***Highlights**

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- Examines spatial accuracy of public participation GIS (PPGIS) data
- Surprisingly low spatial error rate by general public in native vegetation identification
- Spatial accuracy is related to participant familiarity with study region
- Competitive trade-off in PPGIS between increasing participation rates and spatial accuracy

***2) Title Page (WITH author details)**

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# An Empirical Evaluation of the Spatial Accuracy of Public Participation GIS (PPGIS) Data

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# An Empirical Evaluation of the Spatial Accuracy of Public Participation GIS (PPGIS) Data


## Abstract

Public participation geographic information systems (PPGIS) refers to methods that seek to integrate public knowledge of places to inform land use planning and decision making. There is little published information on the spatial accuracy of PPGIS data compared to expert-derived GIS data. This study assesses the spatial accuracy of PPGIS data collected for conservation planning in two regions of New Zealand in 2011 by comparing participant mapped locations of native vegetation with areas identified in the New Zealand Land Cover Database (LCDB) Version 2. Spatial error was operationalized as PPGIS locations having no native vegetation within 1000 meters. The results indicate relatively low PPGIS spatial error of about 6% compared to 22% for randomly selected point locations in the regions. Spatial error is largest in coastal regions and near population centers where native vegetation is sparse and patchy. Participant familiarity with the study region is related to spatial error and is reflected in PPGIS sampling groups, with randomly sampled households having the largest error rate and the self-selected public, the lowest error rate. The results indicate a competitive, trade-off relationship between PPGIS participation rates and spatial accuracy. Future PPGIS research should identify processes with the capacity to increase both participation and spatial accuracy concurrently.


**Keywords:** public participation GIS; PPGIS; spatial accuracy; native vegetation

## Introduction

Public participation geographic information systems (PPGIS) refers to a general set of methods for integrating public knowledge of places to inform land use planning and decision making. Although the formal definition of PPGIS remains "nebulous" (Tulloch, 2007), PPGIS seeks to engage the "public" in participatory processes that use geospatial technologies to inform decisions that have spatial implications. In one type of PPGIS, participants are requested to identify locations on a map, either hardcopy or digital, using stickers, markers, or digital annotations. Participants may be invited through a variety of means including household sampling, on-site contact, mass media advertising, email lists, workshops, and the use of online panels. PPGIS applications have ranged from community and neighborhood planning to regional environmental and natural resource management (see Brown, 2005; Dunn, 2007; Sieber 2006; and Sawicki & Peterman 2002, for a review of PPGIS applications). Of relevance to this study, PPGIS applications have been implemented for protected areas such as national forests (Brown & Reed, 2009; Clement & Chang, 2011; Reed & Brown, 2003), national parks (Brown & Weber, 2011; Raymond & Brown, 2006), urban parks (Brown, 2008; Tyrväinnen, Mäkinen, & Schipperijn, 2007), conservation reserves (Pfueller et al., 2009), wilderness areas (Brown & Alessa, 2005), and national scenic byways (Brown, 2003).

PPGIS applications can involve a wide range of participatory activities, individuals, and processes. Schlossberg and Shuford (2005) argue that the meaning of "public" and "participation" are essential to understanding the public participation dimensions of PPGIS. In their typology, the term "public" may include decision makers, implementers, affected individuals, interested observers, or the random public. The "participation" dimension can range on a spectrum from the public passively receiving information to increasingly complex modes of engagement resulting in citizen control over a decision process. Thus, PPGIS refers to a broad range of participatory engagement methods with various potential publics involving spatial information. The PPGIS process may involve using pre-existing data (physical and social) or "participatory" data collection.

This focus of this study is on the type of PPGIS where the "public" is requested to generate spatial data to inform a planning process. When spatial data collection is participatory, the process shares much in common with "volunteered geographic information" or VGI systems where citizens act as sensors recording information about the environment (Goodchild, 2007).

VGI involves the creation and dissemination of geographic data provided voluntarily by individuals and overlaps with PPGIS in that both involve the investigation and identification of locations that are important to individuals (Tulloch, 2008). A potential distinction between VGI and PPGIS relates to the purpose or motivation for participation; PPGIS projects are often implemented to inform planning and policy issues while VGI systems may have no explicit purpose other than participant enjoyment.

