Title: Demand and supply of cultural ecosystem services: use of geotagged photos to map the aesthetic value of landscapes in Hokkaido

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Abstract

We proposed a mapping method for landscape aesthetic demand and potential supply area based on viewsheds, which is a direct method that provides robust results. Moreover, we mapped the aesthetic value of Hokkaido as a case study in Asia.

The Aichi Biodiversity Target refers to the importance of ecosystem service (ES) mapping methodologies. However, ES mapping in policy and practice has rarely been reported. Robust, reliable indicators are required. Recently, studies estimating aesthetic value have used geotagged photos on social networking services instead of survey results of user preferences. The methods used in these studies were cost effective and provided spatially explicit results. However, these methods used the photography positions. Using the photographed sites is a more direct method to estimate the aesthetic demand.

Therefore, we used geotagged photos on Flickr and viewsheds from each photography position to identify the photographed sites. The demand area was estimated using the viewshed. The potential supply area was estimated using MaxEnt. The demand and potential supply areas were concentrated in natural parks. Comparing the demand and potential supply areas indicates areas with potential supply despite their low demand in forest, farmland, and natural parks. This method will contribute to CES research and decision-making.

Keywords

Cultural ecosystem service, Aesthetics, Flickr, MaxEnt, GIS, Social networking service

## 1. Introduction

Various scales of decision-making require the measurement and visualization of the value of ecosystem services (ES), which is not included in the market price (MEA, 2005; TEEB, 2010; WBCSD, 2010). The value of cultural ecosystem services (CES) is particularly difficult to measure, both physically and monetarily, because such values are intangible and subjective (MEA, 2005). However, researchers and practitioners know that some CESs contribute to human well-being (Milcu et al., 2013). CES also motivates environmental action compared with other ESs (Hirons et al., 2016). Many CES studies have been conducted in Europe and North and Central America. In Asia, many CES studies have been carried out in China but not in Japan (Hernández-Morcillo et al., 2013; Wolff et al., 2015a). There are many CES studies on recreation, ecotourism, and the aesthetic value of landscapes because of their strong economic relevance and relative ease of estimation (Hernández-Morcillo et al., 2013; Milcu et al., 2013).

Travel and tourism accounted for 9.8% (US$7.2 trillion) of global GDP in 2015, and this contribution is expected to increase to 10.8% (US$11 trillion) by 2026 (WTTC, 2016). Growth will mostly come from nature-based tourism (Balmford et al., 2009); thus, the potential economic value is high. The aesthetic value of landscapes is the pleasure derived from natural beauty (TEEB, 2010). Aesthetic value is an especially important factor in recreation (Daniel et al., 2012), and is strongly related to market price. For example, residential price is affected by the amount of ocean or lake views (Benson et al., 1998; Crossman et al., 2013a). Mapping CES values provides important points of view for the development of conservation plans and for land-use management. The economic evaluation framework in the TEEB (2008) interim report states that quantification and mapping of ES values are necessary. However, only 18% of mapping studies have mapped CESs, far fewer than those that map regulating services (46%) and provisioning services (30%) (Crossman et al., 2013b). The Aichi Biodiversity Target refers to the importance of ES mapping methodologies (CBD Secretariat, 2011). Much CES mapping has reflected people's preferences and has used methods including an empirical method, a participatory approach, and a monetary valuation (Wolff et al., 2015b). The empirical method evaluates CES based on questionnaire surveys or interviews that reflect people's preferences or the value of sites (Casado-Arzuaga et al., 2013; de Vries et al., 2007; Sherrouse et al., 2011; van Zanten et al., 2016b). The participatory approach, which is based on expert knowledge or preferences of specific users (Kenter, 2016; Palomo et al., 2013; Scolozzi et al., 2014), is spatially explicit and has high estimation accuracy in site-specific studies (Wolff et al., 2015b). Therefore, the empirical method is more appropriate than the participatory approach for evaluating CES over a large area (Wolff et al., 2015b). Monetary valuation estimates the monetary value of CES using concepts such as willingness to pay (Häyhä et al., 2015; Kenter, 2016; Nahuelhual et al., 2014). These methods have been used frequently in combination in many studies (Kenter, 2016).

Mapping the aesthetic value of landscapes reflects people's preferences in the same way as the other CESs. It has been mainly based on the results of questionnaire surveys (Casado-Arzuaga et al., 2013; Peña et al., 2015) or interviews on preferences (van Zanten et al., 2016b) gained by empirical methods, and by participatory approaches combined with environmental factors that represent attractiveness such as naturalness (Crossman et al., 2013a; de Vries et al., 2007). However, such surveys are often costly and time-consuming. One study used an Internet survey to improve the survey efficiency (Peña et al., 2015), but the preparation of the questionnaire itself remains a time-consuming process.

In recent years, the widespread use of mobile devices has led to the development of social networking services (SNS), through which text messages and photos of food, landscapes, portraits, and so on are shared on the Internet. Geotagged photos are also increasingly shared, and many of these can be collected from wide areas. SNS data uploaded by users provides user preferences and experiences, and thereby contributes to improving the empirical method. In studies related to the aesthetic value, Casalegno et al. (2013) showed the effectiveness of geotagged photos in estimating the aesthetic value on a regional scale and van Zanten et al. (2016a) demonstrated it at a continental scale. Richards and Friess (2015) demonstrated the rapidness and cost effectiveness of using geotagged photos. Martínez Pastur et al. (2016) showed that classified tags of geotagged photos and their positions can be used to map some CES values such as aesthetic and recreation values. However, many studies have also highlighted the shortcomings of SNS data. The bias of the user group was one of the big concerns (Guerrero et al., 2016; Tenerelli et al., 2016). Therefore, the points of usage of SNS data have been reported (Crampton et al., 2013), and demographic studies have also been conducted to clarify the bias of SNS data (Garcia-Palomares et al., 2015; Wood et al., 2013).

The use of ES mapping applications in policy and practice have rarely been reported. Robust, reliable indicators and shared understanding of ES values are needed (Wolff et al., 2015b). The methods of estimating aesthetic value with geotagged photos have used the photography positions not the photographed sites. Therefore, they have usually used density of users who uploaded photos in a grid and models, such as the general linear model, to estimate the aesthetic value. However, using photographed sites is a more method direct than using photography positions and should provide robust results.

We improved the empirical method that uses geotagged photos to estimate the aesthetic value for use in policy and in practice. Mapping both the demand and supply potential of ESs also helps to understand the current state of ES. First, we developed a method to estimate aesthetic demand and potential supply area based on viewsheds and MaxEnt, which provided robust results. Second, we applied the method to Hokkaido, the northernmost island of Japan, to assess the current aesthetic value of the landscapes as a case study in Asia.

## 2. Materials and Methods

### 2.1. Study area

Our study area, which was used to develop a method for mapping aesthetic value, was Hokkaido, Japan (43° 31′ N, 142° 40′ E) (Fig. S1). The area is about 7.8 million ha, and its population in 2010 was 5.5 million (Statistics Bureau Ministry of Internal Affairs and Communications, 2016). The annual average temperature was about 9.8 °C in 2010 (Statistics Bureau Ministry of Internal Affairs and Communications, 2016). The area includes rich natural resources and 23 natural parks. Many tourists utilize the resort areas in Hokkaido to enjoy natural features such as wetlands, lakes, and snow. Moreover, Hokkaido is also a famous agricultural area in Japan and has rice paddies, corn fields, wheat fields, and dairy farms. The number of tourists in 2014 was 7.2 million, comprising 21.3% from overseas and 78.7% from domestic areas (Hokkaido Bereau of Tourism, Depart of Economic Affairs, 2015).

### 2.2. Mapping method

We developed a method for mapping the aesthetic value of landscapes in terms of demand and potential supply, by using geotagged photos on Flickr as preference data for aesthetics. Flickr was launched in 2004 and has been operated by Yahoo, Inc. since 2005. As of August 2011, Flickr hosted approximately 6 billion uploaded photos (Flickr, 2011). Wood et al. (2013) reported that the number of Flickr users uploading photos has a positive correlation with the annual number of tourists, and thus this number can be used as a proxy for visitation. To confirm Flickr data characteristics in the studied area, we compared the number of tourists to each municipality between 2010 and 2014 (Hokkaido Bureau of Tourism, Depart of Economic Affairs, 2015) with the number of Flickr users who uploaded photos in the same municipality for the same period. This comparison revealed a positive correlation on a log–log scale ($R^2 = 0.61$, $p < 0.001$).

**2.3. Developing photo datasets**

Flickr provides an Application Programming Interface (API) (Flickr, 2016) that allows photos to be searched based on metadata such as photo ID, user ID, Where On Earth IDentifier (WOEID) that identifies the location, coordinates, title, tags, date, and positional accuracy. We created three datasets using this API (Table S1). Recently, photos taken with mobile phones are being increasingly uploaded to the Flickr database (Flickr, 2015). The accuracy of GPS in mobile phones is almost within 10 m (Zandbergen and Barbeau, 2011), and mobile phones use has increased since around 2010. We were able to download statistics of visitors to the study area up to 2014. We collected metadata from geotagged photos taken from 2010 to 2014 to confirm the relation between the number of Flickr photos and visitors. We created a first dataset (the Filter 1 dataset) containing geotagged photos uploaded during this time with street-level positional accuracy (provided positional accuracy level by Flickr ≥ 12 (Flickr, 2016)) and taken within 500 m of the coastline in the study area (WOEID = 7153351). This dataset has 136,023 geotagged photos including coastal area photos taken from boats. Filter 1 dataset photos included landscape photos and all other types of photos such as portraits with food and monuments. Therefore, we extracted only landscape photos using the “landscape” keyword. A sample of extracted photos is shown in Fig. S2. By this filter, portraits containing landscapes were removed.

There were 13,202 photos in the Filter 2 dataset, which included many photos taken by heavy users who had uploaded dozens of photos of a certain area or continuous-shot photos. To avoid bias, we sampled photos at random to limit the number of photos per user in each municipality to one (Filter 3). There were 2982 photos in the Filter 3 dataset, and we used this dataset to map the demand for aesthetic value of landscapes.

