
Yes No

3*
I would like to receive a copy of research thesis and any published papers and have provided my email address below:
Yes No

Name of participant:

Email:

Figure 3. 10. Consent form

2. The second page of the survey (Figure 3.11) contained a definition of each of the three social values (Recreation, Aesthetics, and Historical/cultural) and a map with drawing and editing tools. Various base maps were provided to ease location identification, including NZ imagery, Open Street map, NZ community map, and a topographic map. Standard navigational tools were available to pan and zoom the map to find the desired area and to adjust map resolution.

A participant could check and edit the results before the final submission. A tutorial video was uploaded to guide participants on how to draw and rate their contributed area.

The respondents could add as many areas as they wished, and the areas could be as large or small as required. Areas could also overlap. If the participant drew several areas, a clean base map was provided to avoid clutter. Each participant rate their area of interests (AOIs) based on the importance of recreation, aesthetic, and cultural/historical values; very low, low, medium, high, and very high. The provided instructions emphasised that the participant should provide social values based on their understanding of public preferences (rather than their own individual opinions).

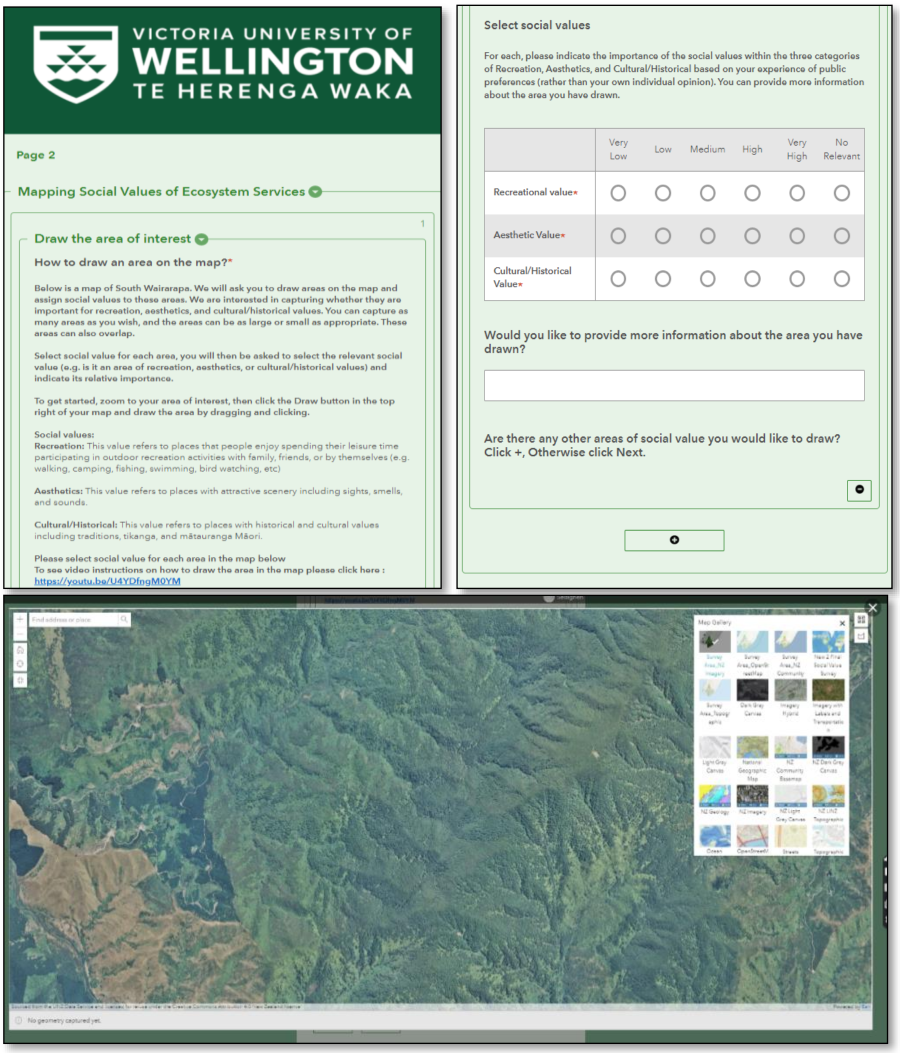
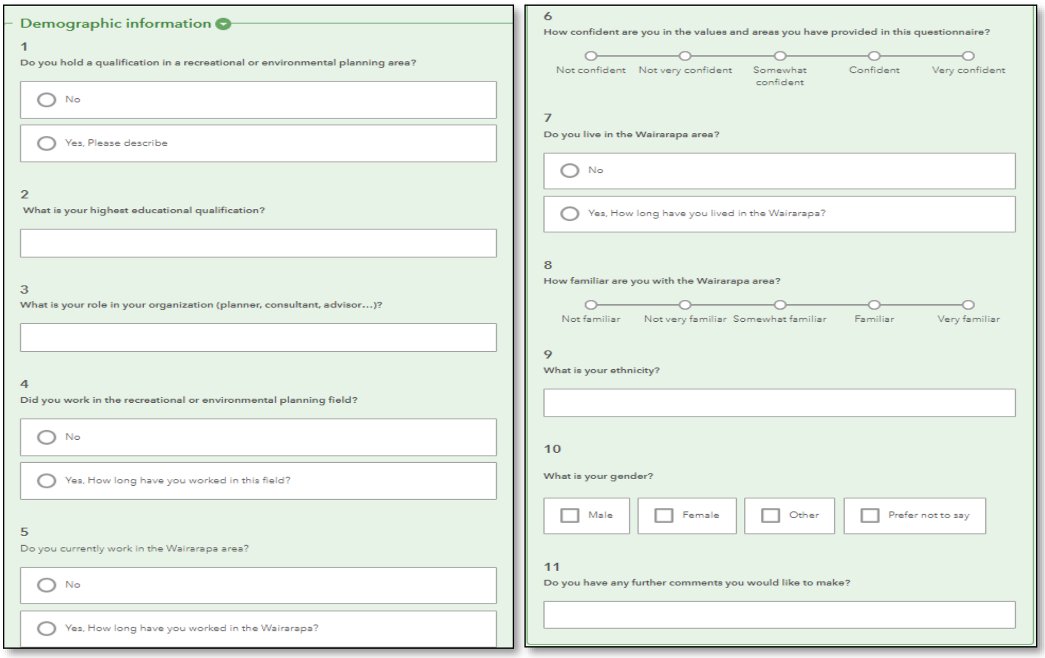


Figure 3. 11. Social value mapping process

3. Questions to describe the experts' professional backgrounds, skills, experience, and familiarity with the study area. This information was intended assess the representativeness of experts to provide confident social values data in the South Wairarapa district.


Demographic information

1
Do you hold a qualification in a recreational or environmental planning area?
No
Yes, Please describe

2
What is your highest educational qualification?

3
What is your role in your organization (planner, consultant, advisor…)?

4
Did you work in the recreational or environmental planning field?
No
Yes, How long have you worked in this field?

5
Do you currently work in the Wairarapa area?
No
Yes, How long have you worked in the Wairarapa?

6
How confident are you in the values and areas you have provided in this questionnaire?
Not confident | Not very confident | Somewhat confident | Confident | Very confident

7
Do you live in the Wairarapa area?
No
Yes, How long have you lived in the Wairarapa?

8
How familiar are you with the Wairarapa area?
Not familiar | Not very familiar | Somewhat familiar | Familiar | Very familiar

9
What is your ethnicity?

10
What is your gender?
Male | Female | Other | Prefer not to say

11
Do you have any further comments you would like to make?

Figure 3. 12. Demographic questions

The online survey was tested by 5 individuals. They were asked the following questions:

1. Was it obvious at every stage what you were supposed to be doing? If not, where was it unclear?
2. Was the map of the South Wairarapa appropriate? How did it help you find the locations? Where did you encounter problems?
3. Was the length of the questionnaire OK? Were there any questions you did not want to answer? Were there any questions that were unclear?
4. How long did it take to complete the questionnaire?
5. Do you have any other feedback or improvements for this questionnaire?

A number of issues were identified and then amended. For example, the definition of recreation, aesthetics, and historical/cultural values were partly unclear for respondents. Difficulty navigating to their area of interest using the grey and black background base map was experienced by participants in the testing process. They struggled with the small size of map and drawing/editing tools. We provided a more clear definition of social values, and several base maps added to allow participants to choose an appropriate background.

3.4.2. Technical implementation

We used a purposive sampling method and looked at local experts with adequate proficiency in ecosystem services and the social values assessment field, as well as considerable knowledge about the study area and familiarity with the geography of the South Wairarapa district. We selected experts from local councils, Department of Conservation (DOC), local NGOs, and other related groups.

3.4.3. Data collection

The survey link was emailed along with information about the survey (goals, methodology of data collection and maintenance, and research team contact information) to 55 experts. No reward or incentive was offered to participants. The online survey ran from November 2020 to January 2021.We established a target of 15 participants based on the number of identified experts in the case study area.

After the initial launch, we had a low response rate of only 4 participants. A follow up email was sent to selected local experts. We also applied to amend ethics approval to conduct face to face interviews. Our final participants were 15 for the online survey and 1for the face-to-face interview.

A single structured interview with a local expert was conducted using a hard copy of the online questionnaire in the South Wairarapa district. The study area map was split into 14 sections and printed separately. The social values were drawn, and their importance were scored on a map. The researcher digitised the results and then the interviewee checked and approved these data. We combined the digitised data with online survey data to analyse it.

3.4.4. Data cleaning

We downloaded the polygons provided by experts, called area of interest (AOI) from here, and errors were removed. Although the case study boundary was indicated on the map, some areas were drawn outside of this boundary. Areas outside of the boundary were deleted (Figure 3.13).

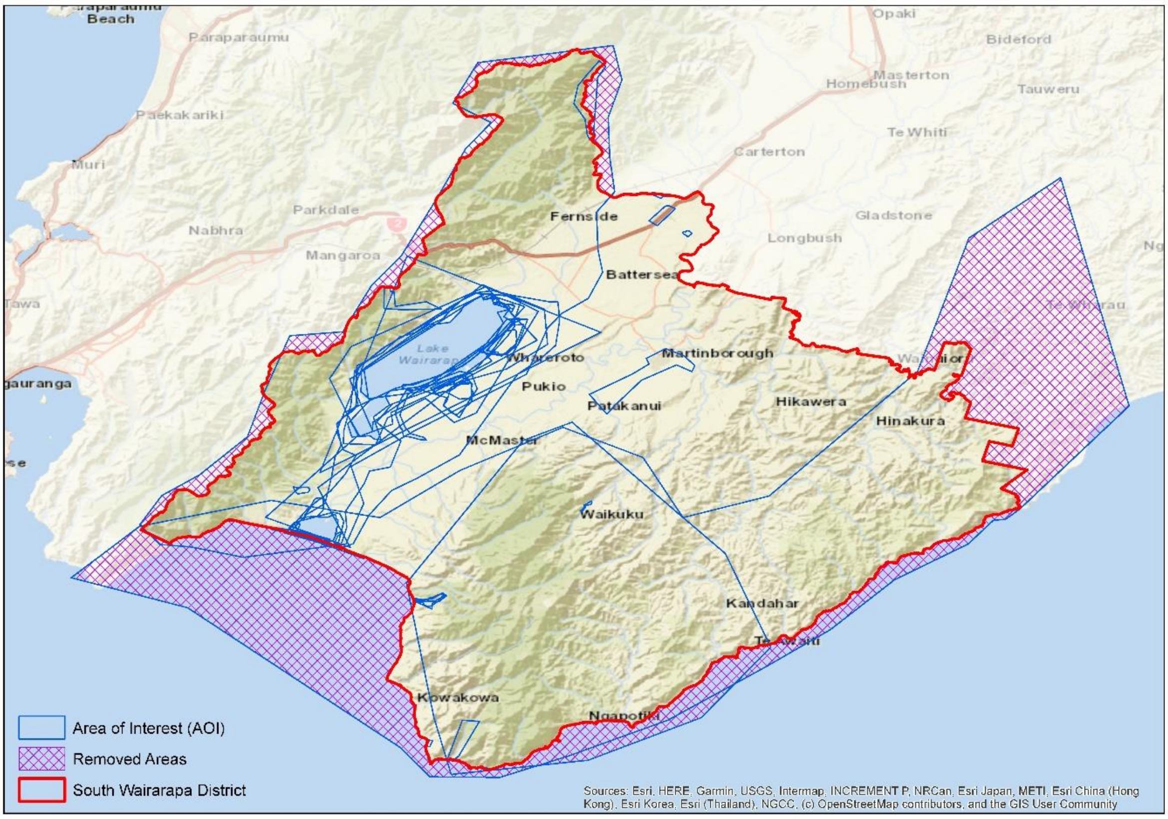


Figure 3. 13. Removed areas

3.4.5. Creating expert-based dataset

After data cleaning, 110 polygons (59 from the online survey and 51from a single interview) were obtained, each polygon representing an area with a score for each of the three social values: recreation, aesthetics, and historical/cultural.

3.4.6. Statistical Analysis

We calculated the common level of experts' consensus for recreation, aesthetic, and historical/cultural values of ecosystem services using the following process:

1. To ensure the comparability of the spatial configuration of the outcomes of both mapping methods, we used the same sized hexagon grid (100 hectare) applied for the passive VGI method.
2. Three spatial layers for each social value (recreation, aesthetic, and historical/cultural) were created.
3. The average importance of social values for each hexagon was calculated.

3.5. Credibility assessment of social value mapping methods:

3.5.1. Compare spatial distribution of social value abundance and importance of two datasets

To compare the spatial distribution of abundance and importance in spatial units, we used the overlay of both maps to create a spatial layer containing both social value datasets in spatial units. We compared the results using tabulate intersection in ArcGIS (version 10.8).

Following Brown's (2017) approach, we used the Phi-coefficient statistic (φ) in SPSS (version 26) to measure the strength of relationship of spatial distribution of social value abundance between the two datasets. This statistic is used for binary data (Brown, 2017). We calculated the phi-coefficient for all hexagons in the study area and interpreted the results using Brown, 2017 as $\varphi < 0.2$ – little or no association, $0.2 \leq \varphi < 0.4$ - weak association, $0.4 \leq \varphi < 0.6$ - 0.6 - moderate association, and $\varphi \geq$ o.6 - strong association.