Government adoption of PPGIS methods for decision-support has lagged owing to multiple social and institutional constraints (Brown, in process). One barrier to adoption is mistrust of PPGIS data. The imprecise and perceptual nature of PPGIS data stand in contrast to expert-driven GIS systems that are perceived as highly accurate. The centrality of spatial precision and accuracy to expert-driven GIS fosters skepticism about PPGIS data where the participation process may assume more importance than the spatial data generated. Although few studies have empirically benchmarked the spatial accuracy of PPGIS data, the mere perception of spatial inaccuracy can undermine PPGIS processes despite the view that lay knowledge should augment, not substitute for expert knowledge (Brown et al., 2004).

The validity of PPGIS methods depends on participation rates and the quality of the data collected (Brown and Pullar, 2012). The quality of the spatial data is determined, in part, by the precision and accuracy of the attributes identified by participants. Precision is a measure of the exactness in placing PPGIS markers, either hardcopy or digital. The precision of marker placement depends on a number of variables including marker size and map scale as well as participant characteristics such as visual acuity and physical dexterity. Accuracy reflects how well the marker approaches the true spatial dimensions of the attribute being identified. Accuracy in PPGIS is influenced by a number of variables including the nature of the PPGIS attribute being mapped (i.e., clarity in operational definitions and instructions enhance accuracy), the quality of the mapping environment (e.g., map scale and base map features), and respondent characteristics such as familiarity with the study landscape.

For some PPGIS spatial variables such as perceived landscape values, a high degree of spatial accuracy may not be essential to core planning outcomes. Participants can identify general locations or regions with indeterminate boundaries. PPGIS attributes, whether identified with points or polygons, will converge on a collective spatial “truth” provided there are enough observations in the study area (Brown and Pullar, 2012). Although there is spatial error and uncertainty in expert-derived GIS data, the imprecision and potential inaccuracy of PPGIS data is more explicit and can subvert the legitimacy of PPGIS even where a high degree of spatial accuracy is not essential to the application.

This study addresses several simple, but important research questions about PPGIS data quality. How spatially accurate is PPGIS data? Can the general public accurately identify landscape attributes that are typically measured by expert GIS systems? And what variables in the PPGIS process appear to contribute to spatial accuracy/error? PPGIS studies completed in 2011 for the New Zealand Department of Conservation (DOC) in two different regions (Southland and Otago) provide a unique opportunity to address these research questions.

Under the Conservation Act of 1987, the New Zealand DOC is required to prepare 10-year regional conservation plans called Conservation Management Strategies (CMS). A CMS provides an overview of conservation issues in the region and provides direction for the management of public conservation land, waters, and species for which DOC has responsibility. The purpose of a CMS is to implement general policies and establish objectives for the integrated management of natural and historic resources, recreation, and tourism opportunities within a region.

In the CMS community consultation process for the Otago and Southland regions, the DOC collaborated with university researchers to implement web-based PPGIS systems for each region (see www.landscapemap2.org/nzdoc or www.landscapemap2.org/otago) to identify conservation values, visitor experiences, and development preferences. One of the spatial variables in the PPGIS requested that participants identify the location of native vegetation in the regions. Native vegetation is an important natural resource that DOC is obligated to conserve and protect. In 2002, the area of native vegetation in New Zealand was about 43.7 per cent (11.7 million hectares) of the total land area (NZ Ministry for Environment). While many PPGIS mapped attributes cannot be easily assessed for accuracy with actual landscape features, native vegetation is an exception—it has been extensively mapped in New Zealand using remotely sensed data in combination with expert classification in GIS. Thus, the PPGIS native vegetation attribute provides an important opportunity to quantitatively measure the accuracy of PPGIS data against expert-derived GIS data.

For the purpose of this study, the general research questions about the spatial accuracy of PPGIS data are operationalised into the following specific research questions: What is the spatial error rate in PPGIS identification of native vegetation in the two regions? How does PPGIS spatial error in native vegetation identification compare with spatial error that would be expected by chance through random selection of locations? What participant and PPGIS implementation variables are related to spatial accuracy/error?