### 2.4. Mapping demand

We considered landscape sites where photos were likely to have been taken by Flickr users as sites with high landscape demand. The latitude and longitude of photography positions are stored on Flickr, but not those of the photographed sites. Since photographic orientation is rarely recorded (Shirai et al., 2013), it is hard to identify target sites. Thus, we developed an index of target probability using viewsheds calculated from photographing positions. A viewshed is a visible area from each photographing position and therefore should include the photographed target site. We assumed that the more viewsheds overlap, the higher the probability the overlapping area was a target site. However, more photos including landscape photos were likely to have been taken at crowded sites, such as popular destinations, potentially leading to the overestimation of the value of sites with high popularity and good accessibility. To adjust for this bias, we determined a viewshed score, which is the ratio of the number of landscape photos to the total number of photos taken around each photography position. We then summed scores for overlapping areas to map aesthetic demand (Fig. 1). The ratio was calculated in a 3 km radius from the photographing position considering the distribution density of Flickr photo points.

We defined and calculated each viewshed using a 50-m digital elevation model from a height of 170 cm and within a maximum radius of 10 km. Because there was no reference to the distance from the photographing position to the target site of Flickr photos, the maximum view range was set in reference to previous studies of the visible distance of wind farms (Bishop and Miller, 2007; Sullivan et al., 2013, 2012). The spatial resolution of demand mapping was 50 × 50 m, and the result was normalized as 0 to 1 and mapped with five ranks. The normalizing method was a Fuzzy MS Large function (ArcGIS10.3.1, ESRI Inc.). In this method, large input values were more likely to be 1. Transformation of 0 to 1 was based on mean and standard deviation (ESRI Inc., 2014).

### 2.5. Mapping potential supply

We can map potential supply by analyzing the relation between demand area and its environmental factors because the demand map represents the aesthetic preferences of visitors (Fig. S3). Openness, variety, and the presence of water are reported as preference factors for aesthetic value of landscapes (Uuemaa et al., 2013). In a study of Japanese preferences, Kojima et al. (1994) also reported naturalness, uniformity or variety, openness, and the presence of water as preference factors.

We collected geospatial data as environmental factors to map the potential supply according to three categories based on the above studies: naturalness, water influence, and topography (Table S2). These data were published by the Japanese government and can be downloaded for free (Biodiversity Center of Japan, 1998; Japanese Ministry of Land Infrastructure Transport and Tourism, 2016). We also referred to previous studies of mapping CES values such as aesthetic value (Casado-Arzuaga et al., 2013; de Vries et al., 2007; Howley, 2011; Peña et al., 2015). Naturalness was based on vegetation type, and it was classified into 10 ranks according to human impact. Distances from rivers, lakes, or coastline were used as factors for the influence of water. Moreover, specific riverine landscapes, such as snaking streams, were used as geological interest for rivers. Topographic factors included 10 classes of topography, including ridges, valleys and flat plains, variety of topography, and distance from volcanic and non-volcanic topography, such as terrain caldera and cirque, as geologically interesting. Shannon's diversity index was used to calculate the variety of topography (Frank et al., 2013). None of these variables had a significant correlation with each other (all $r < 0.4$). The spatial resolution of the potential supply mapping was $50 \times 50$ m.

We used maximum entropy modeling software, MaxEnt version 3.3 (http://www.cs.princeton.edu/~schapire/maxent/) to estimate and map potential supply (Phillips et al., 2006, 2004). The software uses machine-learning to estimate a probability distribution by finding the probability distribution of the maximum entropy of given observed points such as species, plant, and environmental factors. The observed points are called presence data. An advantage of MaxEnt is that absence data is not required (only presence data is required). Therefore, MaxEnt is widely used to estimate species distribution (Elith et al., 2011), and it can also be used to map the social value of nature (Richards and Friess, 2015; Sherrouse et al., 2014, 2011). Flickr data is presence data, because the places where Flickr users did not upload their photos were not always the places where other social media users or people who do not use SNS did not take photos. Therefore, MaxEnt was also suitable for analyzing Flickr data.

Our demand map was the probability of distribution of demand, which was based on presence data. It had five ranks, but rank data was not used as presence data in MaxEnt. We then created new 1000 random points as presence data from the entire demand area (rank 1 to 5). The density was about one point per 1100 ha. The Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) plot is used to assess the MaxEnt model. ROC is the relation between sensitivity and 1-specificity. Sensitivity is the true positive rate (predicted value is true and actual value is also true) in a contingency table. 1-Specificity is the false positive rate (predicted value is true and actual value is false). Sensitivity and 1-specificity are calculated using thresholds that represent the probability of occurrence in MaxEnt. ROC can measure the efficiency of a binary classifier, such as the MaxEnt model, and AUC represents the probability of sensitivity. An AUC value of 0.5 indicates a random model, and a value of 1 indicates a model that perfectly classifies given presence data. An AUC value of 0.50 to 0.70 suggests a somewhat accurate model, a value of 0.70–0.90 suggests an accurate model, and a value exceeding 0.90 indicates a highly accurate model (Swets, 1988). In the preliminary analysis, the AUC value of a 10 km radius as maximum viewshed distance was higher than that of the 20 km radius maximum; thus, we decided the maximum radius as 10 km. We made a model of potential supply using 80% of the above presence data and validated using the others. This process was repeated 10 times for cross-validation and sensitivity and AUC was averaged as a final model.

We identified the potential supply area with similar environmental conditions to the demand area with two cutoff points. One was called the 10th percentile training presence, which is a cutoff point that includes 90% of presence data (10% threshold). Another was called equal training sensitivity and specificity, which is a cutoff point with a minimum distance between ROC and the upper left corner of the ROC plot whose sensitivity was 1. The latter is a stricter criterion than the former.

## 3. Results

### 3.1. Demand map

Figure 2 shows a demand map based on the Filter 3 dataset. This map provides an overview and detailed distribution of the aesthetic demand. For example, when enlarging high-demand areas located at the center of this study area (Fig. 3), we found that high-demand areas were located on the west side of the Tokachidake Mountain Range, and the Daisetsu Mountain Range and in the farmland at its foot. The urban area near the high-demand area also had a high demand. Comparing the photography positions and topography, we found that demand areas depended on viewshed.

Overall, the total demand area was about 1,092,266 ha, 13.7% of the study area. Areas of high demand, especially those with ranks 4 and 5 were located in forest, farmland, river-lake, and wetland-bareland (Fig. 4). The ratio of demand area in each land use type was in the order river-lake > urban areas > sea > grassland-golf courses. The demand area corresponded well to places with tourism resources. Table 1 shows the area of demand for each natural park. Natural parks contained 24.4% of the demand area. Focusing on rank 4 and 5 areas, 40.8% of these areas were located in natural parks. The area of natural parks corresponds to 10.9% of the total study area. Therefore, rank 4 and 5 and total demand area were significantly biased toward natural parks ($\chi^2$ = 190375.4, 160381.2, both d.f. = 1, $p < 0.001$).

Areas of demand, especially those with rank 4 and 5, were located in national parks rather than in quasi-national or prefectural natural parks. However, focusing on the ratio of demanded areas in each national park, a large non-demanded area was located in the Daisetsuzan National Park; its percentile of demanded area was low, despite having the largest total area. A non-demanded area was also found in every national park, although ratios differed from park to park.

**3.2. Supply map**

Figure 5 shows a potential supply map and Table 2 shows the contribution of environmental factors. Environmental factors that contributed highly to the model were, in order, distance from volcanic topography (23.2%), type of topography (23.2%), variety of topography (19.6%), naturalness (13.3%), and distance from lakes (8.0%). Distance from specific riverine landscapes did not contribute to the model greatly (0.8%). In terms of the response to demand for types of topography, plains, u-shape valleys, and mountain tops-high ridges were the major contributors to the model, and low (0.0) and high (1.7) topographic variety contributed more than medium topographic variety (1.3) (Fig. S4). In the category of naturalness, 1 (urban areas), 2 (farmland, urban and residential districts with many trees), 4 (secondary short grassland), 8 (natural broad-leaved forest), and 10 (alpine heathland and wind-exposed grassland) contributed to the model. Bodies of water also contributed. Volcanic topography (23.2%) contributed more than non-volcanic topography (6.2%). Areas near and far from volcanic topography strongly contributed for volcanic topography. The AUC value of the model was 0.802.

Overall, the total potential supply area was estimated as 1,723,345 ha (equal threshold) to 2,985,729 ha (10% threshold). The area corresponded to 21.6 to 37.4% of the study area, which was wider than the demand area (13.7%). We compared the demand area of each land use type with the potential supply area (10% threshold) of that (Fig. 6). The trend of the potential supply area between land use types was similar to that of the demand area. However, the area of potential supply in each of the land use types was wider than that of demand. Many areas that had potential supply without demand (supply gap area) were located in forest and farmland. Focusing on the natural parks, few supply gap areas were located in wetland-bareland and river-lake, but there were larger supply gap areas in forest. Outside of natural parks, the large supply gap areas were located in forest and farmland. 16.6–19.0% (496,320–326,696 ha) of potential supply area were located in natural parks, and it was significantly biased to natural parks ($\chi^2$ = 10% threshold: 49620.5, equal threshold: 63482.6, both d.f. = 1, $p < 0.001$).

We compared the potential supply with demand in areas of each natural park (Table 1). In natural parks, areas of potential supply exceeded the demand area at both the 10% threshold and equal threshold. More areas of potential supply were located in national parks than in quasi-national or prefectural natural parks. At the 10% threshold, the area of potential supply exceeded the area of demand in the Daisetsuzan National Park and Shikotsu Toya National Park, which had low ratios of demand areas. However, areas of demand were almost same as that of potential supply in the Kushiro Shitsugen National Park.