We used Pearson's correlation coefficient to measure the statistical relationship between social value importance levels in two datasets. The null hypothesis for this test was that the means of importance of social values from the two datasets are equal. Indeed, for two social value datasets, the Pearson's correlation statistic evaluates whether the importance level means of social values are significantly different.

The Cohen's kappa statistic (k) was used to explore the degree of spatial agreement for each importance level in the two datasets. Cohen's kappa (κ) ranges from -1 to +1. The results interpreted as no agreement for $K<0$, slight agreement for $0.0< K< 0.2$, fair agreement for $0.21< K< 0.4$, moderate agreement for $0.41< K< 0.60$, substantial agreement for $0.61< K< 0.80$, and almost perfect agreement for $0.81< K< 1.00$).

We investigated the spatial clustering of importance of social values in two datasets. We considered that the less clustering level is more appropriate to support recreational planning because a planner will have a detailed information about the social value importance in the neighbouring spatial unit. To determine spatial clustering, spatial autocorrelation (Moran's I) was calculated for social value importance level based on the contiguity of spatial units in two datasets at edges and corners.

3.5.2. Identify spatial relationship between social value datasets and landscape units

Landscape is an important concept in decision making (de Groot et al., 2010), as landscape units with similar physical and geographic characteristics (Campos-Campos et al., 2018) provide an inventory of environmental characteristics for planners. Also, Landscape classification has been used by researchers to compare results and create a consensus of knowledge to support planning process.

This study aims to investigate both the overrepresented and missed landscape units in different social value mapping methods. We create a spatial layer of landscape units using the New Zealand Landscape Classification (NZLC) and a database from Department of Conservation[1] (DOC). The NZLC were created by Brabyn in 1996 and updated in 2009 (Brabyn, 2009). The combination of GIS layers of landform, land cover, infrastructure, and water views which extracted from the NZLC used to create 23 landscape units. We also applied specific criteria to the NZLC, including naturalness and recreational facility. We used the map database of DOC to obtain spatial information for significant natural protected areas, trails, and campsites (Table 3.5).

We used Langemeyer et al's, (2018) procedure to classify landscape units. We created a relatively coarse classification based on four major landforms (mountain, hill, flat area, coastal area, and lake) and split these four classes to 23 landscape units based on land cover, water views, and naturalness factors (Figure 3.14).

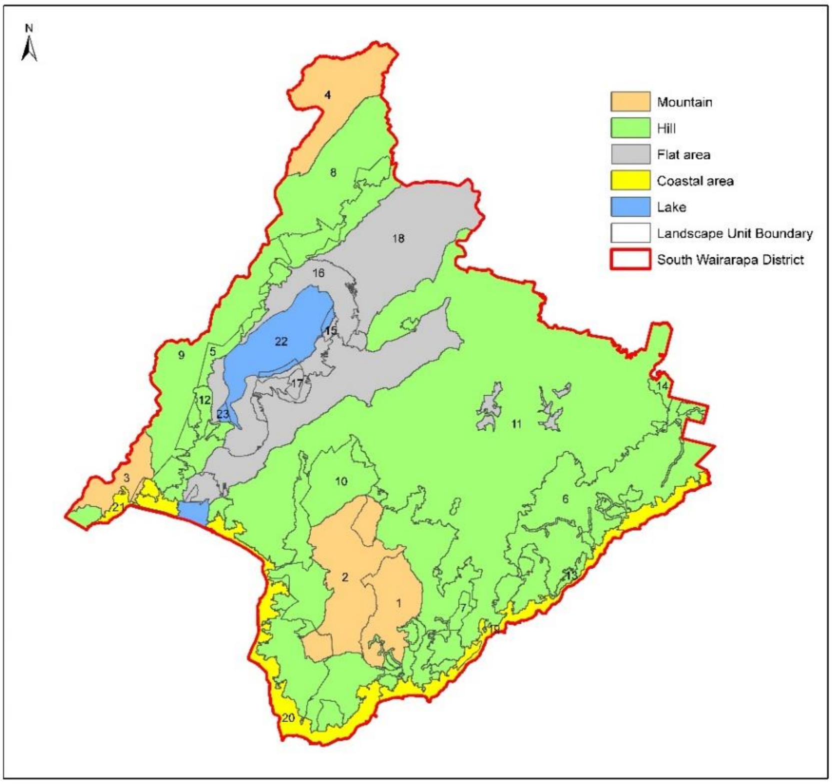


Figure 3. 14. Landscape classification map for the South Wairarapa District

[1] https://www.doc.govt.nz/our-work/maps-and-data/

Table 3. 5. Components of landscape units in the South Wairarapa district

Landform	Landscape unit	Land cover	Water views	Naturalness	Recreational facility and infrastructure
Mountain	1	Indigenous landcover	No close view of lake or sea	No protected area	-
	2			Aorangi forest park	Tramping track
	3			Remutaka forest park	Tramping track
	4			Tararua forest park	Tramping track
Hill	5	Indigenous landcover	Lake view	No protected area	
	6		No close view of lake or sea	No protected area	Natural with vehicle track Tramping track Walking trail Highway-tramping track
	7			Tora Bush scenic reserve	-
	8			Tararua Forest park	Highway-tramping track Waiohine Gorge campsite Walking trail
	9			Remutaka Forest park	Tramping track Walking trail
	10			Aorangi Forest park	Tramping track
	11	Developed agriculture	No close view of lake or sea	No protected area	Trampling track Railway Walking trail Bucks Road campsite
	12		Lake view	No protected area	-
	13		View of open ocean	No protected area	-
	14	Exotic forest and scrub	No close view of lake or sea	No protected area	-
Flat area	15	Developed agriculture	Lake view	Lake Wairarapa wetland conservation area	-
	16		Lake view	No protected area	Walking trail
	17		Lake view	Matthews & Boggy pond wildlife reserve	Walking trail
	18		No close view of lake or sea	No protected area	Walking trail Highway-transmission line
Coastal area	19	Developed agriculture	View of open ocean	No protected area	-
	20	Indigenous landcover	View of open ocean	No protected area	Tramping track Putangirua Pinnacles Campsite
	21		View of open Ocean	Remutaka forest park	Corner Creek campsite
Lake	22	Lake	Lake view	Lake Wairarapa wetland conservation area	-
	23			Allsops Bay wildlife reserve	-

We calculated the total number of AOIs in each landscape unit and the total number of photographs in in each landscape unit using passive VGI. Then, we produced a ratio for each landscape unit by dividing the count of provided polygons in each landscape by the total number of polygons in expert-based evaluation. Also, a ratio was calculated in passive VGI by dividing the number of uploaded photographs in each landscape unit by the total number of photographs.

We used a look-up table to explore missed or overrepresented landscape units. We divided the provided polygons ratio in the three classes (low, medium, and high) in the column and the coverage of social value in landscapes in the row. We calculated the coverage rate of social value using the count of spatial units with data (social value) in each landscape unit in the three categories; low, medium, and high. A similar procedure was applied to the passive VGI using uploaded photographs ratio in the column. The results visualised in separated maps for recreation, aesthetics, and historical/cultural value datasets.

Pearson correlation coefficients were calculated to show the relation between landscape units and social value datasets. Kulczyk et al. (2018) used the Pearson correlation statistics to show a relation between service landscape potential and recreational facilities.

3.6. Limitation of the study

We had a low participation rate in the online survey. We selected this data gathering method in response to Covid-19 restrictions.

Also, the low number of AOIs and quality of features in the online survey affected the suitability of the data. Our single face-to-face interview resulted more data with greater details. We obtained 51 AOIs in the interview in comparison to an average 4.2 per person in the online survey. We recommend the face-to-face interviews to gather more precise and sufficient expert data instead of using online platforms.

Chapter 4: Results and Initial Discussion

This chapter explores the results achieved from both expert-based evaluation and passive VGI social value mapping methods. In the expert-based evaluation, the participants' answers to questions about their expertise and local knowledge about the case study area were analysed using R (statistical software) and compared against the number of provided polygons of social values. Results of statistical analysis between completeness metrics (type, abundance, and importance) are detailed with an explanation the overrepresented and missed landscape units in both mapping methods.

4.1. Participants

This section explored the relationship between participant characteristics and their mapping. We addressed participant expertise and educational background of recreational or environmental planning and their local knowledge of the case study area through analysis of responses to surveys questions

The results showed only 12.5 % of participants had a relevant qualification in recreation or environment planning. Figure 4.1 shows that the highest educational qualification among participants was PhD (37.5 %) while half of participants did not answer this question.

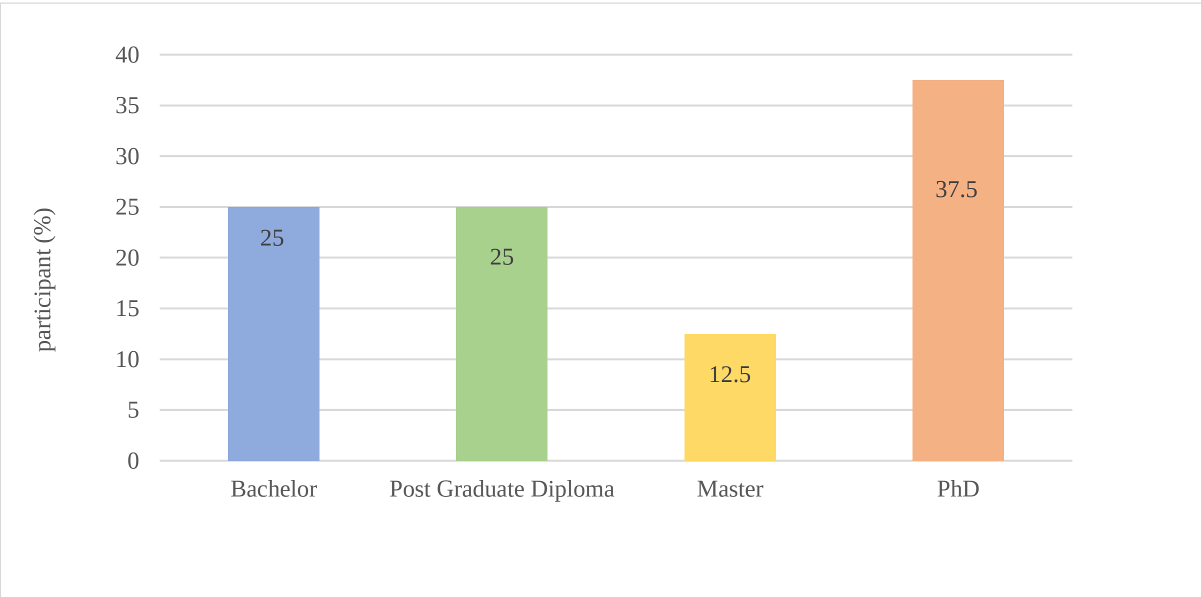


Figure 4.1. Participants' education qualification

56.25 % of participants had the role as environmental consultant or planner in their organisations. The participants' local knowledge about the case study area was captured through each participant's experience of living and working in the Wairarapa area as well as their familiarity with the area

The results showed 68.75 % of participants have lived in the case study area, and 56.25 % currently work there. 22.20 % of participants had more than 20 years' work experience in the case study area. 87.50 % of participants were familiar and very familiar with the case study area (Figure 4.2).

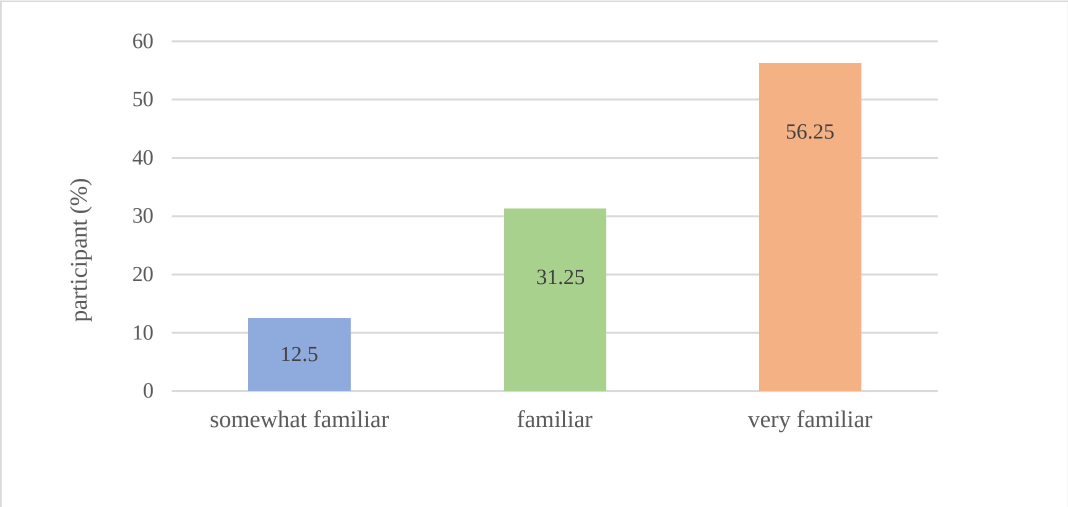


Figure 4.2. Level of familiarity with the case study area

The participants were also asked to answer how confident are you in the values and areas you have provided. 93.75 % were confident or very confident about their provided social value data (Figure 4.3).