## Methods

### *Study Location*

The two regions in this study are the Otago and Southland regions on the south island of New Zealand. The Southland region covers more than 3.1 million hectares, has over 3,400 km of coastline, and includes New Zealand's largest national park, Fiordland National Park. Southland is one of New Zealand's most sparely populated regions, with an estimated population of 94,200 (Statistics New Zealand, 2011) and an economic base in tourism, agriculture, fishing, forestry, and energy resources.

The Otago region covers approximately 3.2 million hectares with an estimated population of 208,500 (Statistics New Zealand, 2011). Major centers of population include Dunedin, Oamaru, and the tourist centers of Queenstown and Wanaka. In the west of the region, high alpine mountains and glacial lakes dominate the landscape including Mt. Aspiring National Park. Tussock grasslands dominate the dry lands of the central region, while the hill country of the Catlins is located in the region's southeast. Key economic sectors include tourism, education, agriculture, and manufacturing.

### *PPGIS Data Collection*

PPGIS websites for each of the regions were developed after consultation and pilot testing with DOC staff. PPGIS data collection consisted of two parts; (a) spatial attribute mapping using a custom Google® Maps application, and (b) general survey questions assessing participants' familiarity with conservation areas in the region and selected socio-demographic information. Participants were recruited through a random mail sample of households in the Southland and Otago regions, by visitor contact at conservation areas, and by advertising in media outlets such as local newspapers.

The spatial attributes to be identified by participants included 30 landscape values, park experiences, and development preference markers located in three panels on the left of the screen. Participants were instructed to drag and drop markers onto the appropriate map locations representing the attribute. The list of markers and their associated definitions was identical for the two regions. Of relevance to this study was the native vegetation attribute defined as areas that are "valuable because they sustain indigenous (native) plants."

PPGIS mapping precision was enforced by only allowing the placement of markers if the participant had zoomed-in to a predetermined zoom level (Level 12) in Google Maps (approximately 1:100,000 scale). Respondents could optionally view the region in different Google map views including "Map", "Terrain", "Satellite", "Hybrid" and 3-D "Earth". The default Google map view, and the one in which the majority of markers were placed, was "Terrain".

Following completion of the mapping activity, participants were asked about their knowledge of places in the region, the number of times they had visited places in the region, and common socio-demographic questions including age, gender, and formal education.

A total of 893 native vegetation points were identified in the two regions by 260 PPGIS participants. These points represent about 6% of the total number of spatial attributes identified (n=14,370) by all participants (n=698) in the two regions.

*Data Analysis Methods*

***Comparing PPGIS native vegetation with expert-derived classification***. PPGIS identified native vegetation areas were spatially intersected with native vegetation identified in the New Zealand Land Cover Database (LCDB) Version 2 which classified land cover using satellite imagery from 1996/1997 and 2001/2002 (see http://www.mfe.govt.nz/issues/land/land-cover-dbase ). The LCDB is used to report on native land cover, land use, and erosion risk indicators. The database was developed with a 1 hectare minimum mapping unit based on satellite imagery with 15 m resolution.

The PPGIS native vegetation areas were identified by making an assumption about marker placement precision in the Google Maps PPGIS application. A precision tolerance was created by buffering each PPGIS native vegetation point to a radius of 1000 m. The areal percentage of native vegetation from the LCDB was calculated for each buffered PPGIS point and could range from 0 to 100% (native vegetation area = LCDB native vegetation within buffer / total area of buffer). A classification rule for spatial error was adopted such that if the buffered area for each point (approximately 314 hectares) contained no native vegetation, the PPGIS marker was deemed placed with “error”. Because both regions contain significant coastal areas and large inland lakes, it was necessary to adjust the area of native vegetation calculation where the buffered areas contained water. Total area in the calculation was reduced by the area of water that fell within the point buffer.