Figure 7 shows the distribution of demand and potential supply area in forest and farmland according to the 10% threshold. Of forest areas, 70.6% did not show aesthetic value. The place that had potential supply with demand (balanced area) was 86,615.3 ha, 6.2% of total forest area. The supply gap area was 287,205.8 ha (20.6%). Many supply gap areas were located around national parks such as Daisetsuzan National Park and Shikotsu Toya National Park. Of farmland areas, 34.5% did not show aesthetic value. The balanced area was 66,321 ha, 19.1% of the total farmland area. The supply gap area was 153,257 ha (44.2%). The supply gap area was the largest in farmland. Focusing on the main agricultural areas in Hokkaido, many balanced areas were located in the Kamikawa, Sorachi, and Tokachi regions, but not many were located in the Abashiri, Nemuro, and Kushiro regions.

## 4. Discussion

We proposed a viewshed-based method for measuring aesthetic demand and potential supply of landscape value using Flickr photos as a preference index. Because the method for estimating the area of aesthetic demand did not use questionnaire surveys or models, such as general linear models, it was considered to be rather direct and provided robust results. MaxEnt, which is frequently used to estimate the distribution of species, was used to estimate potential supply areas. MaxEnt also provides robust results even in the spatial problem of human dimensions (Sherrouse et al., 2014). Because the photography positions of Flickr photos were presence data, the area of demand based on Flickr data also had the same characteristics. Therefore, MaxEnt was considered appropriate for estimating the potential supply area from the demand area. In contrast, because there were many copies that were shared by users or many photos posted by one user, the sample size from SNS data sometimes becomes small after filtering (Crampton et al., 2013). However, MaxEnt retains its prediction accuracy even with small sample sizes (Wisz et al., 2008). Therefore, MaxEnt is useful for CES mapping with SNS data.

Natural areas, such as forest, river-lake, and wetland-bareland, as well as farmland and urban areas, had many high-demand areas in Hokkaido. In particular, the percentage of demand area and highest demand area (rank 5) were very high for river-lake. These results are consistent with other studies that mentioned that natural areas, such as forest, lakes, and wetland, were also preferred (de Vries et al., 2007; Howley, 2011; Peña et al., 2015). Farmland was not preferred as a factor of aesthetic value (Lindemann-Matthies et al., 2010; Van Berkel and Verburg, 2014; van Zanten et al., 2016c), although some studies have reported that it was preferred (Casado-Arzuaga et al., 2013; Peña et al., 2015). Japanese people tended to prefer a single species or nature influenced by people (Kellert, 1991), and uniformness as aesthetic factors (Kojima et al., 1994). Because 70% of visitors were domestic, the fact that farmland was preferred in this study was likely to be affected by Japanese preferences for nature. The urban area had high demand based on the photos taken at viewpoints where people can enjoy city views or the photos taken near urban parks (Guerrero et al., 2016).

Demand and potential supply areas were predominantly in natural parks but were concentrated around restricted areas in many national parks. Japanese national parks are intended to protect scenery and biodiversity and to promote recreation according to the Natural Parks Act (Japanese Ministry of the Environment, 2016, 2014). In the natural parks, many supply gap areas were located in the forest, but very few were in river-lake and wetland-bareland. There were the national parks whose supply gap area was large, such as Daisetsuzan National Park and Shikotsu Toya National Park, and those, such as Kushiro Shitsugen National park, whose supply gap area was very small. The parks with large supply gaps were considered to have poorly accessible areas in their forest, whereas Kushiro Shitsugen National Park is mainly marsh and it was visible from enough viewpoints. This information may help the park manager to understand the current conditions and manage the facility considering aesthetic aspects.

Outside the natural parks, much demand and potential supply area were located in forest and farmland (Fig. 7). Many supply gap areas in forest area were located around Daisetsuzan National Park and Shikotsu Toya National Park. Forest is expected to perform many ES, such as timber production, water purification, carbon stock, and maintaining biodiversity. Aichi Biodiversity Target 11 said that by 2020, at least 17% of terrestrial and inland water, and 10% of coastal and marine areas, especially areas of particular importance for biodiversity and ES, should be conserved having been integrated into the wider landscapes and seascapes (CBD Secretariat, 2011). Therefore, a study to prioritize conservation areas has been conducted (Kadoya et al., 2014). Although the public understanding of biodiversity is not high (CBD Secretariat, 2011), CES such as aesthetic value is well recognized and motivates public environmental awareness (Hirons et al., 2016). The total percentage contribution or importance of the variety of topography, naturalness, and distance from lakes, rivers, and coastline, which were used in this study as the environmental factors, was about 50% (Table 2). These environmental factors are related to the complexity and connectivity of landscapes that often has a strong positive relation to the biodiversity richness on various scales (Amici et al., 2015; Chisholm et al., 2011; Ishii et al., 2004; Loreau et al., 2003; Rösch et al., 2013; Takafumi and Hiura, 2009). Consequently, demand and potential supply area in this study was considered to be related to biodiversity richness. Therefore, overlaying the demand and potential supply area and prioritizing conservation areas can help to find places that are important for conservation and aesthetic enjoyment, improving the stakeholders' understanding of conservation. Farmland with potential supply has the potential for both CES and provisioning services. We found that these regions that had many supply gap areas despite having few balanced areas. These regions were considered to have good potential for developing tourism in agricultural areas. This information could help land managers or the tourist industry identify hidden tourism resources. In addition, the distribution or value of CES varied with the seasons (Tenerelli et al., 2016; Wolff et al., 2015a). Further study related to seasonal changes in the aesthetic value will be needed.

Finally, we discuss the limitations of our proposed method and SNS data in the CES mapping study. In our method, we must consider the estimation error for the target site of each photo; an estimated target site is likely to be wider than the actual site. In this study, we fixed the maximum viewshed range as 10 km, and thus did not consider the distribution of the distance to the target site in landscape photos. Moreover, we did not fix the direction to the target sites, which may improve target site identification. In particular, urban areas near high-demand farmland also had high demand, which was overestimated because the elevation data that was used to calculate the viewsheds did not include the height of buildings or houses.

The positional accuracy of geotagged photos should also be considered. We used viewsheds to estimate locations from Flickr photos, but estimated locations can be directly affected by the positional accuracy of geotagged photos. To reduce this limitation, we used accuracy parameters provided by Flickr and filtered to street-level accuracy. We furthermore considered the data collection period (from 2010, after the spread of mobile devices). Wang et al. (2013) showed that Flickr photos have positional errors from tens to hundreds of meters. We suggest that the positional accuracy of Flickr photos will improve with an increase in the number of photos taken using mobile devices. Positional error of data also depends on the collection period, for example, those taken before the spread of mobile devices.

As of 2012, 200 million geotagged photos had been uploaded to the Flickr database, 40% of which were taken in Europe, 39% in North America, and 13% in Asia; Japan is a region that has many geotagged photos on Flickr, similar to North America and Europe (Wood et al., 2013). However, the problem of sample representativeness remains. The number of Flickr users was positively related to the number of visitors (Wood et al., 2013). Although we found this relation in this study, not all visitors used SNS (Garcia-Palomares et al., 2015). The representativeness was affected by the rate of Internet use, cameras with GPS, and mobile phones in a region (Martínez Pastur et al., 2016). These depended on age, education, and ability or motivation to use SNS (Tenerelli et al., 2016). Moreover, SNS platforms that have different user groups also affected the representativeness (van Zanten et al., 2016a). However, methods based on questionnaire surveys or interviews also have the problem of representativeness (Tenerelli et al., 2016). Using SNS data for CES mapping is cost-effective despite having spatial coverage and spatial explicitness. Therefore, further demographic studies of SNS are needed.

## 5. Conclusion

We demonstrated the viewshed base method to map aesthetic demand and potential supply, which was a more direct method and provided robust results. Moreover, we also clarified the aesthetic value of Hokkaido, as a case study in Asia.

Mapping the aesthetic demand and potential supply can promote awareness of both land value and the importance of nature conservation. We hope that our results will contribute to CES research and decision-making in policy and in practice to maintain a balance between human use and nature conservation based on aesthetic demand and its potential supply.


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Fig. 1 Conceptual diagram of demand mapping

Viewshed score = number of landscape photos/total number of photos, where the number of landscape photos refers to the number of items in the Filter 2 dataset and the total number photos refers to the number of items in the Filter 1 dataset; these are counted within 3 km from every item in the Filter 3 dataset. See also Table S1.

Fig. 2 Demand map of aesthetic value of landscapes. The five ranks are based on 0–1 values normalized by a Fuzzy MS Large function (ArcGIS10.3.1, ESRI Inc.). The most highly demanded areas are ranked 5 (red), and the least demanded areas are ranked 1 (blue). Only tourism resources with at least a B grade as ranked by the Tourism Resources Evaluation Committee in Japan are shown. The grade has four ranks (Special A, A, B, C) mainly based on expert judgment. These grades are decided by the level of attractiveness. Grade Special A is the international level. Grade A is the national level. Grade B is the provincial level. Grade C is the prefectural level.

Fig. 3 Demand map around the Tokachi and Daisetsu Mountain Range (left), and the land-use map (right). Both maps show the same extent. The tourism resources with at least a B grade as ranked by the Tourism Resources Evaluation Committee in Japan are shown. The grade has four ranks (Special A, A, B, C) mainly based on expert judgment. These grades are decided by the level of attractiveness. Grade Special A is the international level. Grade A is the national level. Grade B is the provincial level. Grade C is the prefectural level.

Fig. 4 Areas of demand in each land use type. The stacked chart indicates areas of demand, which were classified by demand rank. The line charts indicate the percentage area of total demand or rank 5.

Fig. 5 Potential supply map. The potential supply area was classified by 10% threshold or equal threshold. The tourism resources with at least a B grade as ranked by the Tourism Resources Evaluation Committee in Japan are shown. The grade has four ranks

(Special A, A, B, C) mainly based on expert judgment. These grades are decided by the level of attractiveness. Grade Special A is the international level. Grade A is the national level. Grade B is the provincial level. Grade C is the prefectural level.

Fig. 6 Areas of demand and potential supply in each land use type. The stacked charts indicate areas of demand or supply potential, which are classified as inside or outside natural parks. The line charts indicate the percentage of demand or potential supply area, to the total area of each land use type.

Fig. 7 Distribution of demand and potential supply area in forest and farmland. The bar chart shows the area of gap area in farmland.

Fig. S1 Land use map study area.

Fig. S2 Sample geotagged photos extracted from Flickr database.