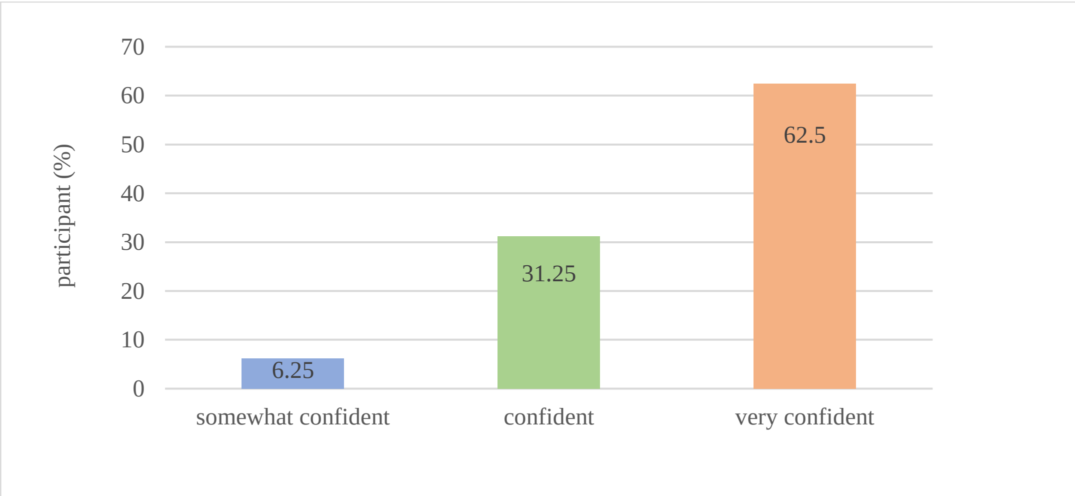


Figure 4.3. Level of confidence in provided social value data

Most participants were male (87.50 %) and had European ethnicity (87.50 %). As planning is a male-dominated field, this gender distribution is not unusual. Given the rich cultural knowledge of the area held by, iwi, a greater Maori participation would have been preferred.

Additional Maori participants were contacted but declined to participant. It is likely the structured data collection format (e.g. an email from an unknown to the source) lead to these lower participant rates.

We assessed the relationship between participants' mapping of social values and their expertise and local knowledge using a Pearson correlation coefficient. 110 polygons were provided using both the online survey and face-to-face interview.

Table 4.1. Relationships between participants' characteristics and average mapping effort

Participants' characteristics	Metrics	Number of provided polygons to identify social values
Relevant educational qualification	Yes	2
	No	7
Confidence level about identified social values	Somewhat confident	1
	Confident	1
	Very confident	10
Living experience in the case study area	Yes	20
	No	1
Working experience in the case study area	Yes	13
	No	2
Familiarity with the case study area	Somewhat familiar	3
	Familiar	3
	Very familiar	10
Relevant job position	Yes	10
	No	3
Gender	Male	8
	Female	2
	Not answered	2

There was no correlation between whether participants have a relevant educational background and the number of AOIs provided to identify social values. Participants with a relevant role in environmental consultancy and planning identified more social values (10 social values) than others (3 social values).

There was a strong positive correlation between living and working in the case study area and the number of polygons provided. The participants with living and working experience identified an average of 20 and 13 social values in comparison to 1 and 2 for other participants. Male participants (87.50%) identified an average 8 values compared with female participants who provided an average 2 AOIs for social values.

Participants very familiar and familiar with the case study area identified 13 social values while participant somewhat familiar only provided 3 polygons. Furthermore, participants familiar and very familiar provided more information about social values particularly historical/cultural values. The number of AOIs provided by online participants totalled 59 polygons for 14 participants. While the single face-to-face interview resulted 51 polygons.

4.2. Thematic analysis of results

This section outlines results of comparisons made between two datasets: type of identified social values, areas of abundant social values (presence/absence), and importance level of recreation, aesthetics, and historical/cultural values.

4.2.1. Recreation

The spatial distribution of the recreation value abundance using passive VGI and expert-based evaluation is presented in Figure 4.4. We used 100 ha hexagons for spatial units as it was discussed in section 3.3.4.1 of chapter 3.

4.96 % of spatial units in the passive VGI dataset included a photograph with a recreation value. This amount was 81.90 % for expert-based evaluation (Table 4.2).

Table 4.2. Abundant of recreation value

Recreation value	Number of spatial units with data	Percent of spatial units with data	No data spatial units	Percent of no data spatial units
Passive VGI	131	4.96	2505	95.04
Expert-based evaluation	2159	81.90	477	18.10

The spatial relationship was calculated based on the abundance of values in the two mapping datasets using the phi-coefficient and recreation value showed little or no spatial association (φ for recreation value = 0.053).

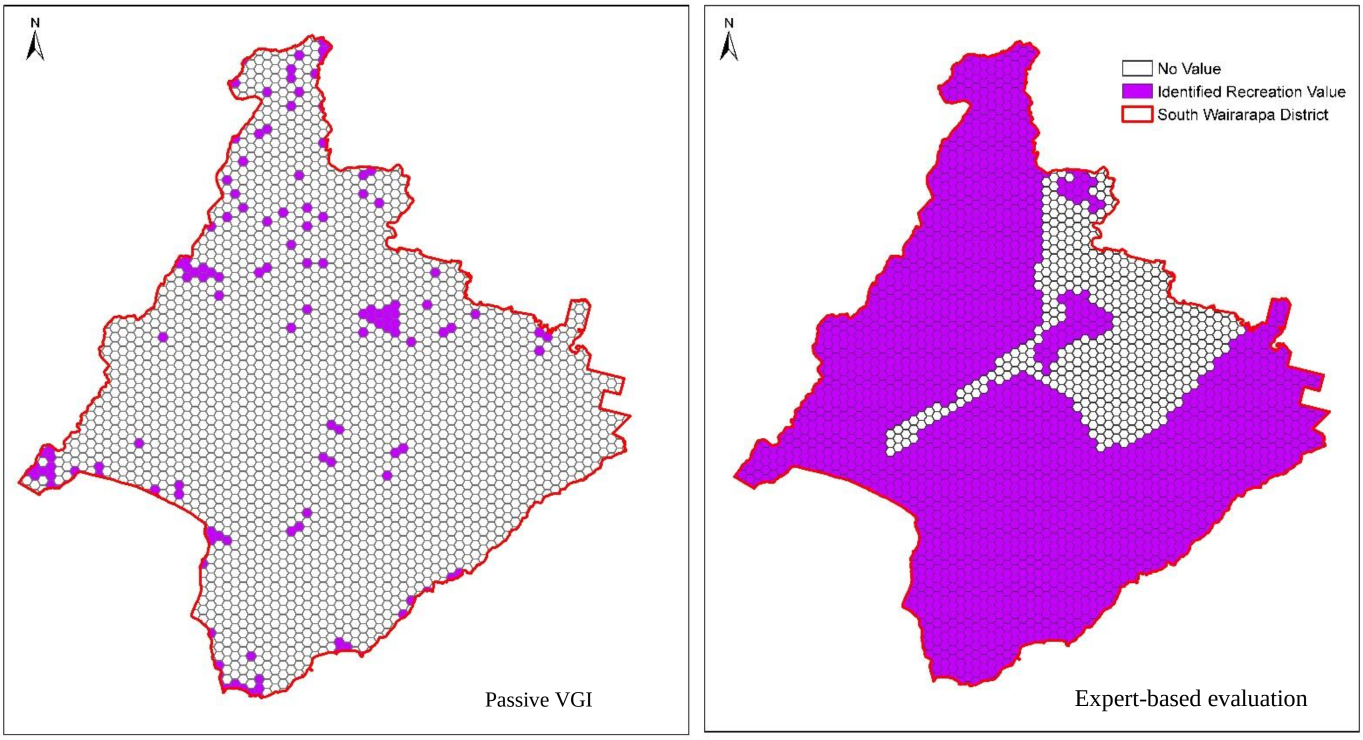


Figure 4.4. Spatial distribution of recreation value abundant

The spatial distribution of the importance of the identified recreation value is given in Figure 4.5. This figure indicates that recreation value importance is distributed across a small group of spatial units in passive VGI. Conversely, expert-based data shows reasonably large areas with a similar importance level.

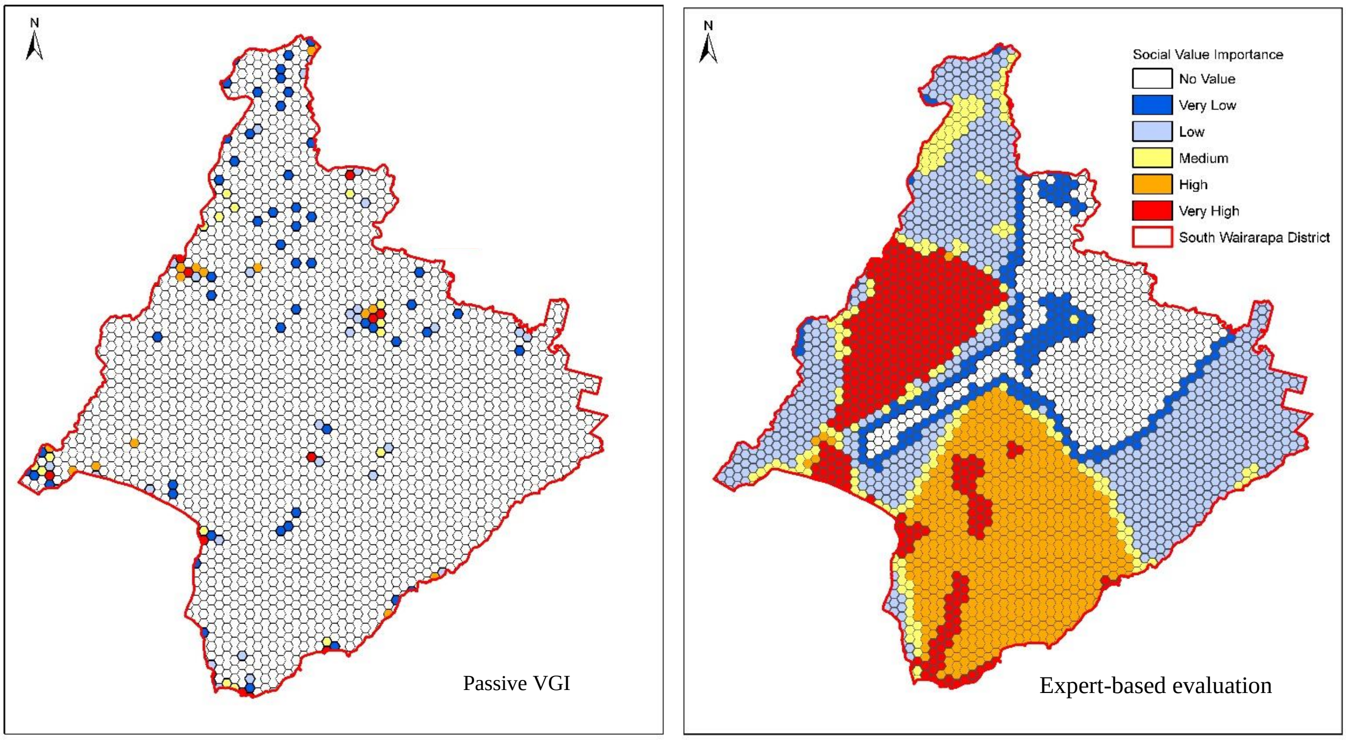


Figure 4.5. Spatial distribution of recreation value importance

42.74 % of recreation values were catagorised as very low important and only 9.90 % were very high important using the passive VGI. While the experts assigned respectively 8.90 % to very low and 17 % to very high importance of recreation value (Table 4.3).

Table 4.3. Importance of recreation value in spatial units

Recreation value importance		Very low	Low	Medium	High	Very high
Number of spatial units	Passive VGI	56	30	17	15	13
	Expert-based evaluation	193	845	197	557	367

We used Pearson's correlation coefficient to measure the statistical relationship between recreation value importance levels in both datasets. There is no statistically significant correlation ($r= 0.058$, $p=0.003$) between importance level of both recreation value datasets.

The Cohen's kappa was separately calculated to address the degree of agreement between each importance level in two recreation value datasets. Cohen's kappa statistics was -0.508, -0.066, -0.161, -0.047, -0.033 respectively for very low, low, medium, high, and very high importance. No agreement was found for different importance of recreation value comparing two datasets.

Spatial autocorrelation (Moran's I) was calculated for importance based on the contiguity of spatial units in two datasets at edges and corners. The recreation value importance using passive VGI produced a Moran's I value of 0.25 ($Z= 21.98$, $p<0.01$) indicating a significant moderate pattern of spatial clustering. This index for expert-based data was 0.95 ($Z= 82.55$, $p<0.01$) presenting a significant high pattern of spatial clustering (Table 4.4). The recreation value importance less spatially clustered in passive VGI.

Table 4.4. Spatial autocorrelation (Moran's I) of recreation value importance

Recreation value importance	Moran's I	Z-Score	p-Value
Passive VGI	0.25	21.98	0.00*
Expert-based evaluation	0.95	82.55	0.00*

* Significant at the 0.01 level

4.2.2. Aesthetics

Figure 4.6 demonstrates the spatial distribution of the aesthetics value abundance using passive VGI and expert-based evaluation. 11.2 % of spatial units in passive VGI included the aesthetics value. While experts identified 82.39 % of spatial units with an aesthetic value (Table 4.5).

Table 4.5. Abundant of aesthetics value

Aesthetics value	Number of spatial units with data	Percent of spatial units with data	No data spatial units	Percent of no data spatial units
Passive VGI	295	11.2	2341	88.8
Expert-based evaluation	2172	82.39	464	17.61

The phi-coefficient was calculated to measure the spatial relationship of the aesthetics value abundance in two mapping methods. The result showed aesthetics value had a weak association (φ for aesthetics value = 0.25) in the two datasets.