***Benchmarking PPGIS native vegetation classification against expected values.*** Native vegetation markers could be placed anywhere by PPGIS participants. What if these markers were randomly placed without any knowledge of native vegetation? How does participant identification of native vegetation compare to results that would be expected by chance placement of markers? To conduct this analysis, 1000 random points within the two regions were identified using stratified sampling based on the proportion of native vegetation markers placed in each region (61% Otago, 39% Southland). These points were buffered to 1000 m and the percentage of LCDB native vegetation was calculated for each point. Similar to the PPGIS markers, adjustments to the native vegetation calculation were made for water that fell within the buffered areas. Histograms of the percentage of native vegetation for both the PPGIS points and the random points were generated for comparison. To spatially examine where the errors occurred, the PPGIS markers were plotted on top of the LCDB vegetation data in both regions and symbolized based on the percentage of native vegetation surrounding the PPGIS native vegetation markers.

***Potential sources of spatial error from PPGIS identification of native vegetation.*** PPGIS participants are not homogenous—personal characteristics and life experiences can influence knowledge of native vegetation and thus accuracy/error in identifying native vegetation. The relationships between spatial error in native vegetation identification and the respondent variables of self-identified region familiarity, number of visits to conservation areas, gender, and level of formal education were examined using Chi-square tests of independence. The relationship between error rate and the three PPGIS participant groups (random household, on-site visitors, and volunteer public) were also examined.

Participant choices in the PPGIS mapping process also have the potential to increase or decrease the spatial error rate. Two PPGIS implementation variables were examined. The relationships between spatial error and map scale at time of marker placement and the Google map type were analyzed using Chi-square tests of independence.

**Results**

The rate of spatial error by PPGIS participants in identifying areas with native vegetation was 6.2% of markers placed. In contrast, 17.8% of markers contained 100% native vegetation. The spatial error by PPGIS participants was considerably lower than results from mapping 1000 random points in the region which had a 21.5% error rate and only 12.8% of points with 100% native vegetation. Histograms showing the distribution of native vegetation contained within 1000 m of the PPGIS markers and the 1000 random points appear in Figure 1. On average, the PPGIS identified areas contained 67% native vegetation compared to 49% for the random points. This difference in mean native vegetation area is statistically significant ($t=10.31$, $df=1861$, $p \leq 0.05$). If the operational definition of spatial error were to be increased to 10% or less native vegetation in the immediate area, the contrast in spatial error becomes even greater with a PPGIS error rate of 14.5% versus 35.6% for the random points.

**[Insert Figure 1]**

The greatest error in identifying native vegetation occurred in coastal areas near population centers that have relatively small and patchy native vegetation in the LCDB. Four areas stand out as having relatively high clusters of spatial error: the east coast near Dunedin, north of Invercargill on the south coast, and near the interior communities of Wanaka in west Otago and Alexandra in central Otago. These areas are identified with arrows in Figure 2.

**[Insert Figure 2]**

The statistical results of possible correlates with spatial error in identifying native vegetation appear in Table 1. The accurate identification of native vegetation in PPGIS appears related to participants' self-identified knowledge of places in the region ($\chi^2=6.10$, $p \leq 0.05$). Individuals that claimed good or excellent knowledge of places had a 5.1% error rate in identifying native vegetation compared to 11.5% for individuals with average, below average, or poor knowledge of places. The accurate identification of native vegetation does not appear related to the number of times participants had visited conservation areas in the region ($\chi^2$ =.053, $p \geq 0.05$). Female participants had a significantly higher rate of spatial error (9.3%) than males

(3.5%) while those with more formal education had a higher rate of spatial error (8.3%) than participants with less formal education (3.3%). A key finding is the error rate associated with the three sampling groups in the PPGIS process: participants from randomly selected households had the highest spatial error (14.5%) followed by participants contacted in conservation areas (7.4%) and the volunteer public (5.9%).

**[Insert Table 1]**

Two PPGIS implementation variables were examined for potential relationship with spatial error. Participants that identified native vegetation locations at the default map zoom level had similar error rates to participants that choose to zoom and increase map scale ($\chi^2$ =.02, $p \geq 0.05$) while the base map type (terrain vs. satellite) did not significantly relate to the error rate ($\chi^2$ =.14, $p \geq 0.05$).