The left photo was taken by Kzaral. “Kushiro Marsh, Kushiro”, 2014, URL: https://www.flickr.com/photos/32811347@N08/14963096953, License: CC by 2.0., detail: https://creativecommons.org/licenses/by/2.0/.

The right photo was taken by Ryuichi Ikeda. “Biei no oka”, 2010, URL: https://www.flickr.com/photos/8205548@N08/5007769687, License: CC by 2.0., detail: https://creativecommons.org/licenses/by/2.0/.

Fig. S3 Process flow to map potential supply. MaxEnt generates potential supply based on the relation between the sampled presence data and environmental variables.

Fig. S4 Response curves of environmental variables. Red lines show mean values and blue ranges show standard deviations over 10 trials.

Fig. S5 ROC curve. The AUC value of the model was 0.802.

Table 1 Comparison of supply potential and demand in each natural park. Percentages are shown in parentheses.

| Type | Name | Area ($\times10^3$ ha) | Demand area ($\times10^3$ ha) | | | | Potential Supply area ($\times10^3$ ha) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Rank 4 and 5 | | All ranks | | Equal threshold | | 10% threshold | |
| National park | Akan | 94.1 | 28.3 | (30.1) | 50.0 | (53.1) | 45.6 | (48.4) | 70.5 | (74.9) |
| | Kushiro Shitsugen | 26.6 | 12.8 | (48.2) | 18.7 | (70.4) | 13.8 | (51.9) | 19.1 | (71.8) |
| | Rishiri Rebun Sarobetsu | 21.4 | 0.6 | (2.6) | 10.8 | (50.5) | 14.1 | (65.8) | 17.5 | (82.0) |
| | Shikotsu Toya | 99.7 | 20.9 | (20.9) | 43.4 | (43.5) | 68.4 | (68.7) | 90.4 | (90.7) |
| | Shiretoko | 38.6 | 4.4 | (11.3) | 10.6 | (27.4) | 8.3 | (21.6) | 19.4 | (50.2) |
| | Daisetsuzan | 227.5 | 17.2 | (7.6) | 62.8 | (27.6) | 102.3 | (44.9) | 161.5 | (71.0) |
| **Subtotal** | | **508** | **84.2** | **(16.6)** | **196.3** | **(38.6)** | **252.5** | **(49.7)** | **378.4** | **(74.5)** |
| Quasi-national park | Abashiri | 37 | 1.6 | (4.4) | 28.6 | (77.4) | 28.9 | (78.4) | 33.3 | (90.2) |
| | Hidaka Sanmyaku Erimo | 104 | 0.5 | (0.5) | 4.3 | (4.1) | 0.7 | (0.7) | 1.3 | (1.2) |
| | Niseko Syakotan Otaru kaigan | 19 | 1.9 | (9.6) | 7.5 | (39.1) | 11.8 | (61.7) | 15.9 | (82.7) |
| | Oonuma | 9 | 2.8 | (30.0) | 7.1 | (76.4) | 7.3 | (77.9) | 8.7 | (93.2) |
| | Shokanbetsu Teuri Yagishiri | 44 | 0.0 | (0.0) | 3.8 | (8.7) | 3.1 | (7.2) | 12.5 | (28.7) |
| **Subtotal** | | **213** | **6.8** | **(3.2)** | **51.2** | **(24.1)** | **51.9** | **(24.4)** | **71.6** | **(33.6)** |
| Prefectural natural park | Akkeshi | 23 | 0.0 | (0.0) | 7.4 | (32.0) | 1.8 | (7.8) | 3.2 | (13.8) |
| | Esan | 3 | 0.0 | (0.0) | 0.4 | (12.4) | 0.5 | (18.5) | 1.5 | (51.8) |
| | Furano Ashibetsu | 36 | 1.1 | (3.0) | 5.8 | (16.1) | 2.0 | (5.5) | 8.4 | (23.2) |
| | Hiyama | 17 | 0.0 | (0.0) | 1.2 | (6.7) | 0.9 | (5.2) | 1.8 | (10.4) |
| | Kariba Motta | 24 | 0.0 | (0.0) | 0.3 | (1.5) | 7.2 | (30.6) | 16.0 | (68.2) |
| | Matsumae yakoshi | 2 | 0.0 | (0.0) | 0.1 | (5.0) | 0.1 | (6.0) | 0.3 | (15.3) |
| | Nopporo Shinrin | 2 | 0.0 | (1.3) | 0.3 | (16.9) | 1.4 | (66.7) | 2.0 | (95.6) |
| | Notsukehuuren | 13 | 0.4 | (2.8) | 1.7 | (13.7) | 7.6 | (60.2) | 9.0 | (71.3) |
| | Kita Okhotsuku | 4 | 0.0 | (0.0) | 0.2 | (5.7) | 0.2 | (5.6) | 0.9 | (20.8) |
| | Syaridake | 3 | 0.0 | (0.0) | 0.3 | (8.9) | 0.5 | (16.6) | 1.7 | (58.5) |
| | Syumarinai | 14 | 0.0 | (0.0) | 1.6 | (11.3) | 0.0 | (0.0) | 0.8 | (6.0) |
| | Teshiodake | 9 | 0.0 | (0.0) | 0.0 | (0.0) | 0.0 | (0.2) | 0.7 | (7.2) |
| **Subtotal** | | **150** | **1.5** | **(1.0)** | **19.3** | **(12.9)** | **22.3** | **(14.9)** | **46.3** | **(30.9)** |
| **Total area of natural parks** | | **871** | **92.5** | **(10.6)** | **266.8** | **(30.6)** | **326.7** | **(37.5)** | **496.3** | **(57.0)** |
| **(% of Hokkaido)** | | **(10.9)** | **(40.8)** | **-** | **(24.4)** | **-** | **(19.0)** | **-** | **(16.6)** | **-** |
| **Total of Hokkaido** | | **7984** | **227** | **(2.8)** | **1092** | **(13.7)** | **1723** | **(21.6)** | **2986** | **(37.4)** |

Table 2 Importance of environmental variables

| Environmental variable | Contribution (%) | Importance (%) |
| --- | --- | --- |
| Distance from volcanic topography | 23.2 | 30.2 |
| Type of topography | 23.2 | 11.0 |
| Variety of topography | 19.6 | 12.3 |
| Naturalness | 13.3 | 7.0 |
| Distance from lakes | 8.0 | 9.7 |
| Distance from non-volcanic topography | 6.2 | 10.2 |
| Distance from rivers | 2.9 | 7.0 |
| Distance from coastline | 2.8 | 9.7 |
| Specific riverine landscape | 0.8 | 3.6 |

Table S1 Photo datasets constructed from the Flickr database

We used three filters to develop photo datasets. The Filter 2 dataset is derived from the Filter 1 dataset, and the Filter 3 dataset is derived from the Filter 2 dataset. Where On Earth Identifier (WOEID) 7153351 is assigned to the Hokkaido region in Japan.

| **Filter** | **Criteria** | **Number of photos** | **Number of total unique users** |
|---|---|---|---|
| 1 | Photos taken in Hokkaido<br>(WOEID = 7153351)<br>Positional accuracy level ≥ 12<br>Within 500 m of the study area coastline | 136,023 | 2620 |
| 2 | Filter 1 +<br>Photos have keyword or tag “landscape” | 13,202 | 1156 |
| 3 | Filter 2 +<br>One photo per user in each municipality | 2982 | 1156 |

Table S2 Database of environmental variables

| Indicator | Layer | Description | Source |
|---|---|---|---|
| **Naturalness** | Naturalness of vegetation | 10 classes of vegetation based on degree of human impact. Bodies of water are not ranked and assigned 0 (urban = 1, high mountain vegetation = 10, etc.) | Natural Environmental Information GIS (Biodiversity Center of Japan, 1998) |
| **Water body** | River | Distance from grade 1 or 2 rivers | National Land Numerical Information download service (Japanese Ministry of Land, Infrastructure, Transport and Tourism, 2016) |
| | Lake | Distance from lakes | |
| | Coastline | Distance from coastline | |
| Geological interest | Special landscape with river | Distance from specific riverine landscapes (snaking stream, waterfall, etc.) | |
| **Topography** | Type of topography | Ten-class Topography Position Index | Calculated by Topography tool (T.E. Dilts, 2015) and 50-m DEM |
| | Variety of topography | Shannon's Diversity Index within 1 km from each cell. | Calculated by Land Facet Corridor Designer (Jenness et al., 2013) and topography type |
| Geological interest | Volcanic topography | Distance from volcanic topography (volcano, caldera, etc.) | National Land Numerical Information download service (Japanese Ministry of Land, Infrastructure, Transport and Tourism, 2016) |
| | Non-volcanic topography | Distance from mountain range, cirque, moraine etc. | |