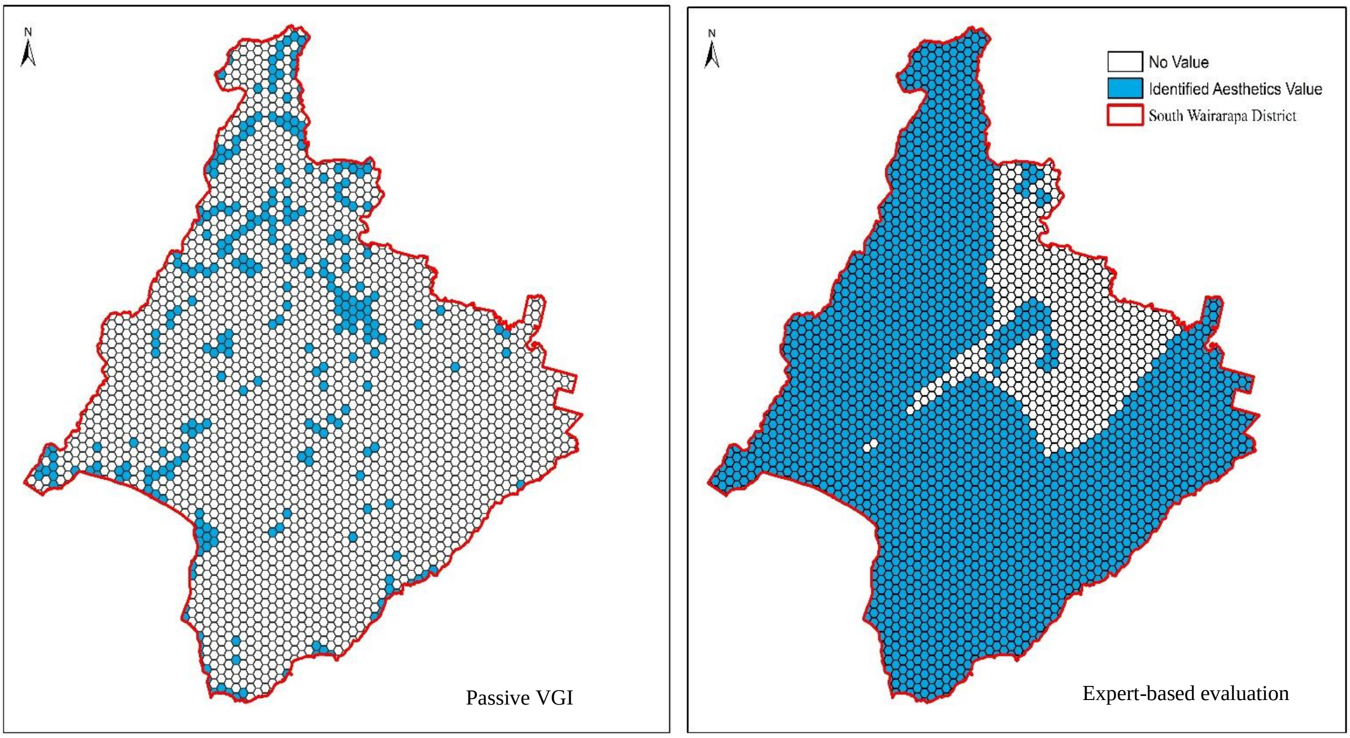


Figure 4.6. Spatial distribution of aesthetics value abundant

A similar distribution of the importance of recreation values was observed in both datasets (Figure 4.7). Passive VGI identified 34.57 % aesthetics value with very low importance and 13.22 % with very high importance. While the experts assigned respectively 8.88 % to low and 16.98 % to high importance of aesthetics value (Table 4.6).

Table 4.6. Importance of aesthetics value in spatial units

Aesthetics value importance		Very low	Low	Medium	High	Very high
Number of spatial units	Passive VGI	102	55	51	48	39
	Expert-based evaluation	193	988	3	619	369

A statistically significant correlations (r =0.31, p=0.109) exists between importance level of both aesthetics value datasets based on the Pearson's correlation coefficient result.

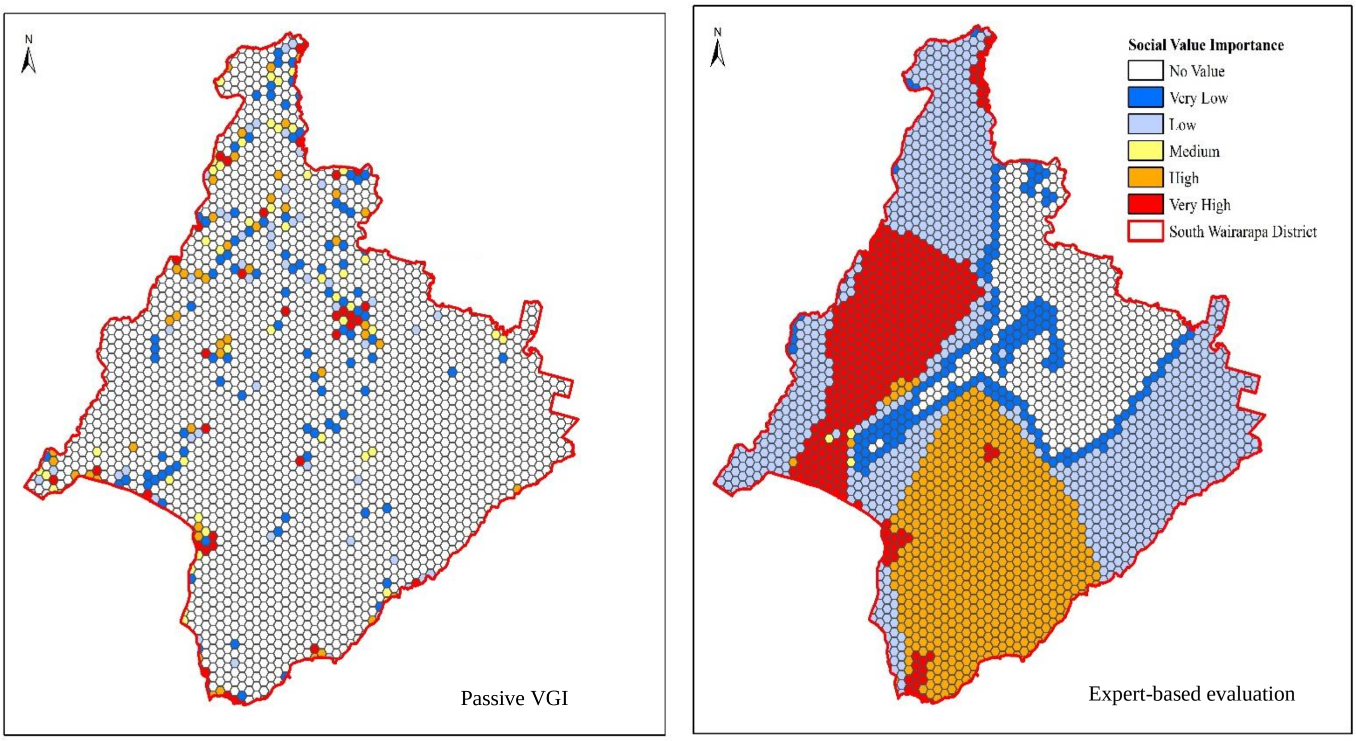


Figure 4.7. Spatial distribution of aesthetics value importance

Cohen’s kappa statistics was measured -0.724, -0.063, -0.117, -0.141, -0.118 respectively for very low, low, medium, high, and very high importance level. We could not find any agreement between the importance levels of the two datasets. This showed the assigned importance levels to aesthetics value was not the same as what the passive VGI showed.

The results of spatial autocorrelation (Moran’s I) analysis for aesthetics value importance level was created a Moran’s I value of 0.26 (Z= 23.17, $p<0.01$) for passive VGI dataset and a Moran’s I value of 0.93 (Z= 81.65, p<0. 01) for expert-based dataset which had respectively a significant moderate and high pattern of spatial clustering (Table 4.7). The result showed the aesthetics value importance less spatially clustered in passive VGI.

Table 4.7. Spatial autocorrelation (Moran’s I) of aesthetics value importance

Aesthetics value importance	Moran’s I	Z-Score	p-Value
Passive VGI	0.26	23.17	0.00*
Expert-based evaluation	0.93	81.65	0.00*

* Significant at the 0.01 level

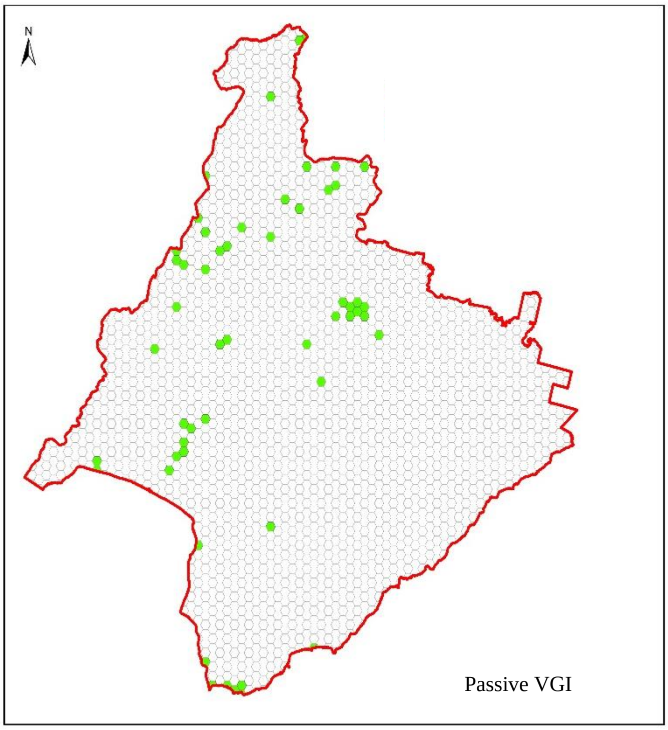
4.2.3. Historical/cultural

Figure 4.8 shows how historical/cultural values were spatially distributed. 2.08 % of spatial units in passive VGI included the historical/cultural value while the experts identified 83.23 % of spatial units with their value (Table 4.8).

Table 4.8. Abundance of historical/cultural value

Historical/cultural value	Number of spatial units with data	Percent of spatial units with data	No data spatial units	Percent of no data spatial units
Passive VGI	55	2.08	2581	97.92
Expert-based evaluation	2194	83.23	442	16.77

The phi-coefficient was calculated to measure the spatial relationship of the historical/cultural value abundance in two mapping methods. The result showed aesthetics value had little or no spatial association (φ = 0.023) between the two datasets.



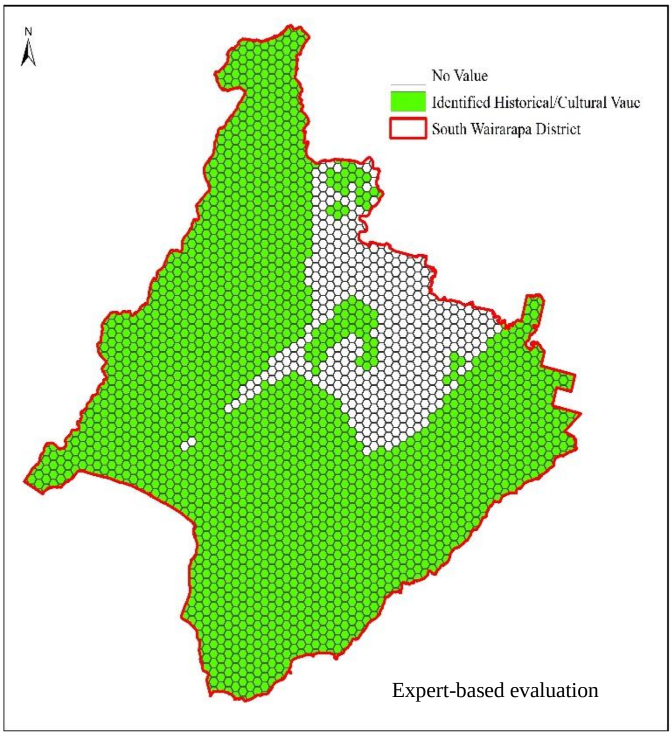


Figure 4.8. Spatial distribution of historical/cultural value abundance

The spatial distribution of historical/cultural value importance is shown in Figure 4.9. Passive VGI identified 54.55 % historical/cultural value with very low importance and 9.10 % with very high importance. While the experts assigned respectively 9.89 % to very low and 14.17 % to very high importance of historical/cultural value (Table 4.9).

Table 4.9. Importance level of historical/cultural value in spatial units

Historical/cultural value importance		Very low	Low	Medium	High	Very high
Number of spatial units	Passive VGI	30	8	7	5	5
	Expert-based evaluation	217	866	181	619	311

The results of the Pearson's correlation coefficient showed no statistically significant correlations (r = -0.003) between importance of both historical/cultural value datasets.

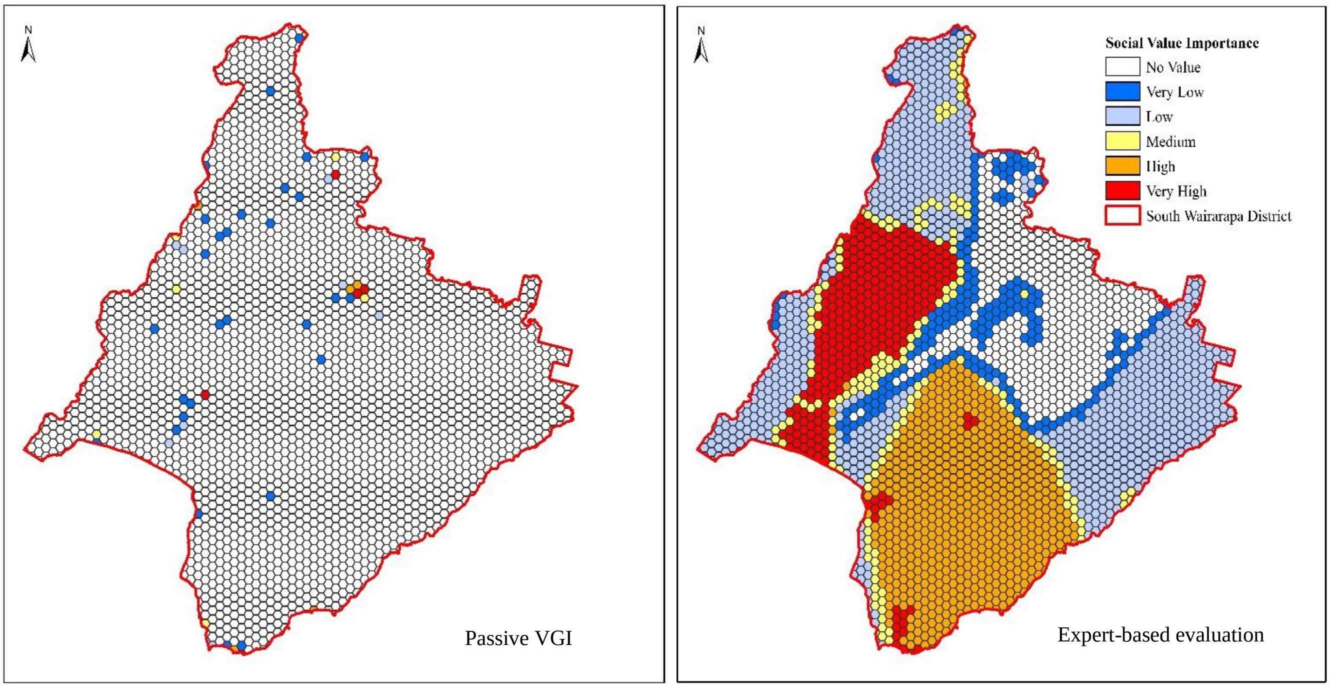


Figure 4.9. Spatial distribution of historical/cultural value importance

Cohen's kappa statistics was measured -0.218, -0.014, -0.066, -0.894, -0.026 respectively for very low, low, medium, high, and very high importance of historical/cultural value. The results showed no agreement for different importance of aesthetics value in two datasets.