## Discussion

The identification of native vegetation in the New Zealand PPGIS provides one of the first opportunities to empirically assess and compare the spatial accuracy/error of public data with expert-derived GIS data. The error rate of about 6% in identifying native vegetation is a major improvement over mapping error rates that would be expected by chance, about 22%. Collectively, PPGIS participants were clearly not randomly placing points in the two regions. These error estimates likely provide a worst case scenario because the true spatial error rate would actually be lower if some participants were identifying patches of native vegetation smaller than one hectare or the minimum mapping unit for the LCDB database.

Identifying the probable sources of the individual spatial error is speculative, but these study findings indicate that familiarity with the study region is the key variable in explaining the results. A higher proportion of self-selected participants (volunteer public) in the PPGIS process rated their knowledge of places in the regions as good or excellent compared to the other PPGIS sampling groups. These results are consistent with other PPGIS studies where participants with greater familiarity of the study region identified more spatial attributes than less familiar participants (Brown and Reed 2009).

The initial finding that women and individuals with less formal education had higher error rates appears puzzling without further investigation. Closer examination of the responses reveals proportionately fewer women than men were in the volunteer public sampling group which had the lowest error rates of the three sampling groups. Similarly, there were proportionately more PPGIS participants with higher levels of formal education in the random household sampling group which had the highest error rates. Thus, the empirical evidence points back to the sampling group as the key correlate of spatial error which is related to the participants' familiarity with the study region.

Given the reported differences in spatial accuracy by sampling groups, it would be helpful to understand the motivations of the self-selected group for participating in the PPGIS process. Unfortunately, there were no survey questions following the mapping activity that directly asked about participant motivations. There are a variety of possible motivations for self-selection and engagement with the PPGIS process so the explanation here is necessarily speculative. This study's self-selected participant group shares the volunteerism feature of a VGI system and Tulloch (2008) has offered that people engage in VGI primarily for enjoyment. Although this motivation may apply to a few self-selected individuals, this explanation doesn't sound convincing for the majority of participants in this study. A more plausible explanation is that self-selected participation was motivated by the desire to maintain the quality of the public lands in New Zealand. Conservation lands in southern New Zealand have outstanding natural and recreational qualities that many people want to see protected. From other PPGIS studies, it is known that the quantity and type of PPGIS mapping activity is related to place attachment (Brown & Raymond, 2007). An individual's decision to participate in the PPGIS process may be motivated by the desire to protect and preserve those areas where the individual has become attached, meaning the individual has come to personally identify with, or depend on the places identified. Other variables that may have contributed to an individual's motivation for participation include the novelty of the PPGIS internet application (this was the first application of PPGIS in New Zealand) and trust (or lack thereof) in the New Zealand DOC to manage the region's public lands in the participant's best interests.

Other PPGIS studies with data collection involving multiple sampling groups (including this NZ study) indicate that the self-selected public demonstrates somewhat greater mapping effort, defined as the exertion of physical and mental power to complete the PPGIS mapping activity (Brown et al., in process). The increased mapping effort results in more map markers being placed and more time spent (on average) in the PPGIS activity. These results suggest that both participant familiarity/knowledge and mapping effort contribute to higher data quality in the PPGIS data collection process. But is the marginal improvement in data quality achieved by self-selected participants more important than stronger claims of public representation in the participatory process?

These study results reveal the intrinsic challenge of using PPGIS for public engagement in land use planning processes. To achieve greater legitimacy for the consultation process, participation is needed from individuals that are broadly representative of community interests. Random household sampling is an important means to engage the "silent majority" in the process to achieve public representativeness, particularly for outcomes related to public conservation lands in New Zealand. But for PPGIS, there appears to be a genuine tradeoff between achieving greater public representation through random sampling and introducing more spatial error into the PPGIS mapping process.

A well-conceived PPGIS system would not force or even encourage responses from participants for spatial variables that are beyond the intellectual or experiential capacity of the participant. Encouraging participants to identify spatial attributes beyond their capacity for the sake of participation appears counter-productive as the higher participation rate would introduce greater spatial error for some PPGIS attributes.