Fig.1

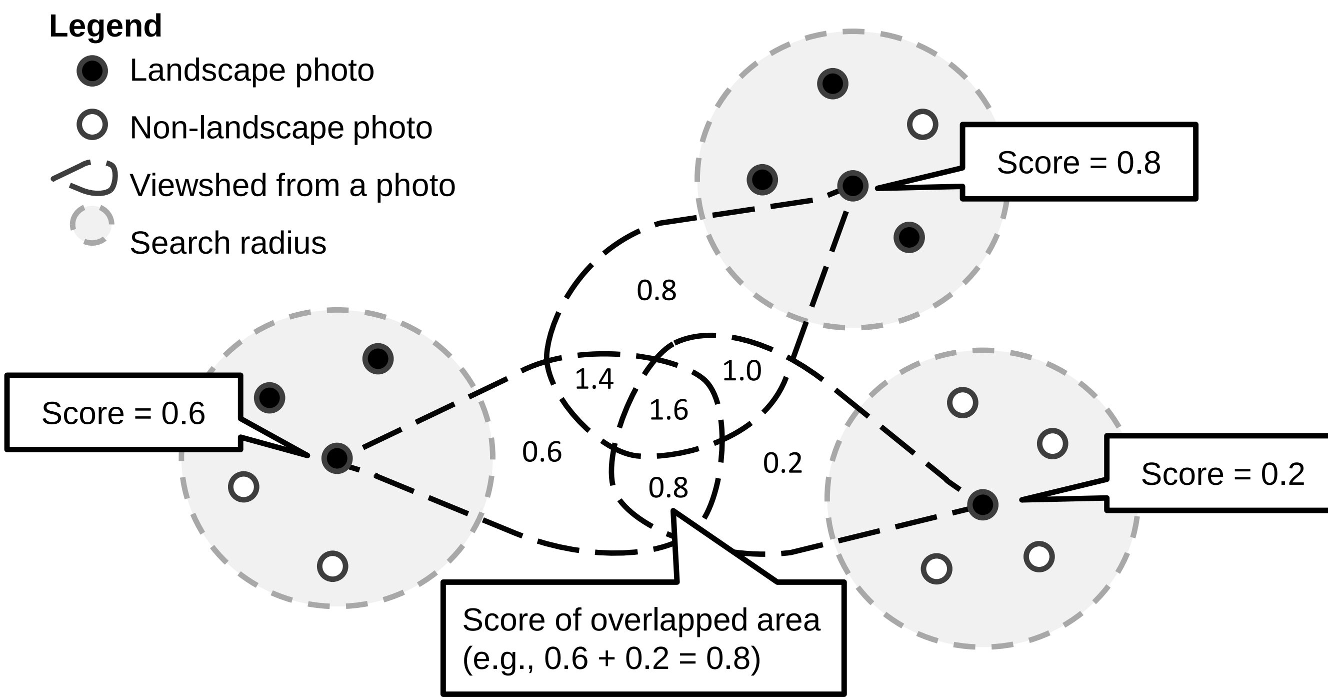
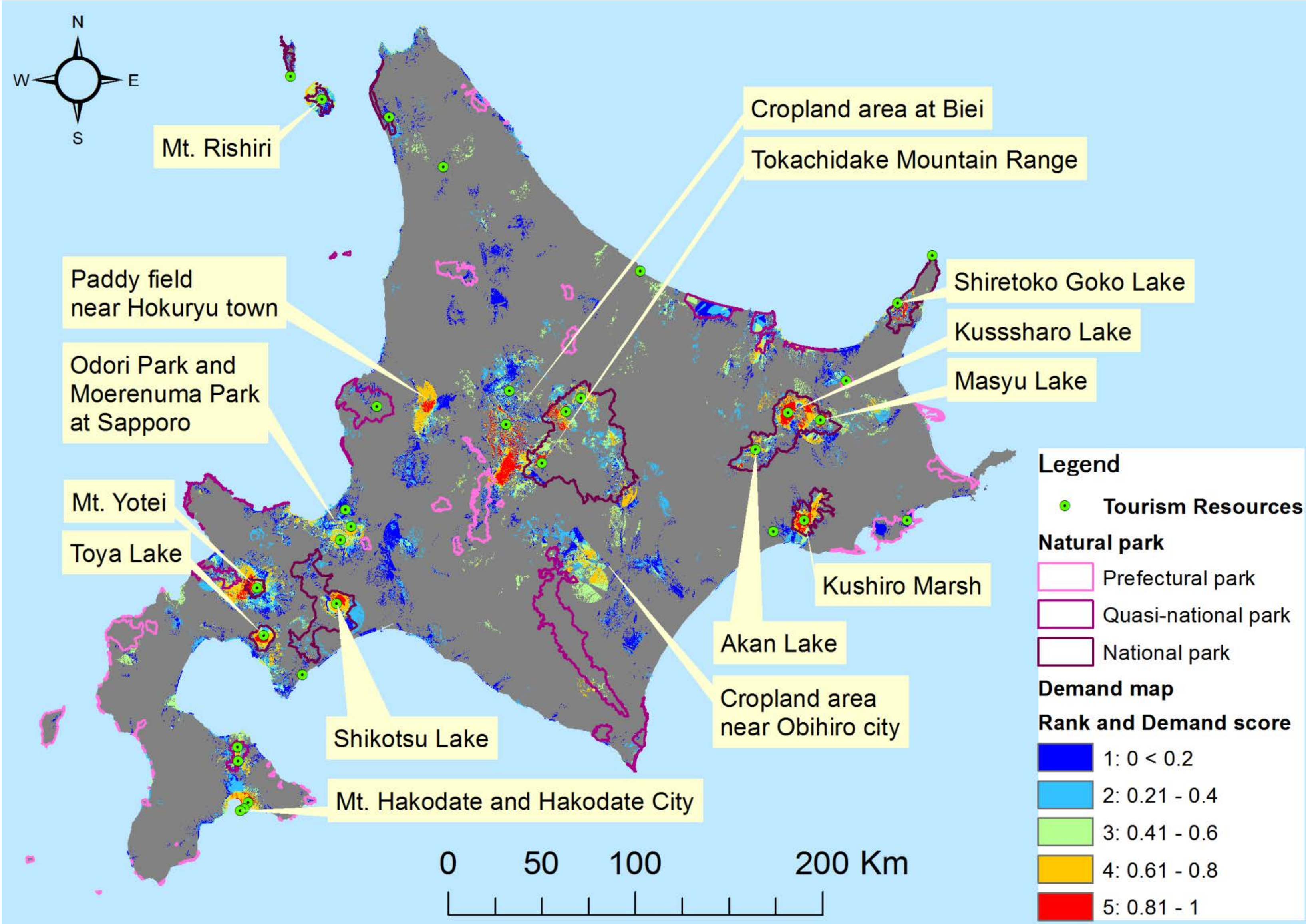
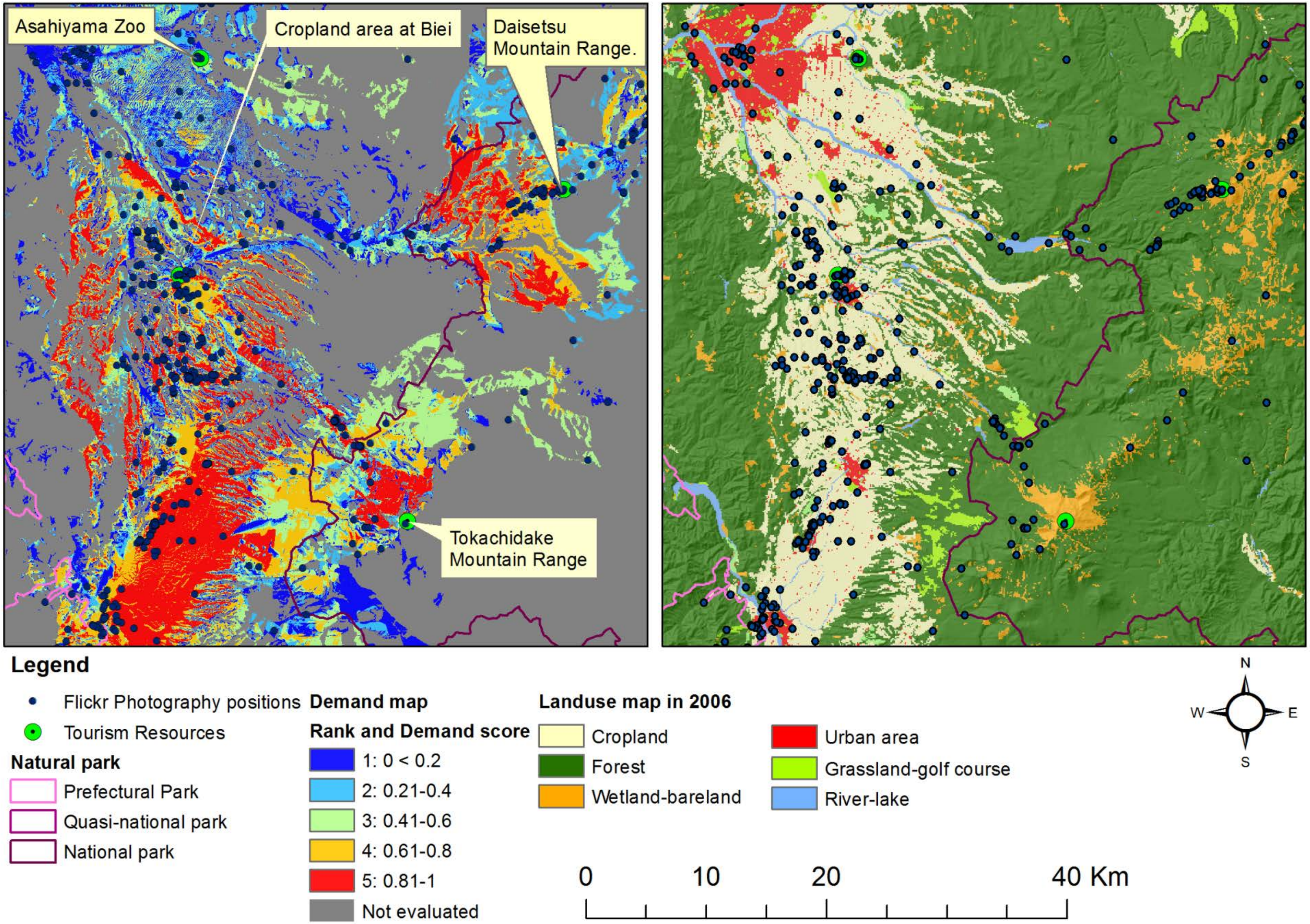

Legend
Landscape photo
Non-landscape photo
Viewshed from a photo
Search radius
Score = 0.8
Score = 0.6
Score = 0.2
0.8
1.4
1.0
1.6
0.6
0.2
0.8
Score of overlapped area
(e.g., 0.6 + 0.2 = 0.8)