However spatial autocorrelation (Moran's I) index in historical/cultural value shows the same pattern of spatial clustering as recreation and aesthetics values (significant moderate and high), the z-score was lower (Table 4.10). This means the both datasets provided relatively less clustered and more detailed information for importance of historical/cultural value that is useful for planners particularly at local scale.

Table 4.10. Spatial autocorrelation (Moran's I) of historical/cultural value importance

Historical/cultural value importance	Moran's I	Z-Score	p-Value
Passive VGI	0.21	19.29	0.00*
Expert-based evaluation	0.95	83.02	0.00*

* Significant at the 0.01 level

4.3. The relationship between social values and landscape units

We used a look up table to explore missed or overrepresented landscape units using both mapping methods (Table 4.11). The look up table included three coverage rates (low (0-25), medium (26-75), and high (> 75)) as columns and three provided polygons rates (low (< 0.015), medium (0.16 - 0.23), and high (> 0.24)) as rows for expert-based evaluation. We used three categories for the number of uploaded photographs (low (< 0.01), medium (0.01 - 0.03), and high (> 0.031)) in row.

Table 4.11. Look-up table for finding missed or overrepresented landscape units

Provided polygons or uploaded photographs rate		Social value coverage rate of landscapes		
		Low	Medium	High
	Low			
	Medium			
	High			

Tables 4.12 shows the coverage rate, uploaded Photographs rate, and provided polygons rate of recreation value in each landscape unit using both methods.

Table 4.12. Spatial distribution of recreation value in landscape units

Landform	Landscape unit	Recreation value					
		Passive VGI			Expert-based Evaluation		
		identified spatial units	coverage rate	Uploaded Photographs rate	identified spatial units	coverage rate	Provided polygons rate
Mountain	1	0	0.00	0.000	54	100.00	0.2
	2	3	2.46	0.004	122	100.00	0.2
	3	11	25.00	0.022	44	100.00	0.11
	4	12	13.33	0.032	89	98.89	0.1
All mountain units	-	**26**	**8.39**	-	**309**	**99.68**	-
Hill	5	0	0.00	0.000	2	100.00	0.3
	6	1	0.32	0.010	311	99.68	0.14
	7	0	0.00	0.000	1	100.00	0.2
	8	14	10.94	0.037	128	100.00	0.11
	9	8	5.59	0.077	142	99.30	0.17
	10	1	1.30	0.006	77	100.00	0.2
	11	31	3.16	0.112	584	59.59	0.1
	12	0	0.00	0.010	5	100.00	0.35
	13	0	0.00	0.000	10	100.00	0.14
	14	0	0.00	0.000	4	80.00	0.1
All hill units	-	**55**	**3.31**	-	**1264**	**76.01**	-
Flat area	15	0	0.00	0.000	3	100.00	0.66
	16	2	3.03	0.019	66	100.00	0.56
	17	0	0.00	0.000	3	100.00	0.61
	18	16	5.61	0.082	208	72.98	0.23
All flat units	-	**18**	**5.04**	-	**280**	78.43	-
Coastal area	19	11	13.25	0.099	83	100.00	0.26
	20	16	14.16	0.472	113	100.00	0.2
	21	2	50.00	0.014	4	100.00	0.15
All coastal units	-	**29**	**14.50**	**0.585**	**200**	100.00	-
Lake	22	3	2.88	0.004	104	100.00	0.71
	23	0	0.00	0.000	2	100.00	0.8
All lake units	-	**3**	**2.83**	-	**106**	100.00	-

The hill landscape units (7, 13, and 14) the flat landscape units (15 and 17) and the lake landscape unit (23) are missing in the recreation value dataset using passive VGI. Although, all missed landscape units in the passive VGI dataset were identified and represented in expert-based dataset.

There is no relationship between landscape units in terms of provided polygons (or uploaded photographs) and the coverage rate for both methods (Table 4.13).

Table 4.13. Representation degree of recreation value in landscape units

Coverage of landscape units	Provided polygons or uploaded photographs rates	Landscape units	
		Passive VGI	Expert-based evaluation
High coverage	High rate of provided polygons or uploaded photographs	-	5,12,15,16,17,19,22,23
	Medium rate of provided polygons or uploaded photographs	-	1,2,7,9,10,20
	Low rate of provided polygons or uploaded photographs	-	3,4,6,8,13,14,21
Medium coverage	High rate of provided polygons or uploaded photographs	-	-
	Medium rate of provided polygons or uploaded photographs	21	18
	Low rate of provided polygons or uploaded photographs	17	11
Low coverage	High rate of provided polygons or uploaded photographs	8,9,19,11,18,20	-
	Medium rate of provided polygons or uploaded photographs	3,4,6,16	-
	Low rate of provided polygons or uploaded photographs	2,10,22	-

The lowest coverage of recreation value and a low uploaded photograph rate in passive VGI was discovered in unit 2 (mountain), 10 (hill), and 22 (lake). We could not find high coverage rate of recreation value in any landscape unit using passive (Figure 4.10).

We found the highest coverage rate of recreation value with high provided polygon rate in the lake landform (units 22 and 23) using expert-based evaluation. However, units 5, 12 (hill), 15, 16, 17 (flat), and 19 (coastal) were also overrepresented (high coverage and high uploaded polygon rate).

Landscape unit 7 (hill landform) was one of the units missed in passive VGI. This unit is located in Tora Bush Scenic Reserve with indigenous landcover. This scenic Reserve is classified as a Recreational Hunting Area and expected to identify recreation value. We assume this unit was missed in passive VGI was due to a lack of access road to this area resulting in less uploaded photographs on Flickr. Also, we found a medium rate of AOIs in this unit. It can be interpreted as a place with potential recreation services and no public demand due to lack of recreational facility and infrastructure.

The landscape units of 15, 17, and 23 are located respectively in the Lake Wairarapa Wetland Conservation Area, Matthews, Boggy Pond Wildlife Reserve, and Allsops Bay Wildlife Reserve. Although these landscape units are expected to have recreational value due to the lake view, they are missed in the recreation value dataset of passive VGI. Missing these landscape units can be explained by the limited public access to private land or lack of access road.

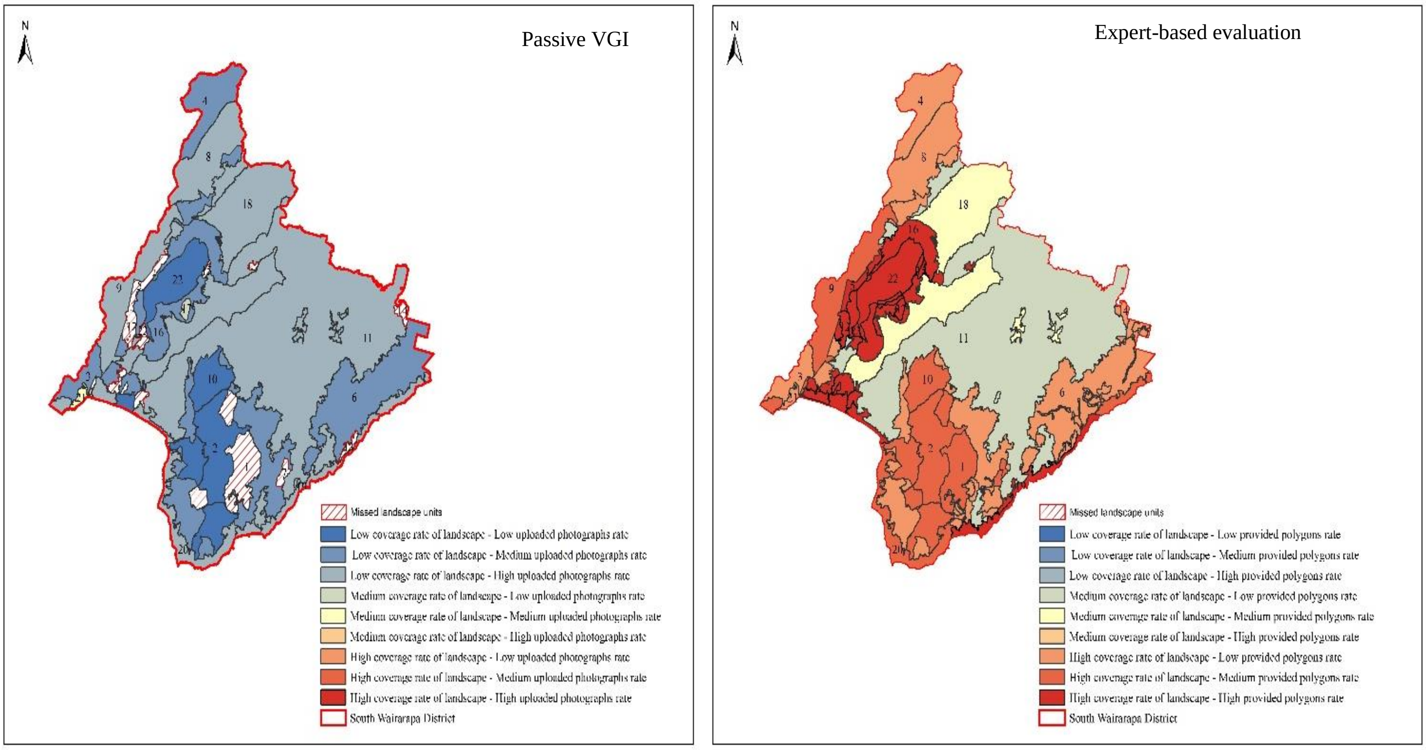


Figure 4.10. Landscape representation in recreation value datasets

Tables 4.14 show coverage, uploaded Photographs, and AOI rates for aesthetics value in each landscape unit using both methods. Aesthetics value has an approximately similar distribution of recreation value in landscape units for both mapping methods.

The landscape unit 1 of mountain landform, units 5, 7, 12, 13, 14 of hill landform, unit 15 of flat landform, and 23 of Lake Landform missed the aesthetics value using passive VGI, while there were not any missed landscape units in the expert-based dataset. The missed landscape units in aesthetic value of passive VGI dataset were the similar of the recreation value. Additionally, we missed landscape unit 1 of mountain and units 5 and 12 of hill landform using passive VGI, although, there were a lake view or indigenous cover in these units. These missing landscape units shows a limitation of the passive VGI method which relies on the number and content of uploaded photographs. Photograph contents cannot represent the entirety of social values in an area.

We found the landscape unit 8 with the medium coverage of aesthetics value and high uploaded photograph rate in passive VGI (Figure 4.11). This could be explained due to accessibility of Tararua Forest Park using tramping track and walking trail that helped to reflect its aesthetics value on the uploaded photographs on Flickr.

Table 4.14. Spatial distribution of aesthetics value in landscape units

Landform	Landscape unit	Aesthetics value					
		Passive VGI			Expert-based Evaluation		
		identified spatial units	coverage rate	Uploaded Photographs rate	identified spatial units	coverage rate	Provided polygons rate
Mountain	1	0	0.00	0.000	54	100.00	0.2
	2	3	2.46	0.002	122	100.00	0.2
	3	11	25.00	0.011	44	100.00	0.11
	4	20	22.22	0.061	89	98.89	0.1
All mountain units	**-**	**34**	**10.97**	**-**	**309**	**99.68**	**-**
Hill	5	0	0.00	0.004	2	100.00	0.3
	6	2	0.64	0.095	311	99.68	0.14
	7	0	0.00	0.000	1	100.00	0.2
	8	37	28.91	0.073	128	100.00	0.11
	9	7	4.90	0.037	142	99.30	0.17
	10	1	1.30	0.011	77	100.00	0.2
	11	81	8.27	0.161	598	61.02	0.1
	12	0	0.00	0.006	5	100.00	0.35
	13	0	0.00	0.000	10	100.00	0.14
	14	0	0.00	0.000	5	100.00	0.1
All hill units	**-**	**128**	**7.70**	**-**	**1279**	**76.91**	**-**
Flat area	15	0	0.00	0.000	3	100.00	0.66
	16	15	22.73	0.035	66	100.00	0.56
	17	1	33.33	0.004	3	100.00	0.61
	18	50	17.54	0.148	206	72.28	0.23
All flat units	**-**	**66**	**18.49**	**-**	**278**	**77.87**	**-**
Coastal area	19	20	24.10	0.092	83	100.00	0.26
	20	28	24.78	0.238	113	100.00	0.2
	21	4	100.00	0.010	4	100.00	0.15
All coastal units	**-**	**52**	**26.00**	**-**	**200**	**100.00**	**-**
Lake	22	15	14.42	0.014	104	100.00	0.71
	23	0	0.00	0.000	2	100.00	0.8
All lake units	**-**	**15**	**14.15**	**-**	**106**	**100.00**	**-**

Table 4.15 shows the 8 overrepresented landscape units from all landforms except mountain in expert-based dataset. We explored landscape units 11 and 18 had the medium coverage of aesthetics value with respectively low and medium provided polygon rates. The presence of a railway, a highway, and transmission lines probably negatively impacted the aesthetics of these landscape units which are reflected on expert-based dataset.