In the design of PPGIS systems, it may be advisable to identify and separate spatial attributes that appear to require greater intellectual or experiential knowledge and handle these differently from spatial attributes that merely require the expression of spatial preferences. The results of this study, combined with those of an exploratory study of PPGIS to identify ecosystem services (Brown, Montag, & Lyon, 2011), indicate that PPGIS can be used to identify spatial attributes that qualify as expert knowledge. This "lay" knowledge can and should provide an important check and balance on expert system results. However, the present generation of PPGIS systems does not adequately tailor the elicitation of spatial information to the intellectual and experiential constraints of the participants. The tailoring process could be implemented through carefully crafted screening questions related to knowledge and experience or through a PPGIS system design that allows the participants to sequentially progress from the identification of low-investment spatial variables (e.g., preferences and experiences) to those requiring greater familiarity and knowledge of the study landscape (e.g., location of biophysical attributes).

At present, PPGIS participants are required to sift through a range of spatial variables and self-select those for which they think they can reasonably map in the process. One possibility for a revised PPGIS interface would be to organize and label the PPGIS spatial variables into broad categories defined by level of familiarity with the study region (e.g., low, medium, and high familiarity). The participant could then self-select the group of spatial variables to map consistent with their familiarity. Another variation offering even more control over the process would be to prompt the participant at the start of the PPGIS application for their level of familiarity with the study region. The participant's response would then trigger the dynamic loading of pre-selected spatial variables associated with varying levels of study region familiarity.

With the first web-based PPGIS application for protected areas being implemented in 2006 (Beverly et al., 2008), internet PPGIS methods are relatively new. Technological advances in PPGIS implementation using digital and internet mapping have outpaced our understanding of PPGIS methodological limitations and the psychology of response. Further, PPGIS methods are now being implemented at a time when public participation rates are low (Pocewicz et al., 2012). Greater social acceptance of PPGIS methods will depend on demonstrating both the accuracy of the spatial data and the representativeness of participants in the process. Because these two outcomes appear competitive rather than complementary, future PPGIS research should work to advance our understanding of this relationship by identifying processes with the capacity to increase both participation and spatial accuracy concurrently.

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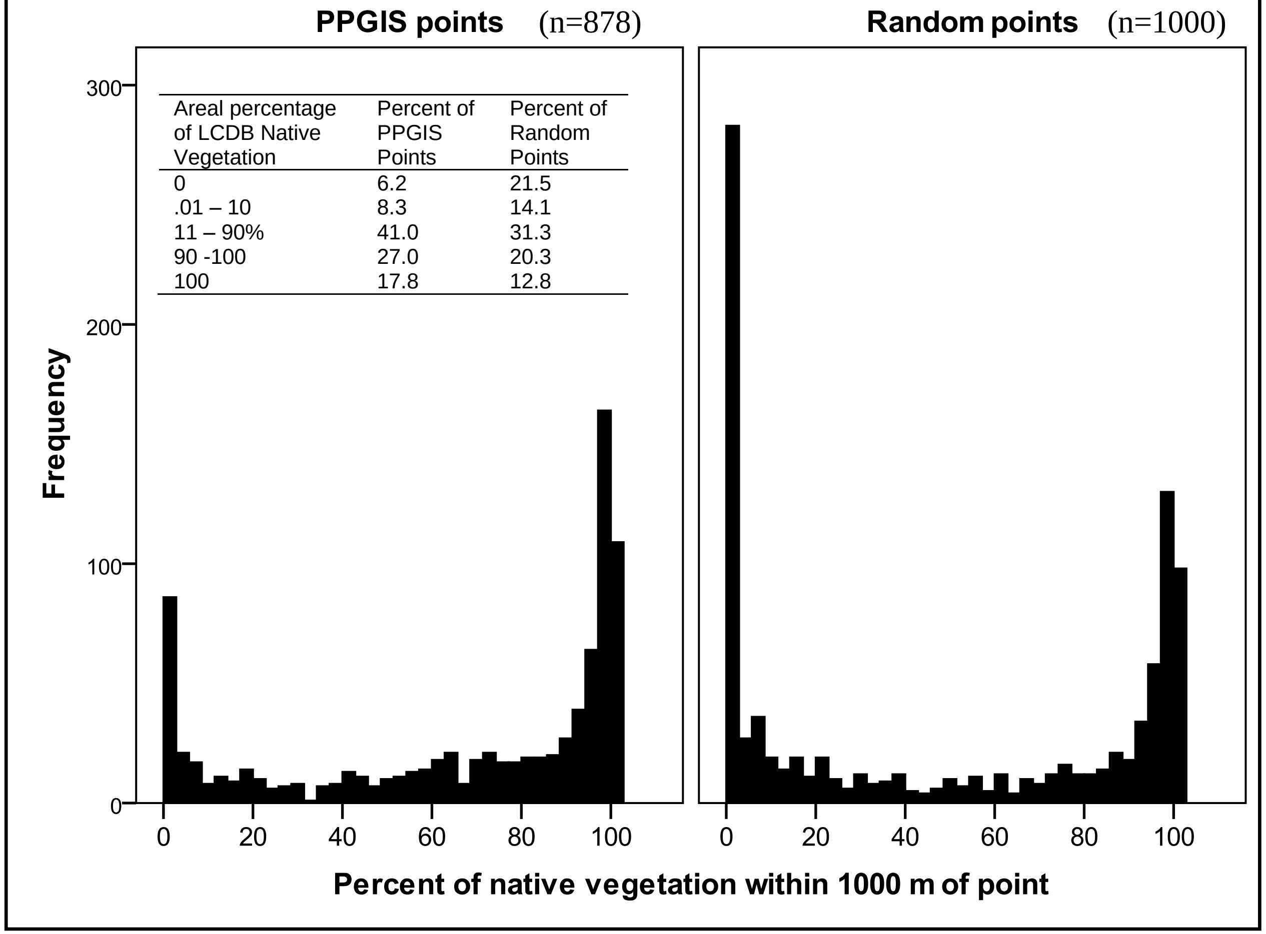
**Figure 1**