Fig.2



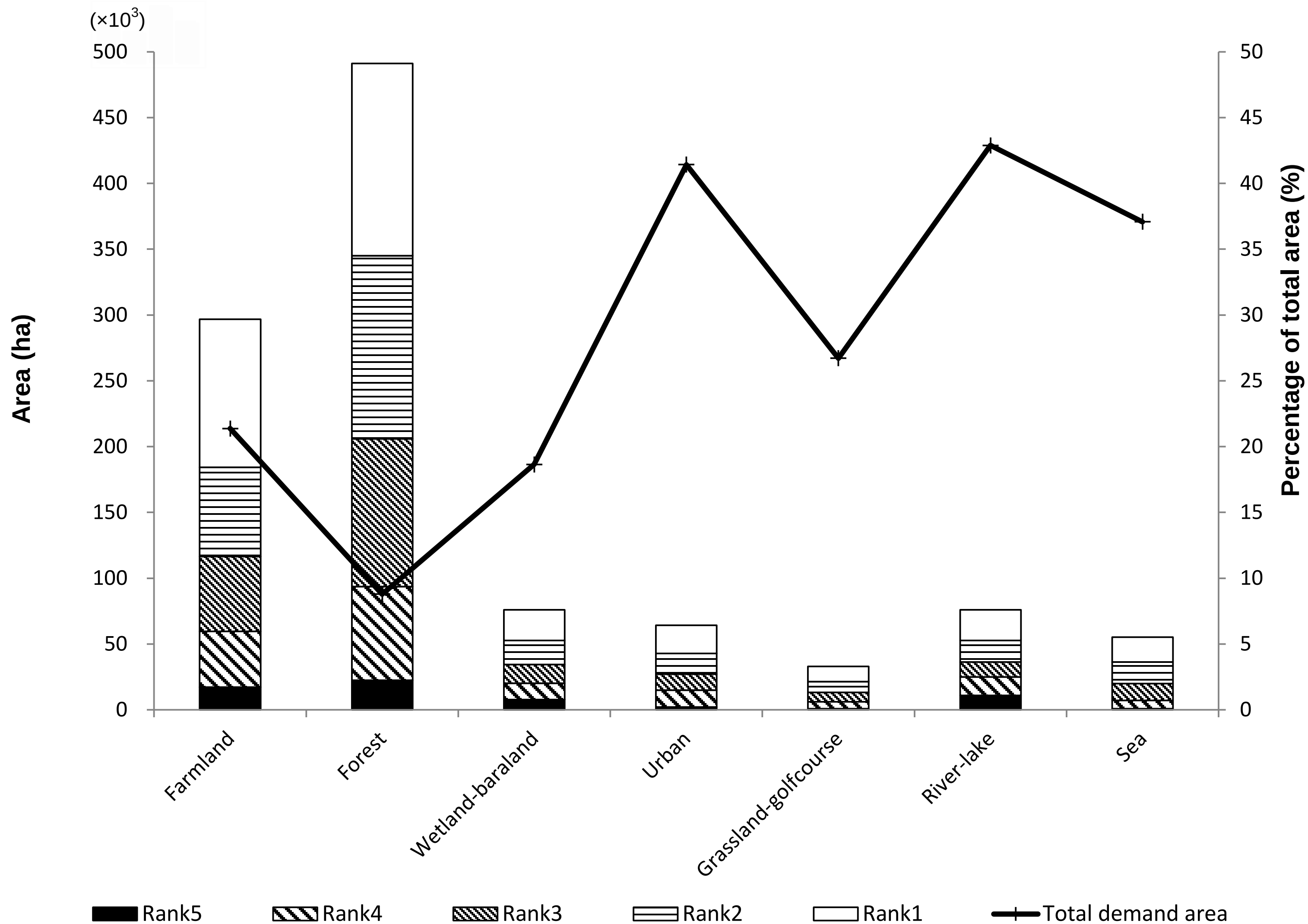
N
W
E
S
Mt. Rishiri
Cropland area at Biei
Tokachidake Mountain Range
Paddy field
near Hokuryu town
Odori Park and
Moerenuma Park
at Sapporo
Shiretoko Goko Lake
Kusssharo Lake
Masyu Lake
Mt. Yotei
Toya Lake
Kushiro Marsh
Akan Lake
Cropland area
near Obihiro city
Shikotsu Lake
Mt. Hakodate and Hakodate City
0 50 100 200 Km
Legend
Tourism Resources
Natural park
Prefectural park
Quasi-national park
National park
Demand map
Rank and Demand score
1: 0 < 0.2
2: 0.21 - 0.4
3: 0.41 - 0.6
4: 0.61 - 0.8
5: 0.81 - 1

Fig.3



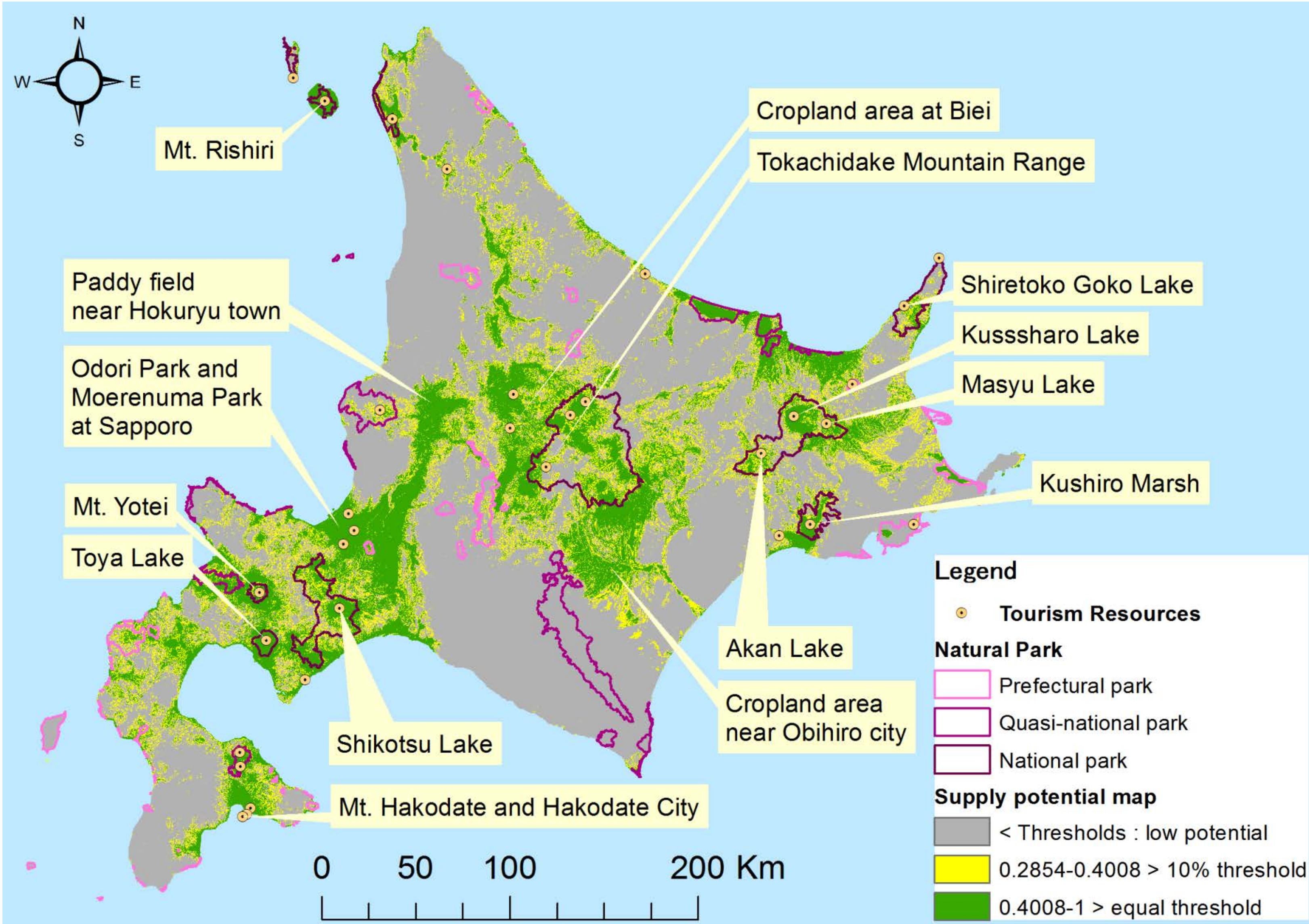
Asahiyama Zoo
Cropland area at Biei
Daisetsu Mountain Range.
Tokachidake Mountain Range
Legend
Flickr Photography positions
Tourism Resources
Natural park
Prefectural Park
Quasi-national park
National park
Demand map
Rank and Demand score
1: 0 < 0.2
2: 0.21-0.4
3: 0.41-0.6
4: 0.61-0.8
5: 0.81-1
Not evaluated
Landuse map in 2006
Cropland
Forest
Wetland-bareland
Urban area
Grassland-golf course
River-lake
N
W
E
S
0
10
20
40 Km

Fig.4



(×10³)
Area (ha)
Percentage of total area (%)
0
50
100
150
200
250
300
350
400
450
500
0
5
10
15
20
25
30
35
40
45
50
Farmland
Forest
Wetland-baraland
Urban
Grassland-golfcourse
River-lake
Sea
Rank5
Rank4
Rank3
Rank2
Rank1
Total demand area

Fig.5



N
W
E
S
Mt. Rishiri
Cropland area at Biei
Tokachidake Mountain Range
Paddy field
near Hokuryu town
Odori Park and
Moerenuma Park
at Sapporo
Mt. Yotei
Toya Lake
Shiretoko Goko Lake
Kusssharo Lake
Masyu Lake
Kushiro Marsh
Akan Lake
Cropland area
near Obihiro city
Shikotsu Lake
Mt. Hakodate and Hakodate City
0 50 100 200 Km
Legend
Tourism Resources
Natural Park
Prefectural park
Quasi-national park
National park
Supply potential map
< Thresholds : low potential
0.2854-0.4008 > 10% threshold
0.4008-1 > equal threshold