Table 4.15. Representation degree of aesthetics value in landscape units

Coverage of landscape units	**Provided polygons or uploaded photographs rates**	**Landscape units**	
		Passive VGI	**Expert-based evaluation**
High coverage	High rate of provided polygons or uploaded photographs	-	5,12,15,16,17, 19,22,23
	Medium rate of provided polygons or uploaded photographs	-	1,2,7,9,10,20
	Low rate of provided polygons or uploaded photographs	-	3,4,6,8,13,14,21
Medium coverage	High rate of provided polygons or uploaded photographs	8	-
	Medium rate of provided polygons or uploaded photographs	-	18
	Low rate of provided polygons or uploaded photographs	17	11
Low coverage	High rate of provided polygons or uploaded photographs	4,6,9,11,16,18,19,20,22	-
	Medium rate of provided polygons or uploaded photographs	3,10	-
	Low rate of provided polygons or uploaded photographs	2	-

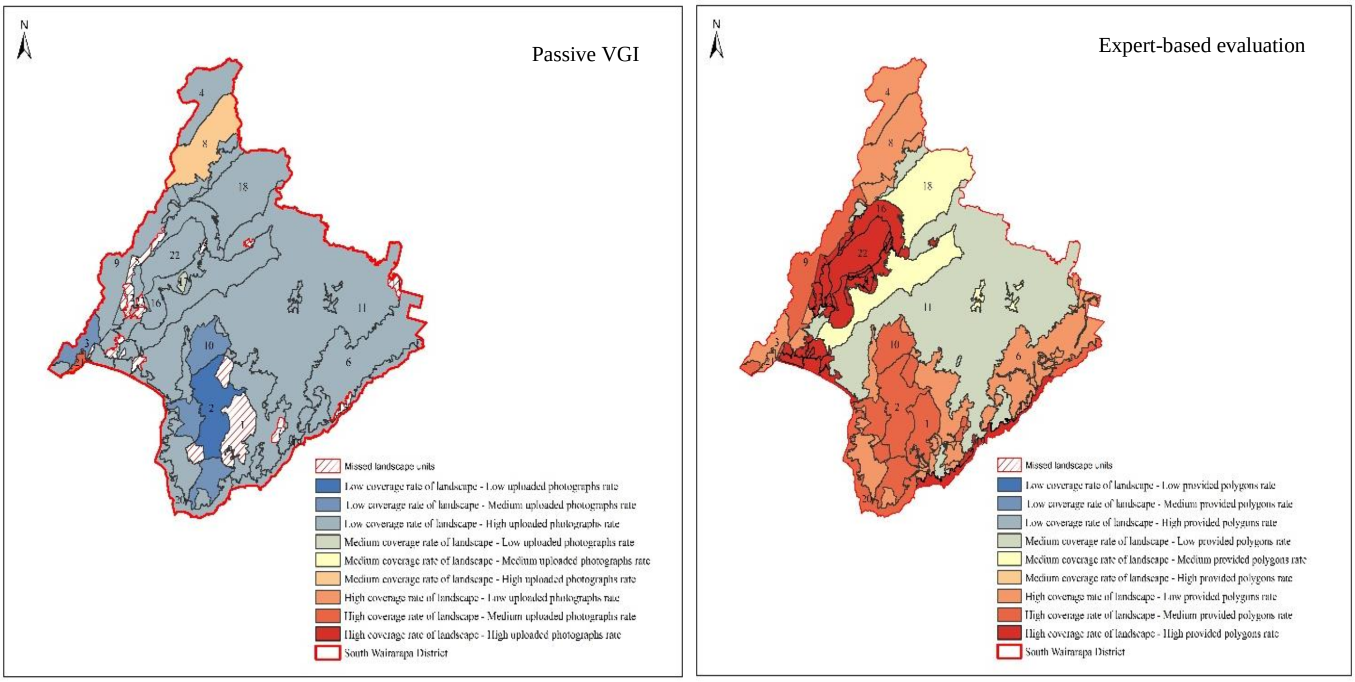


Figure 4.11. Landscape representation in aesthetics value datasets

Tables 4.16 shows the coverage, uploaded Photographs, and AOI rates of historical/cultural value in each landscape unit using both methods.

Table 4.16. Spatial distribution of historical/cultural value in landscape units

Landform	Landscape unit	Historical/cultural value					
		Passive VGI			Expert-based Evaluation		
		identified spatial units	coverage rate	Uploaded Photographs rate	identified spatial units	coverage rate	Provided polygons rate
Mountain	1	0	0	0.000	54	100.00	0.2
	2	1	0.82	0.003	122	100.00	0.2
	3	0	0	0.000	44	100.00	0.1
	4	2	2.22	0.012	89	98.89	0.1
All mountain units	**-**	**3**	**0.97**	**-**	**309**	**99.68**	**-**
Hill	5	0	0	0.000	2	100.00	0.3
	6	0	0	0.003	312	100.00	0.14
	7	0	0	0.000	1	100.00	0.2
	8	3	2.34	0.028	128	100.00	0.11
	9	4	2.8	0.025	142	99.30	0.17
	10	0	0	0.000	77	100.00	0.2
	11	13	1.33	0.168	607	61.94	0.1
	12	0	0	0.000	5	100.00	0.31
	13	0	0	0.000	10	100.00	0.12
	14	0	0	0.000	5	100.00	0.1
All hill units	**-**	**20**	**1.2**	**-**	**1289**	**77.51**	**-**
Flat area	15	0	0	0.000	3	100.00	0.66
	16	5	7.58	0.025	66	100.00	0.56
	17	1	33.33	0.003	3	100.00	0.61
	18	14	4.91	0.208	219	76.84	0.23
All flat units	**-**	**20**	**5.6**	**-**	**291**	**81.51**	**-**
Coastal area	19	4	4.82	0.040	83	100.00	0.3
	20	7	6.19	0.485	113	100.00	0.2
	21	0	0	0.000	4	100.00	0.1
All coastal units	**-**	**11**	**5.5**	**0.525**	**200**	**100.00**	**-**
Lake	22	1	0.96	0.000	104	100.00	0.71
	23	0	0	0.000	2	100.00	0.8
All lake units	-	1	0.96	-	106	100.00	-

The most landscape units (12 units) were missed for historical/cultural value using passive VGI. Historical/cultural value were more attached to landscape unit 17 (flat landform) with low rate of intersecting photographs in medium degree of coverage. The lowest value identified using passive VGI in the mountain landform (landscape unit 2). The least historical/cultural value was attached to landscape unit 11 in hill landform by experts while hill and mountain landscape units overrepresented (Table 4.17).

Table 4.17. Representation degree of historical/cultural value in landscape units

Coverage of landscape units	Provided polygons or uploaded photographs rates	Landscape units	
		Passive VGI	Expert-based evaluation
High coverage	High rate of provided polygons or uploaded photographs	-	5 12,15,16,17,19,22,23
	Medium rate of provided polygons or uploaded photographs	-	1,2,7,9,10,20
	Low rate of provided polygons or uploaded photographs	-	3,4,6,8,13,14,21
Medium coverage	High rate of provided polygons or uploaded photographs	-	-
	Medium rate of provided polygons or uploaded photographs	-	18
	Low rate of provided polygons or uploaded photographs	17	11
Low coverage	High rate of provided polygons or uploaded photographs	11,18,19,20	-
	Medium rate of provided polygons or uploaded photographs	4,8,9,16	-
	Low rate of provided polygons or uploaded photographs	2,22	-

Historical/cultural value in both datasets was represented in Tararua, Aorangi, and Remutaka Forest Parks in both mountain and hill landforms which there were accessibility by trampling track and main roads (The State Highway). Landscape units 22 and 23 (lake landform) overrepresented in expert-based dataset of historical/cultural value similar to recreation and aesthetics values (Figure 4.12).

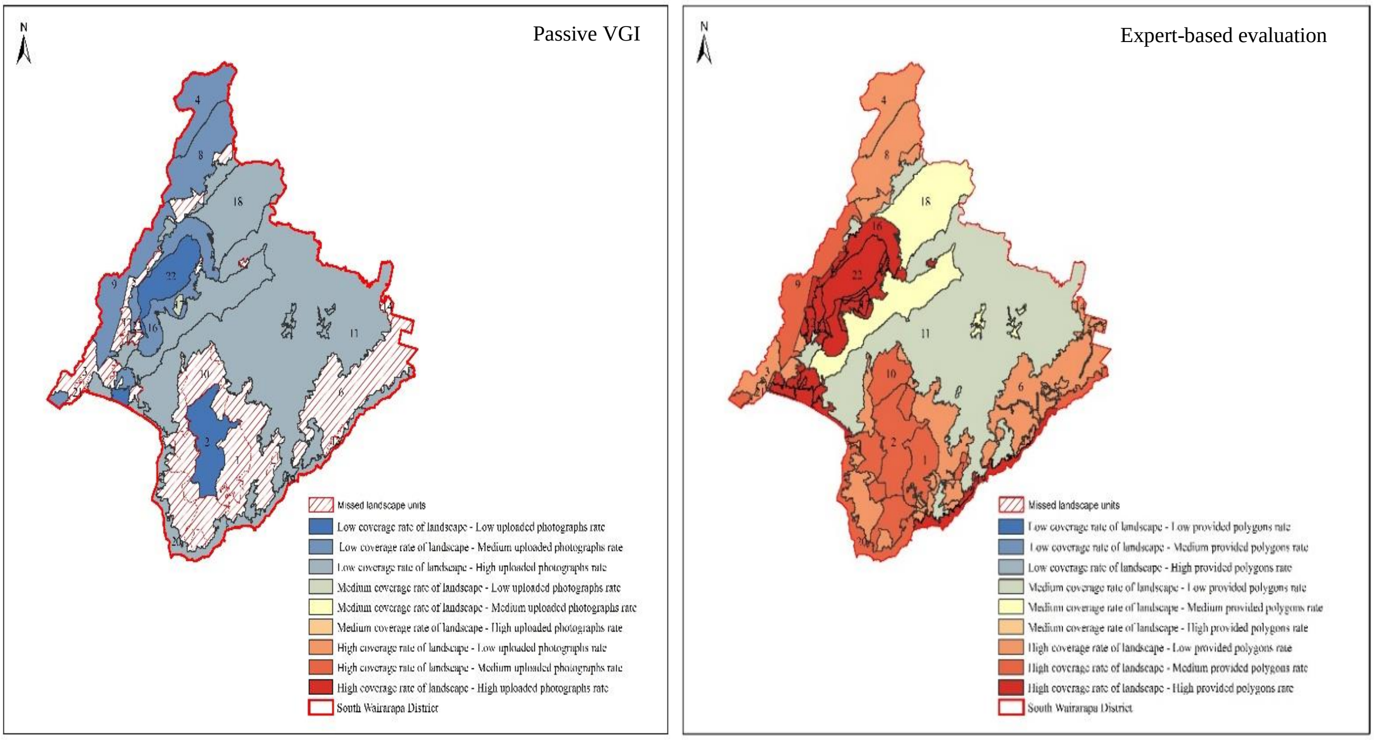


Figure 4.12. Landscape representation in historical/cultural value datasets

We used Pearson Correlation to explore whether there is a significant relationship between identified social values and landscape units in terms of abundance and importance using both mapping methods (Table 4.18).

Table 4.18. Correlation analysis between social value abundance and importance and landscape units

Social value	Mapping methods	Metrics	Pearson Correlation Coefficient
Recreation value	Passive VGI	Abundance	0.056**
		Importance	0.068**
	Expert-based evaluation	Abundance	-0.149**
		Importance	-0.016
Aesthetics value	Passive VGI	Abundance	0.158**
		Importance	0.147**
	Expert-based evaluation	Abundance	-0.145**
		Importance	0.007
Historical/cultural value	Passive VGI	Abundance	0.095**
		Importance	0.090**
	Expert-based evaluation	Abundance	-0.133**
		Importance	0.021

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

The results show a Pearson Correlation Coefficient of 0.056 for recreation value abundance using passive VGI. There is a weak positive relationship of 5.6% between passive VGI data and landscape units at the 99% confidence level. The Pearson Correlation Coefficient of -0.149 for recreation expert-based data showed a weak negative relationship. The results of Pearson Correlation analysis between social value importance level and landscape units showed a weak relationship. Aesthetics and historical/cultural value abundance and importance also showed the weak relationship with landscape units.

Effective recreational planning may be targeted at the specific landscape units with high social value importance. There was a significant difference between results of two mapping methods in terms of the social value importance level in the landscape units. The results showed that the high and very high importance levels assigned to the landscape units 1 and 2 of the mountain landform in expert-based method, although the passive VGI scored low and very low for these landscape units. The hill and flat landscape units, also, showed a different and generally reversed pattern in spatial distribution of importance levels in two mapping methods. The coastal landscape units demonstrated a very slight difference in the spatial distribution of social value importance. Cape Palliser Lighthouse and Putangirua Pinnacles- the two important recreation services in the coastal landform were assigned high and very high importance using both mapping methods. On the other hand, spatial units with historical/cultural value particularly around the Lake Ferry are assigned low and very low importance level using passive VGI, while the experts identified this landscape units with very high importance.

The lake landscape units (Lake of Wairarapa and Ferry) were undervalued in terms of importance. However, the expert-based methods recognized these landscape units as very high importance level in all types of identified social values.

Chapter 5: Discussion

The results of this study assess the credibility of passive VGI and expert-based evaluation of social value mapping methods to support recreation planning. This chapter discusses the research questions introduced in Chapter 1. Each section reviews the results, addresses objectives, makes comparisons between passive VGI and expert-based datasets and previous literature, addresses methodological limitations of social value mapping using these methods, and explains the importance of our findings.

5.1. Type, abundance and importance of identified key values

This section addressed and discussed two first objectives of this research. We explored the key types of social values were identified using passive VGI and expert-based data to determine the usability and completeness for recreational planning. We desired to identify recreation, aesthetics, and historical/cultural values using passive GI and expert-based evaluation. We selected these three social values due to their importance in planning for recreation ecosystem services. Most of the literature in these social value mapping methods has been focused on identifying recreation and aesthetics values (Brown & Pullar, 2012; Adnan, 2018; Ghermandi & Sinclair, 2019; Langemeyer et al., 2018; Nahuelhual et al., 2017), and historical/cultural value is rarely identified using these methods. Our results from both mapping methods captured three types of desired social values: recreation, aesthetics, and historical/cultural.

Next, we compared the spatial distribution of the social value datasets by abundance (presence/absence) and importance. Abundance and importance were relatively heterogeneous and differed between recreation, aesthetics, and cultural/historical values using both mapping methods.

Abundance had identified a significant difference between the both mapping methods. The portion of spatial units with social value data was considerably higher using expert-based evaluation (82.50 %) than passive VGI (6.08 %).