**Figure 1.** Histograms showing the areal percentage of native vegetation found within 1000 m of PPGIS points and 1000 random points in the Southland and Otago regions of New Zealand.




| Areal percentage of LCDB Native Vegetation | Percent of PPGIS Points | Percent of Random Points |
|---|---|---|
| 0 | 6.2 | 21.5 |
| .01 – 10 | 8.3 | 14.1 |
| 11 – 90% | 41.0 | 31.3 |
| 90 -100 | 27.0 | 20.3 |
| 100 | 17.8 | 12.8 |

Figure 2

**Figure 2.** PPGIS mapped locations of native vegetation in the Otago and Southland regions of southern New Zealand showing the percentage of native vegetation found within 1000 m radius of the points. The green areas are native vegetation from the New Zealand LCDB database that were classified based on satellite imagery in 1996/1997 and 2001/2002.

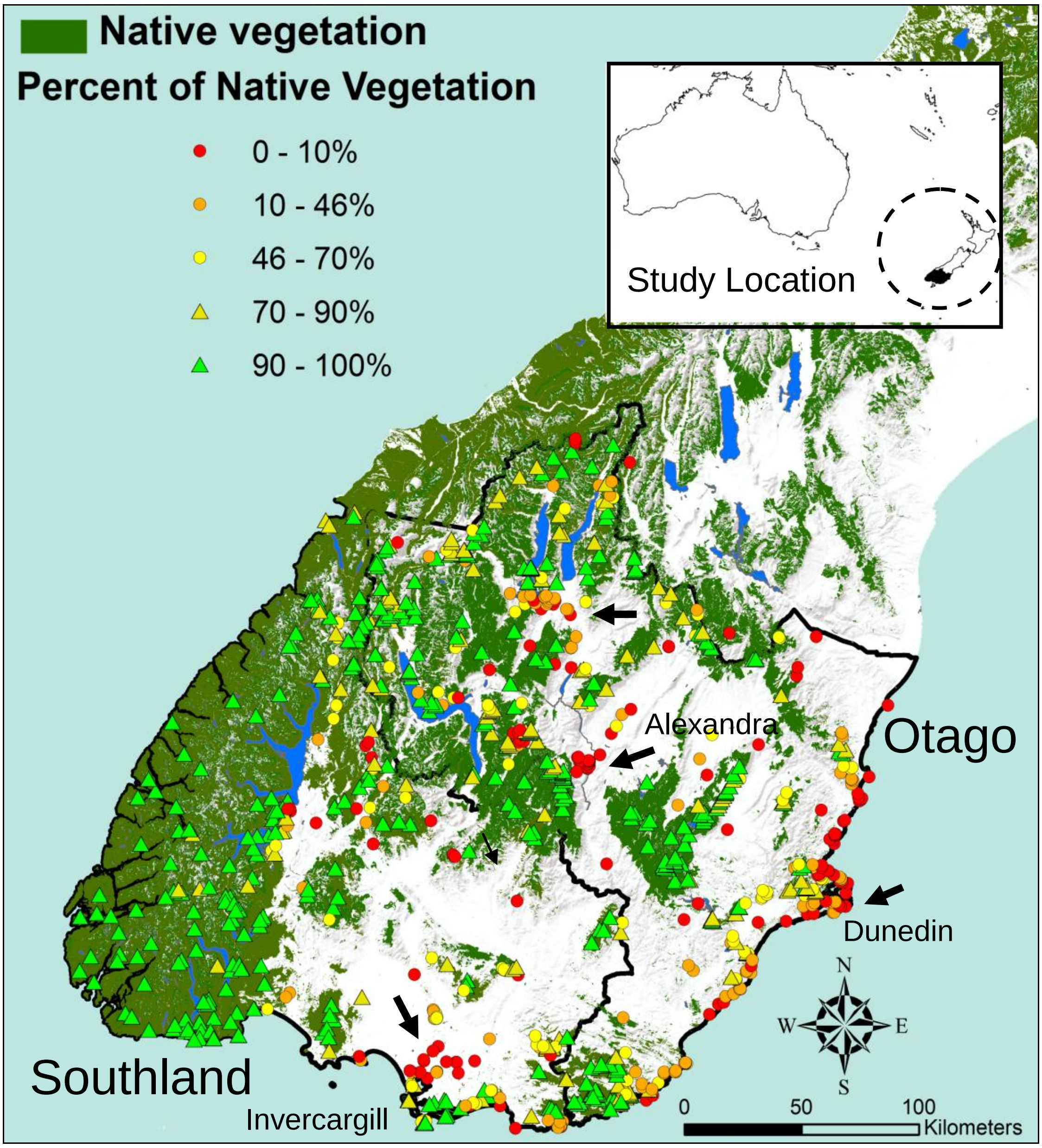


**Table 1**

**Table 1.** Analysis of native vegetation identification error by socio-demographics and PPGIS mapping interface variables.

| Variable | Variable categories | Error rate | Statistical results | Conclusion |
|---|---|---|---|---|
| Self-identified knowledge of places in region | 1=poor, below average, average<br>2=good/excellent | 11.5%<br>5.1% | $\chi^2$ =6.10, p ≤ 0.05 | Individuals with greater familiarity (self-identified) mapped fewer errors |