Fig.6

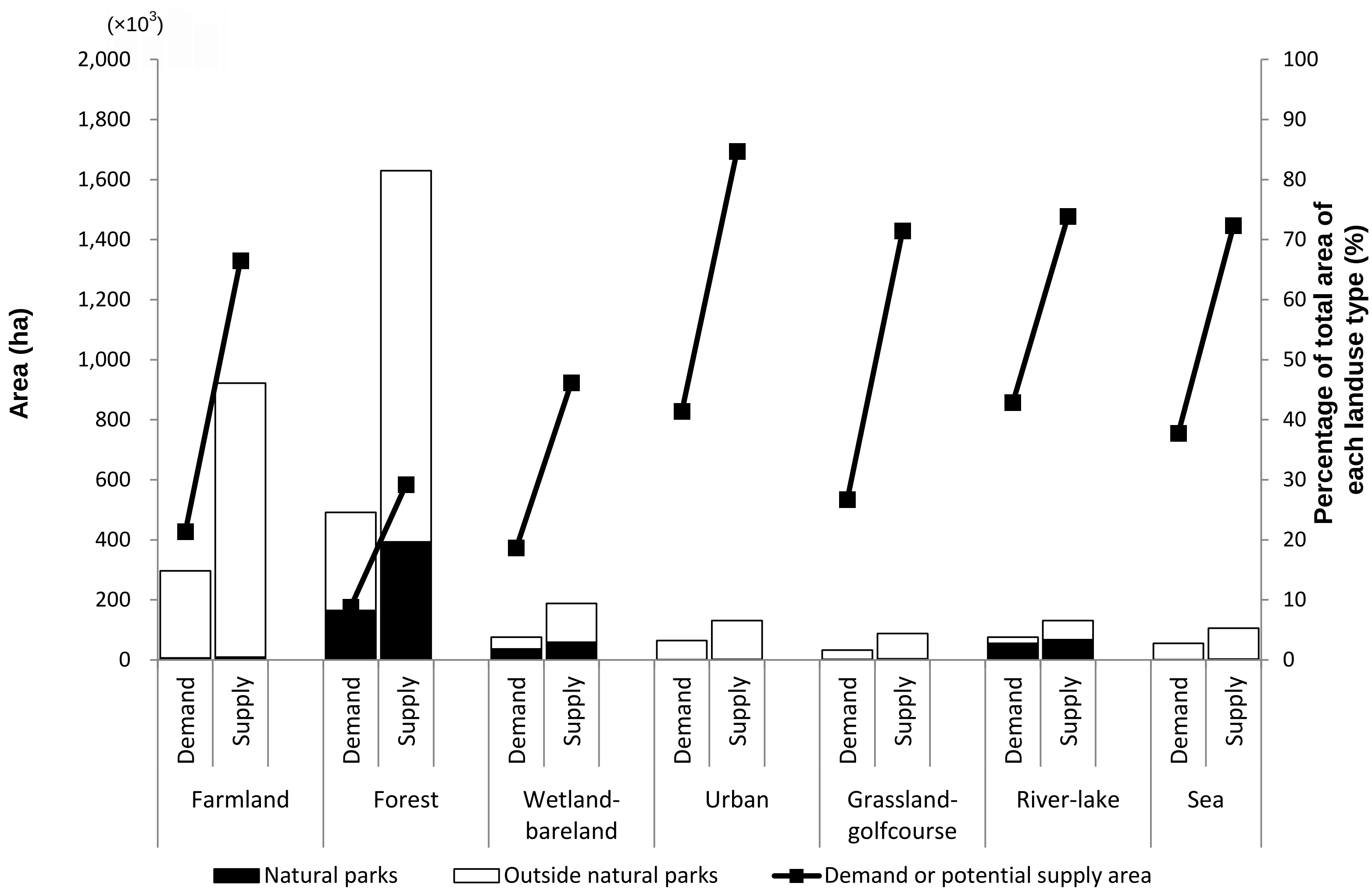
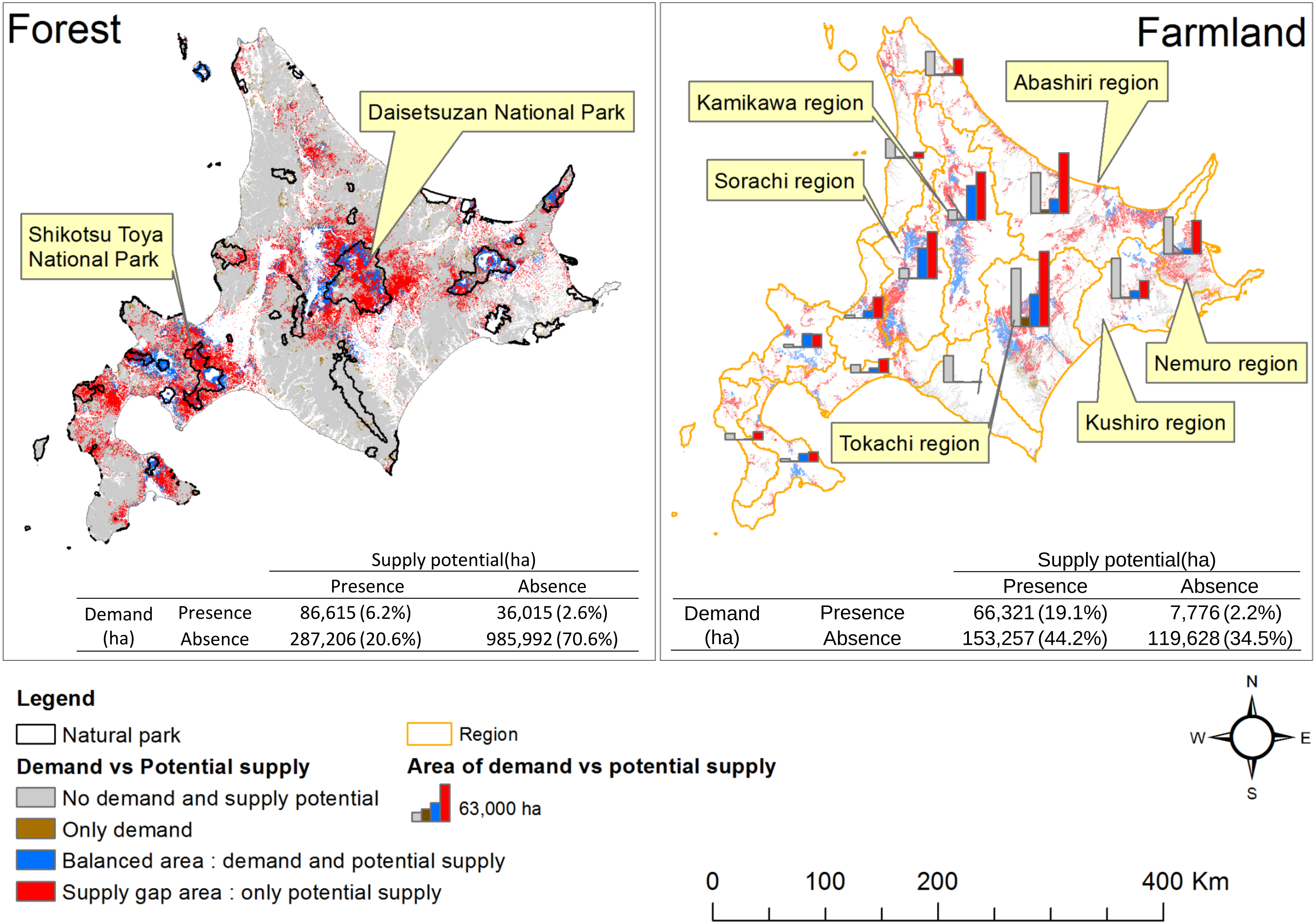

(×10³)
Area (ha)
2,000
1,800
1,600
1,400
1,200
1,000
800
600
400
200
0
100
90
80
70
60
50
40
30
20
10
0
Percentage of total area of each landuse type (%)
Demand
Supply
Farmland
Forest
Wetland-bareland
Urban
Grassland-golfcourse
River-lake
Sea
Natural parks
Outside natural parks
Demand or potential supply area

Fig.7




Forest

| | | Supply potential(ha) | |
|---|---|---|---|
| | | Presence | Absence |
| Demand (ha) | Presence | 86,615 (6.2%) | 36,015 (2.6%) |
| | Absence | 287,206 (20.6%) | 985,992 (70.6%) |

Farmland

| | | Supply potential(ha) | |
|---|---|---|---|
| | | Presence | Absence |
| Demand (ha) | Presence | 66,321 (19.1%) | 7,776 (2.2%) |
| | Absence | 153,257 (44.2%) | 119,628 (34.5%) |