There was weak spatial association from two datasets in all three types of identified social values based on measured phi-coefficient. Expert-based dataset had more abundance of identified social values than passive VGI in the study area.

We found data (identified social values) was highly clustred around urban areas particularly Martinborough and there was low spatial abundance of data in the North-East of study area using both methods Gliozzo et al. (2016) in a study in the South Wales found most clusters of uploaded photographs in social media were around urban area and a smaller number located in non-urban areas. Although, a similar claim for expert-based data was not found in the literature. We compared the spatial abundance of three types of identified social values using both methods. Aesthetics value was comparatively more identified, while historical/cultural value was less identified using passive VGI. This difference was relatively slight using expert-based evaluation.

There was a significant difference between the results of the two datasets in terms of provided attributes of social values. For example, the expert-based evaluation provided useful information about the social value for recreational planning such as identifying the kind of recreation activities and characteristics of historical/cultural values. Although we could extract relatively similar information for recreation and aesthetics values using the content analysis of photographs in passive VGI, there was a limitation to identify the actual nature of historical/cultural value. This limitation made negative impact on the completeness of passive VGI dataset.

Experts identified approximately half of all spatial units as high or very high importance (43.50 %), compared to 23.01 % in the passive VGI dataset. No statistically significant correlation was found between the importance levels of the two datasets for the recreation and historical/cultural values. This indicated that each mapping method created a social value dataset (for example a recreation value dataset) with different characteristics. The aesthetics value had a statistically significant correlation between the importance levels of the two datasets ($r = 0.31$, $p = 0.109$); means the spatial distribution of aesthetics value importance in the passive VGI dataset was relatively confirmed by experts.

Among experts had relatively strong agreement about importance. This finding mirrors Rabe et al. (2018) who used expert-based evaluation to mapping recreation in the riverine zone in Switzerland. A statistically significant difference was detected between all experts' ratings for the selected criteria for recreation suitability in their study.

The clustering of social value abundance was assumed to be an advantage in spatial datasets to support planning in several studies (Han et al., 2020; Tenerelli et al., 2017; Richards et al., 2018). However, identifying a clustered social value pattern with a similar importance (for example a big polygon with high importance) is not useful for planning. A monotony of social value importance does not provide enough detailed information to prioritise plans based on public preferences at a local scale. Our findings showed social value importance less clustered in passive VGI in comparison to expert-based evaluation. For instance, experts identified a very large polygon approximately half of the study area with very high importance for all three social values. This outcome highlighted the capability of passive VGI to generate useful social value data particularly at the local scale.

5.2. Missing or overrepresented landscape units

In the third objective of this thesis, we used the look-up tables to explore the missed and overrepresented landscape units. The results show that spatial distribution of social value data across landscape units is heterogeneous and significantly differs between the two mapping methods. Given the importance of landscape units in recreational planning (De Aranzabal et al., 2009; Langemeyer et al., 2018), we investigated the relationship between the landscape components (landform, landcover, water view, naturalness, and infrastructure/recreation facility) and identified social values. We found a clear link between water views, landcover, and identified social values in landscape units. Both social value mapping methods generally assigned social values to landscape units with lake or ocean views and indigenous landcover.The availability of campsites, walking trails, and tramping tracks - an indicator of recreational facilities were significant associated with social values particularly recreation.Landscape types were not missed where transportation infrastructure (road and railway) were available using both mapping methods.

One third of landscape units were missed by passive VGI, while the expert-based method identified social values in all landscape units. This result contradits Langemeyer et al. (2018) who emphasised the capability of using geo-tagged photographs (passive VGI) to discover social values in landscape units. Langemeyer et al. (2018) showed Flickr's photographs as a comparable dataset to cover multiple types of landscapes. However, this contradictory outcome could has occurred due to limited photographs in our case study area (2551 photo samples for this research in comparison to 13000 photo samples in the Langemeyer et al. 2018).

Passive VGI revealed interesting patterns between landscape and identified social value of ecosystem services. Typical effects of infrastructure and recreation facilities with spatial distribution of social value abundance were visible. Infrastructure and recreation facilities contributed to create accessibility to potential recreation ecosystem services in the case study area. For instance, Cape Palliser Lighthouse and the seal colony in South-East of the case study area were identified as valuable cultural ecosystem services for the public for recreation and historical/cultural. These places are located at the farthest point of the South Wairarapa district and about 65 km to the major town in the area (Martinborough with a resident population of 1,680). However, due to the accessibility by road, there were two highly preferred areas with 527 photographs only in two spatial units for both places. This result confirms Gliozzo et al. (2016) which stated the importance of accessibility in presenting cultural ecosystem services using Flickr data in South Wales. Also, our result shows a significant difference between two social value datasets in lake landscape units. Experts identified the entirety of Lake Wairarapa and Lake Ferry as very high importance level. The landcover in the study area is a combination of natural conditions (Indigenous Landcover, Exotic Forest, and Scrub) and human action (developed agriculture).

We found social value abundance was more present in the natural landcover where people had access to the ecosystem services of the landscape. Also, accessibility can explain several missed units in developed agriculture located in hill or flat landforms.

We found landscape units with lake or open ocean views have more social values in both datasets. This results mirrors the outcomes of Gliozzo et al. (2016) who saw a positive impact of accessible views over specific landscapes (particularly in peaks and beaches) on social values of cultural ecosystem services.

Our findings about the relationship between the naturalness and social value datasets showed protected areas were mainly valuable for the public in both methods. There were seven major protected areas in the South Wairarapa district comprising, Aorangi Forest Park, Remutaka Forest Park, Tararua Forest Park, Tora Bush Scenic Reserve, Lake Wairarapa Wetland Conservation Area, Matthews & Boggy Pond Wildlife Reserve, and Allsops Bay Wildlife Reserve. We found social values in protected areas were affected by infrastructure and recreational facility. The lack of access roads or recreational facilities limited the identified social values in protected areas particularly using passive VGI dataset that was based on actual presence of people in a place.

5.3. Advantage and disadvantages of the social value mapping methods

We found that the outcomes differed in terms of the abundance and the importance of social value using the two different mapping methods. In this research, the passive VGI dataset covered average 6.08 % of the spatial units across the case study area. This coverage can be considered a disadvantage for this method as several landscape units are not included.

Expert-based evaluation created large polygons of social values which showed a high degree of generalisation and provided a coarse dataset for recreational planning particularly at an administrative or local scale. This limitation is similar to Brown & Pullar (2012) who compared the results of using point and polygon features to identify social values. Their outcomes showed some large polygons caused an inferential error in spatial areas.

Our finding highlighted the potential of the face-to-face interview to capture more and exact spatial data compared to the online survey. 51 polygons provided by the single interview while an average 4.2 polygons are provided using the online survey in the expert-based evaluation. Our outcomes aligned with Krueger et al. (2012) regarding different results of various elicitation methods in expert-based evaluation. Krueger et al. (2012) stated using remote questionnaire or software tools to extract expert knowledge have disadvantages of a low response rate and biases in results. The experience of this research showed the online survey was not an appropriate method to gather expert-based data in comparison to the face-to-face interview. This was either due to a lack of familiarity with drawing tools and social value concepts on the online mapping platform or the time-consuming nature of the process. We found the low participation rate and low data quality in online survey are a significant threat to credibility of created data. However, our finding is based on one single interview and we were restricted to the use of the online survey due to Covid 19.

Passive VGI provided data that indicated the actual distribution of outdoor recreation services on small areas (capability to provide relatively small polygons with adequate accuracy) in contrast to expert-based evaluation. The provided social value data substantively differ using different mapping methods in recreational planning. The expert-based data provided useful data of social values for future development planning as it showed the potential supply of ecosystem services for recreational planning. This issue was discussed in Jacobs et al's. (2015) review of expert-knowledge in ecosystem services assessment. They found the generalization nature of expert-based estimates a key challenge to support decision-makers.

Passive VGI is appropriate for the management of existing recreational areas based on demand for recreation ecosystem service. This finding is mirrored by Langemeyer et al. (2018) who demonstrated the results of social media data particularly Flickr as useful data to show flow of aesthetics and the outcomes of expert-based evaluation to assess capacity of aesthetics in landscape. Sottini et al. (2019) in the agricultural landscape of Italy showed that Flickr data provides a reliable estimate of the demand for cultural ecosystem services.

The highly clustered nature of the expert-based data made these maps a poor method to capture importance at a local scale in comparison to passive VGI. Experts in the online survey generally provided large polygons with similar importance. The clustered nature of the expert dataset for abundance might be considered as an advantage but for importance, useful information is not provided for local scale planning. In contrast, passive VGI showed less clustered social value importance. Creating an expert-based dataset was time-consuming and the motivation of participants had a direct and strong effect on the results.

Participants’ local knowledge of the case study area and the relevant professional experience were important in identifying social values. We found that participants with more familiarity of the case study area and planning practices were more motivated to contribute to the survey and mapped a large number of polygons. These participants identified more social values and provided more attributes. This finding was consistent with Brown (2017) who represented higher mapping efforts in an Internet-based PPGIS survey for participants familiar with the case study area. Therefore, a careful choice of experts must be considered in any expert-based evaluation that may be difficult due to a lack of availability or contribution of topical and local experts. Expert-based datasets provide more information about the characteristics of identified social values particularly about the historical/cultural value of ecosystem services in comparison to passive VGI.

We found the passive VGI was not an appropriate method to map historical/cultural value due to low portion of values and lack of relevant information about the nature of historical/cultural ecosystem service compared to expert-based evaluation.

5.4. Credibility assessment

In this thesis, we assessed the credibility of two social value mapping methods to provide useful and complete information for a broader audience and also to be able in support of decision making. Credibility in this context refers to the extent to which extracted spatial data represents various types of social values, appropriate spatial distribution in the terms of abundance and importance, and covers landscape units to support recreational planning. These metrics were used to compare the results of passive VGI with expert- based data for usability in recreation planning in the South Wairarapa district.

We found the usability of provided social value maps varied considerably in their ability to support recreational planning. Table 5.1 compares the credibility metrics in passive VGI and expert-based evaluation.

Table 5.1. Comparison of credibility metrics in the two social value mapping methods

Metrics	Passive VGI	Expert-based evaluation
Recreation, aesthetics, and historical/cultural values are identified.	Yes	Yes
Types of locations are identified using each method	Localised	Generalised
Importance of social value data are identified using each method	More varied importance	More clustered importance
Missed or overrepresented landscape units.	Several landscape units missed	All landscape units covered

Both mapping methods identified sites for all three types of social values (recreation, aesthetics, and historical/cultural) and revealed importance. Although the abundance of social value using passive VGI was low (6.08 % of the study area), the results were provided in a spatially explicit form and at a larger scale. The passive VGI dataset matched with peoples' actual behaviour and showed the spatial distribution of demand for recreational ecosystem services.

Identified social value using the expert-based evaluation covered 82.5 % of the study area, however, it only created a general view of spatial distribution of potential valuable recreation ecosystem service in a regional scale and did not represent social values well locally.

Expert-based evaluation had capability to provide valuable information about attributes of social values (particularly historical/cultural value) comparing passive VGI. Passive VGI provided useful and detailed information about the social value importance of spatial units. This data contributes to confidently prioritise planning areas for recreation at the local scale as there is adequate information about the importance of each spatial unit for the public.

Passive VGI identified social values in landscape units differently from the expert-based results. Passive VGI presented social values of an average 13 landscape units in comparison to all 23 landscape units revealed by expert-based data. Similar to Oteros-Rozas et al, (2018) in exploring cultural ecosystem services across five European sites, who found uncertainty about the representativeness of geo-tagged photographs in various landscapes.

To assess data credibility, we should consider whether each of the social value mapping methods (passive VGI and expert-based evaluation) could be used alone as a data source to support recreation planning. Our results suggest that ideally more than one social value mapping method is used to create an adequate social value database to ensure an appropriate the quality and quantity of data. A social value map could be created in several steps using several mapping methods.

Chapter 6: Conclusion

6.1. Key findings

Today, geo-tagged photographs have been used as a data source in various planning practices, such as tourism, urban planning, etc. Ecosystem services assessment can use this data source for social value mapping to support recreation planning. This data source provides useful information about preferences of people for recreational activities, historical/cultural issues among locals, and services provided for people by ecosystems and can be used to promote peoples' wellbeing through supporting sustainable planning.

This thesis critically analysed of the identified spatial social value data using geo-tagged photographs of Flickr (passive VGI) in comparison to expert-based data to support recreational planning. Our findings confirmed that both the passive VGI and expert-based evaluation could identify all three types of social value data of ecosystem services (recreation, aesthetics, and historical/cultural). However, passive VGI identified a comparatively smaller number of historical/cultural value in comparison to other values.

Although the passive VGI recognised the relatively low portion of the social values which could be assigned to landscape units, this data largely conforms to the actual recreational pattern in the case study area. This source can provide reasonably reliable information on the recreational preferences of people.

On the other hand, the expert-based data in this research identified a large portion of social values, particularly historical/cultural values. Although identified social values included useful information about current public preferences and a potential supply of recreation ecosystem services, it only captured a general view of the study area due to providing the large areas of interest (large polygons) by each expert in the online survey. This issue must be considered by regional planning bodies, such as local councils, that desire to identify social value at an efficient scale such as local scale. However, the online survey to gather expert-based data maybe a problematic feature. Although we attempted to design a simple online survey to encourage experts to contribute to identify more social value data, the low number of provided polygons indicated its limitation. We also captured data by conducting a single face-to-face interview with an expert.

Several landscape units were missed by passive VGI while expert-based dataset overrepresented a majority of landscape units

The results of this research demonstrated that spatial social value data are limited to show by a single method. Applying several mapping methods (PPGIS, expert-based evaluation, passive

VGI, etc.) can create a more useful and credible social value dataset to appropriately support recreational planning.

6.2. Recommendation

To improve social value mapping methods, we recommend examining the following procedure for social value mapping:

1- Select experts with relevant career expertise as well as experience living and working in the case study area. Recruitment of 10-15 motivated and knowledgeable experts should create an adequate dataset in terms of abundance and quality.

2- Conduct an initial workshop to clarify the concepts of ecosystem services and desired social value to experts.