| Self-reported number of visits to conservation areas | 1=1 to 2 times<br>2=3 or more times | 3.2%<br>4.1% | $\chi^2$ =.053, p ≥ 0.05 | No relationship |
| Gender | 1=Male<br>2=Female | 3.5%<br>9.3% | $\chi^2$ =8.07, p ≤ 0.05 | Males mapped fewer errors than females |
| Formal Education | 1=Secondary/high school<br>2=University degree or higher | 3.3%<br>8.3% | $\chi^2$ =4.82, p ≤ 0.05 | Lower levels of formally educated individuals mapped fewer errors |
| Sampling group | 1=Random household<br>2=Conservation area visitors<br>3=Volunteer public | 14.5%<br>7.4%<br>5.9% | $\chi^2$ =8.54, p ≤ 0.05 | Random household sample respondents mapped more errors than visitors or volunteer public |
| Map scale at time of marker placement | 1=Default map zoom level<br>2=Greater zoom level | 6.9%<br>6.7% | $\chi^2$ =.02, p ≥ 0.05 | No relationship between map scale and mapped errors |
| Base map type at time of marker placement | 1=Terrain view (default)<br>2=Satellite view | 6.7%<br>12.8% | $\chi^2$ =.14, p ≥ 0.05 | No relationship between type of base map and mapped errors |