3- Conduct independent face-to-face interviews with each expert and use a mapping platform (instead of a printed map) to identify areas of interest (AOIs). This stage helps to avoid the dominance of individuals that often occurs in group workshops. Using mapping software to draw the AOIs by an expert during the interview reduces the error of digitizing data by others after the interview.

4- Conduct a group discussion with all interviewed experts to discuss and revise as necessary the final social values for the case study area. These revisions will increase consensus and confidence in provided data.

5- Use an explanatory variable or dataset to check the validity of produced data. Passive VGI as an illustration of public demand as well as information about the potential ecosystem services can be used for validity assessment of expert-based data.

6- Run an online survey to engage various stakeholders to score the importance of the final social value areas or add a valuable area if it is neglected in expert-based evaluation.

We suggest integrating passive VGI and expert-based datasets with biophysical data for recreational planning. The results can be assessed by planners to determine the usability of provided data in practice. Also, trade-offs between biophysical data and social values must be assessed and compared with the actual supply and demand of recreation services. This helps to assess whether the combined result of these two mapping methods able to provide useful data for recreational planning.

Given various groups of audiences in different social media, we recommend using more than one platform to extract social value in passive VGI. This helps to provide a complete dataset in a case study area.

There is a need to explore the change of social values in response to change of the benefits of ecosystem services (for example because of climate change issues). Assessing the usability of social value mapping approaches is needed in order to have a better understanding of this issue.

7. References

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Appendix A

```
import flickrapi
import csv
import os, time
import multiprocessing
from multiprocessing import Pool
from functools import partial
from shapely.geometry import box, Point, Polygon
import pandas as pd
import geopandas as gpd
import pyproj
from shapely.geometry import shape
from shapely.ops import transform
'''
USER INPUTS
'''
## Output folder
outputfolder='D:\\results2'
## Input shapefile (should be WGS84 EPSG:4326)
inputshape='D:\\input2\\border2.shp'

## Connect to Flickr API
global api_key
api_key="5331f0f63b67f8592e8edd11bf3dc172"
secret_api_key="750861a73f1a6328"
flickr=flickrapi.FlickrAPI(api_key, secret_api_key)
'''
FUNCTIONS
'''
# Function to get a specific page result from Flickr API for a specific BBOX
def get_pagenumber_result(bbox,pagenum):
    query_succeed=False
    starttime=time.time()
    while query_succeed==False and (time.time()-starttime)<600: # If 10 minutes after first attempt to
connect to Flicker's server
        try:
            time.sleep(1)  #Wait for 1 second
            page=flickr.photos.search(api_key=api_key, bbox=bbox,format='parsed-json',
per_page=results_per_page, page=pagenum, extras='geo')
            query_succeed=True
        except:
            print("API request failed. Try again in 5 sec.")
            time.sleep(5) #Wait a bit before retry
            continue
        return page['photos']['photo']

# Function to get a result for multiple pages from Flickr API for a specific BBOX
def get_multiplepages_result(bbox,ncores=2):
    # Create a list of page number to request
    number_page=check_number_result_bbox(bbox)[1]
    time.sleep(1.5)
    list_pagenum=list(range(number_page+1))[1:]
```

```
    # Check for number of cores doesnt exceed available
    nbcpu=multiprocessing.cpu_count()
    if ncores>=nbcpu:
        ncores=nbcpu-1
    # Launch parallel computing
    p=Pool(ncores)
    func=partial(get_pagenumber_result,bbox)
    returnlist=p.map(func,list_pagenum) # the ordered results using map function
    p.close()
    p.join()
    # Return
    return returnlist

# Function saving info of photo for a single page of results
def get_photoinfo_singlepageresults(singlepageresult):
    return_list=[]
    for photo_dict in singlepageresult:
        current_row=[]
        current_row.append(photo_dict['id'])            # Photo ID
        current_row.append(photo_dict['latitude'])      # Location - Latitude
        current_row.append(photo_dict['longitude'])     # Location - Longitude
        current_row.append(photo_dict['accuracy'])      # Location - Accuracy
        current_row.append(photo_dict['owner'])         # User ID
        current_row.append(photo_dict['farm'])          # Farm
        current_row.append(photo_dict['server'])        # Server
        current_row.append(photo_dict['secret'])        # Secret

photo_static_url='https://farm%s.staticflickr.com/%s/%s_%s.jpg'%(photo_dict['farm'],photo_dict['ser
ver'],photo_dict['id'],photo_dict['secret']) # Photo static URL
        current_row.append(photo_static_url)

photo_flickr_website='https://www.flickr.com/photos/%s/%s'%(photo_dict['owner'],photo_dict['id'])
# Photo on Flickr website
        current_row.append(photo_flickr_website)
        return_list.append(current_row)
    return return_list

# Function saving info of photo for a multiple pages
def get_photoinfo_multiplepageresults(listofpages, ncores=2):
    # Check for number of cores doesnt exceed available
    nbcpu=multiprocessing.cpu_count()
    if ncores>=nbcpu:
        ncores=nbcpu-1
    # Launch parallel computing
    p=Pool(ncores)
    returnlist=p.map(get_photoinfo_singlepageresults,listofpages) # the ordered results using map
function
    p.close()
    p.join()
    # Return
    return returnlist

# Function that check number of results for a bbox API request
def check_number_result_bbox(coord, accu=16):
    # Get number of photo and number of pages
```

```
    a=flickr.photos.search(api_key=api_key,
                           bbox=coord, format='parsed-json',
                           per_page=results_per_page, accuracy=accu)  # By default look for more accurately
located information (could be not real accuracy according to my experience)
    total=int(a['photos']['total'])
    nb_pages=int(a['photos']['pages'])
    return total,nb_pages

# Function returning the area (squared meters) for a geometry provided in WGS84
def planar_area_from_wgs84_geom(geom):
    s = shape(geom)
    proj = partial(pyproj.transform, pyproj.Proj(init='epsg:4326'),
                   pyproj.Proj(init='epsg:3857'))
    s_new = transform(proj, s)
    projected_area = transform(proj, s).area
    return projected_area

def main():
    '''
    MAIN
    '''
    ## Set projections definitions
    proj4326={'init': 'epsg:4326'}
    proj3857={'init': 'epsg:3857'}

    ## Define maximum number of result per page (250) and maximum results per request (4000)
    global results_per_page, maxresult
    results_per_page=250  #Max 250
    maxresult=4000

    ## Import the Area Of Interest (AOI) polygon
    aoi_gdf=gpd.read_file(inputshape)

    #### Initial checking
    # Check if outputfolder exists
    if not os.path.exists(outputfolder):
        os.mkdir(outputfolder)
        print("The outputfolder <%s> didn't exist and just have been created."%outputfolder)
    # Check if AOI shapefile exists
    if not os.path.isfile(inputshape):
        os.error("No file found on path <%s>."%inputshape)
    # Check if CRS is EPSG:4326
    #if aoi_gdf.crs['init']!='epsg:4326':
    #    os.error("Input Shapefile's EPSG is not 4326.")
    # Check if only one item in the shapefile
    if len(aoi_gdf.index)!=1:
        os.error("The shapefile should contains exactly one item.")
    # Check if only shapefile geometry is POLYGON
    if str(aoi_gdf['geometry'][0])[:7] != "POLYGON":
        os.error("The shapefile geometry should be POLYGON.")

    ## Set up the initial BBox
    minLon=float(aoi_gdf.bounds['minx'])
    minLat=float(aoi_gdf.bounds['miny'])
    maxLon=float(aoi_gdf.bounds['maxx'])
```

```
    maxLat=float(aoi_gdf.bounds['maxy'])
    global bbox_sizeok
    initial_bbox=[minLon,minLat,maxLon,maxLat]
    bbox_sizeok=[]
    bbox_toolarge=[]
    bbox_toolarge.append(initial_bbox)  # List which will contain the coordinates of bbox

    ## Print number of result in the initial BBox
    nb=check_number_result_bbox("%s,%s,%s,%s"%(minLon,minLat,maxLon,maxLat))[0]
    if nb < maxresult:
        print("There are %s results in the initial BBox."%nb)
    else:
        print("There are %s results in the initial BBox. It is too much for a single API request and the
BBox will be sudivided (could take a while)."%nb)

    ## Export Initial BBox as GeoJson for visualization in GIS
    path_to_initial_bbox=os.path.join(outputfolder,"Initial_bbox.shp")
    geom=[box(minLon,minLat,maxLon,maxLat)]
    gdf=gpd.GeoDataFrame(crs=proj4326, geometry=geom)
    gdf.to_file(path_to_initial_bbox)

    ## Subdivide the BBox if needed
    loop_count=0
    while len(bbox_toolarge)>0:
        newbboxes=[]
        loop_count+=1
        print("-------- Start bbox(es) subdivision loop number %s. --------"%loop_count)
        print("Currently %s bbox(es) in the <bbox_sizeok> list."%len(bbox_sizeok))
        print("Currently %s bbox(es) in the <bbox_toolarge> list."%len(bbox_toolarge))
        for i,bbox in enumerate(bbox_toolarge):
            geombox=box(bbox[0],bbox[1],bbox[2],bbox[3]) #Geometry of the bbox
(minLon,minLat,maxLon,maxLat)
            if gpd.GeoSeries(geombox)[0].disjoint(gpd.GeoSeries(aoi_gdf['geometry'])[0]):  # If the
current bbox is completely outside the AOI, remove it
                bbox_toolarge.remove(bbox)
                continue # Leave the current loop and start the next iteration
            try:
                coord="%s,%s,%s,%s"%(bbox[0],bbox[1],bbox[2],bbox[3])
                total=check_number_result_bbox(coord)[0]
            except:
            print("Check of number of result failed for item %s in the list. Retry in 5 seconds."%i)
            time.sleep(5)  # Wait a bit before continuing
            continue # Leave the current loop and start the next iteration
        if total < maxresult:
            bbox.append(total)  # Save the number of result (< max) for this bbox (at index 4)
            bbox_sizeok.append(bbox)
            bbox_toolarge.remove(bbox)
        else:
            area=planar_area_from_wgs84_geom(geombox) #Get area in squared meters (EPSG:3857)
            density=total/float(area)
            if density < 500000:
                minLon=bbox[0]   # Current coordinates
                minLat=bbox[1]
                maxLon=bbox[2]
                maxLat=bbox[3]
```

```
            centLon=(minLon + maxLon)/2.0   # Average
            centLat=(minLat + maxLat)/2.0
            bbox_toolarge.remove(bbox)
            newbboxes.append([minLon, minLat, centLon, centLat]) #New bbox 1
            newbboxes.append([centLon, minLat, maxLon, centLat]) #New bbox 2
            newbboxes.append([minLon, centLat, centLon, maxLat]) #New bbox 3
            newbboxes.append([centLon, centLat, maxLon, maxLat]) #New bbox 4
        else:  # If photo density more than 1000000 per square meter
            print("Current bbox seems to be a black hole and will be removed from the list.")
            bbox.append(-1)  # Save -1 as number of result to highlight it was a black hole
            bbox_sizeok.append(bbox)
            bbox_toolarge.remove(bbox)
    [bbox_toolarge.append(i) for i in newbboxes]

## Export divided BBox as shapefile
path_to_divided_bbox=os.path.join(outputfolder,"Divided_bbox.shp")
geom=[box(p[0],p[1],p[2],p[3]) for p in bbox_sizeok]
df=pd.DataFrame([p[4] for p in bbox_sizeok],columns=['nb_results'])  # Create a dataframe with
number of result per bbox
gdf=gpd.GeoDataFrame(df, crs=proj4326, geometry=geom)
gdf.to_file(path_to_divided_bbox)

## Export Too Large BBox as shapefile
if len(bbox_toolarge)>0:
    path_to_toolarge_bbox=os.path.join(outputfolder,"Toolarge_bbox.shp")
    geom=[box(p[0],p[1],p[2],p[3]) for p in bbox_toolarge]
    gdf=gpd.GeoDataFrame(crs=proj4326, geometry=geom)
    gdf.to_file(path_to_toolarge_bbox)

## Get a list with all result pages for all bbox
listofpages=[]
for bbox in bbox_sizeok:
    coord="%s,%s,%s,%s"%(bbox[0],bbox[1],bbox[2],bbox[3])
    if bbox[4]>0: # Request API only if number of result for the BBOX is more than 0
        pages_current_bbox=get_multiplepages_result(coord,ncores=4)
        [listofpages.append(page) for page in pages_current_bbox]

## Extract information from the pages results and build content of the ouput .csv file
outputcsv_photos=os.path.join(outputfolder,"FlickR_points.csv")
content=[]
content=get_photoinfo_multiplepageresults(listofpages, ncores=5)  # Create content of the file
content=[a for sublist in content for a in sublist]  # Flat the results
content.insert(0,['id','latitude','longitude','accuracy','owner','farm','server','secret','URL_static','URL_w
ebsite']) # Insert header in first position
f=open(outputcsv_photos,'w')
writer=csv.writer(f,delimiter=',')
writer.writerows(content)
f.close()

## Create Shapefile with results
path_to_results=os.path.join(outputfolder,"Flickr_photos.shp")
df=pd.read_csv(outputcsv_photos)  # Create a dataframe with number of result per bbox
geom=[Point(xy) for xy in zip(df.longitude, df.latitude)]
df=df.drop(['longitude', 'latitude'], axis=1)
gdf=gpd.GeoDataFrame(df, crs=proj4326, geometry=geom)
```

```
within_aoi=gpd.GeoSeries(gdf['geometry']).within(aoi_gdf.unary_union)
within_aoi=gpd.GeoSeries(gdf['geometry']).within(aoi_gdf.ix[0])
res_intersection=gdf[within_aoi] ## Keep only locations which intersects the AOI
res_intersection.to_file(path_to_results)

## Export .csv file with list of unique user IDs
list_of_user=[]
reader=csv.reader(open(outputcsv_photos,'r'),delimiter=',')
next(reader) # Pass the first row (header)
[list_of_user.append(row[4]) for row in reader]
list_of_user=[[x] for x in set(list_of_user)] # Get unique values of user ID ising 'set'
outputcsv_listuser=os.path.join(outputfolder,"FlickR_users.csv")
f=open(outputcsv_listuser,'w')
writer=csv.writer(f,delimiter=',')
[writer.writerow(x) for x in list_of_user]
f.close()
```