Fig. S1

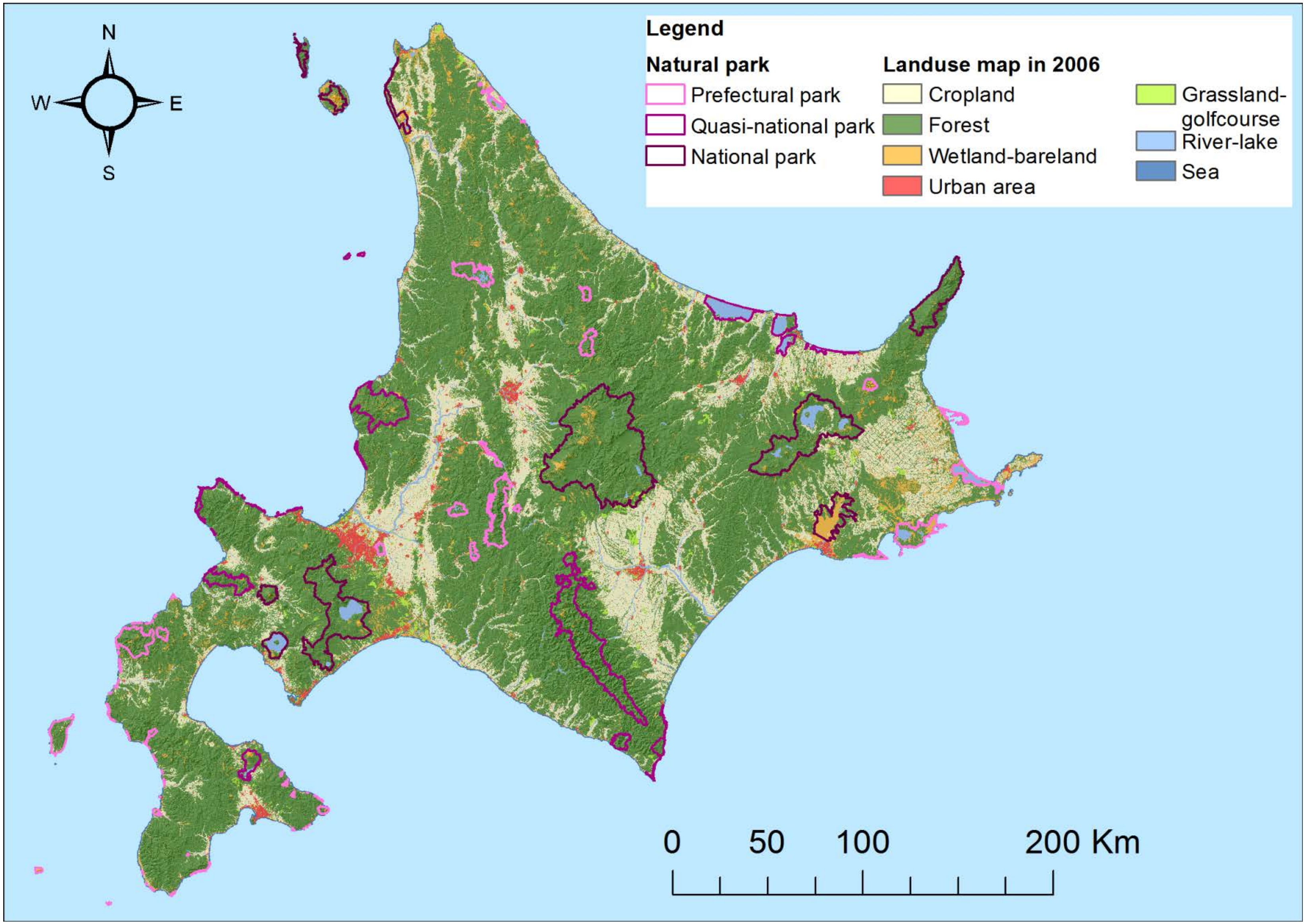
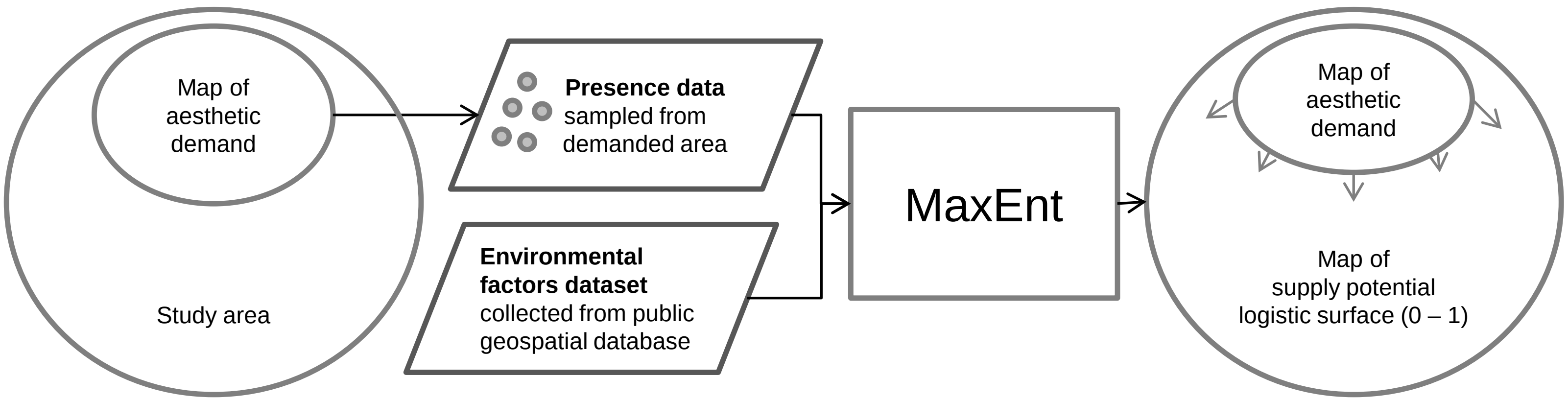

N
W
E
S
Legend
Natural park
Prefectural park
Quasi-national park
National park
Landuse map in 2006
Cropland
Forest
Wetland-bareland
Urban area
Grassland-golfcourse
River-lake
Sea
0
50
100
200 Km

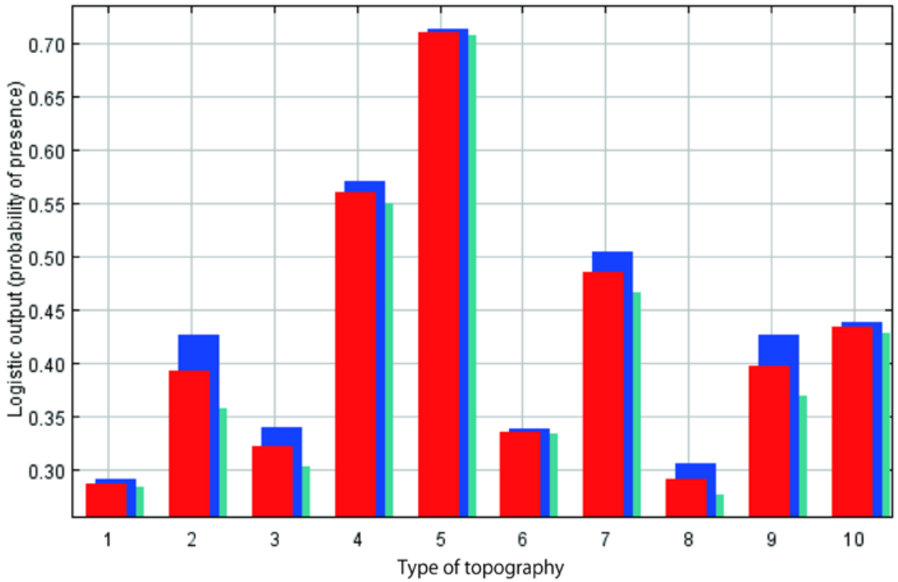
Fig.　S2

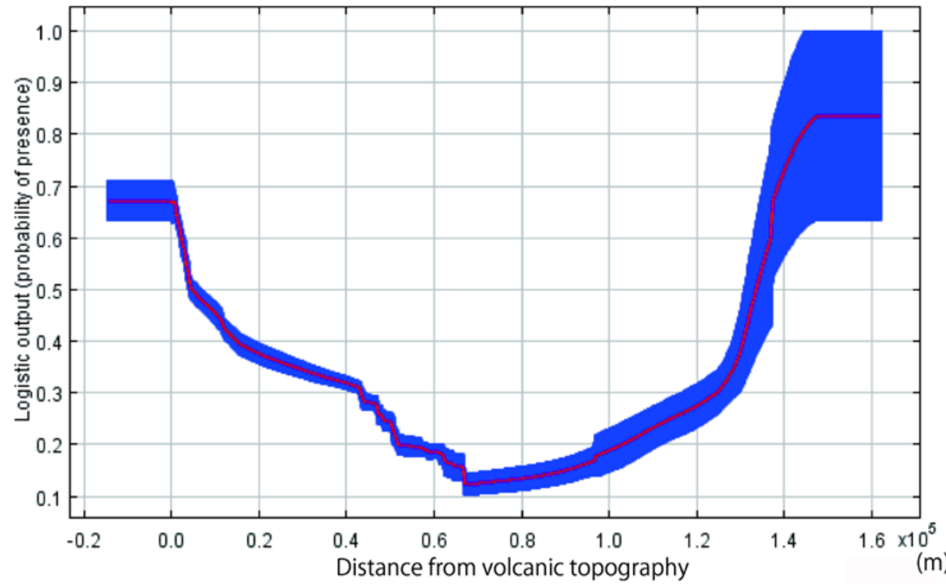
Fig. S3



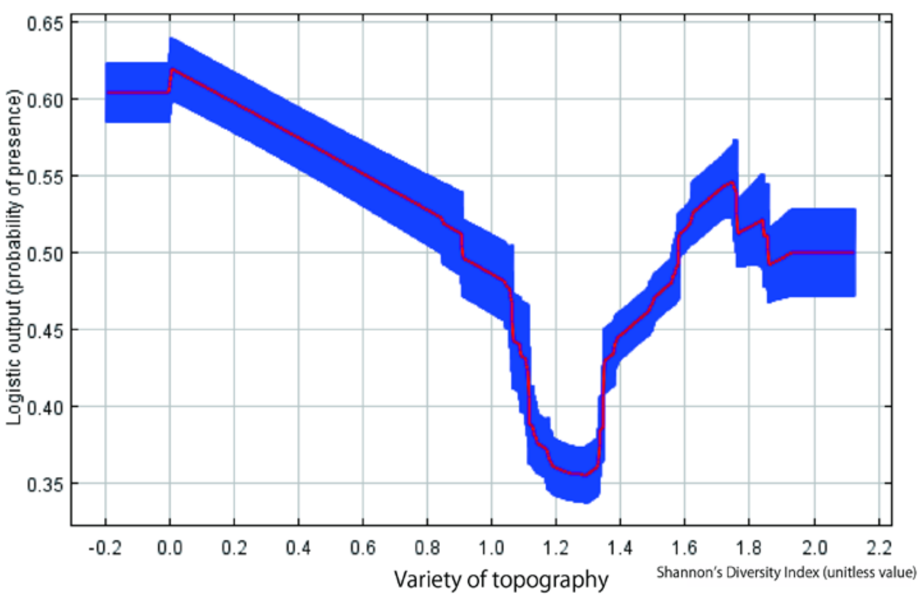
Map of aesthetic demand
Study area
Presence data sampled from demanded area
Environmental factors dataset collected from public geospatial database
MaxEnt
Map of aesthetic demand
Map of supply potential logistic surface (0 – 1)

# Fig.S4 Response of demand to topography




1 Canyons, deeply incised streams
2 Midslope drainages, shallow valleys
3 Upland drainages, headwaters
4 U-shaped valleys
5 Plains
6 Open slopes
7 Upper slopes, mesas
8 Local ridges, hills in valleys
9 Midslope ridges, small hills in plains
10 Mountain tops, high ridges



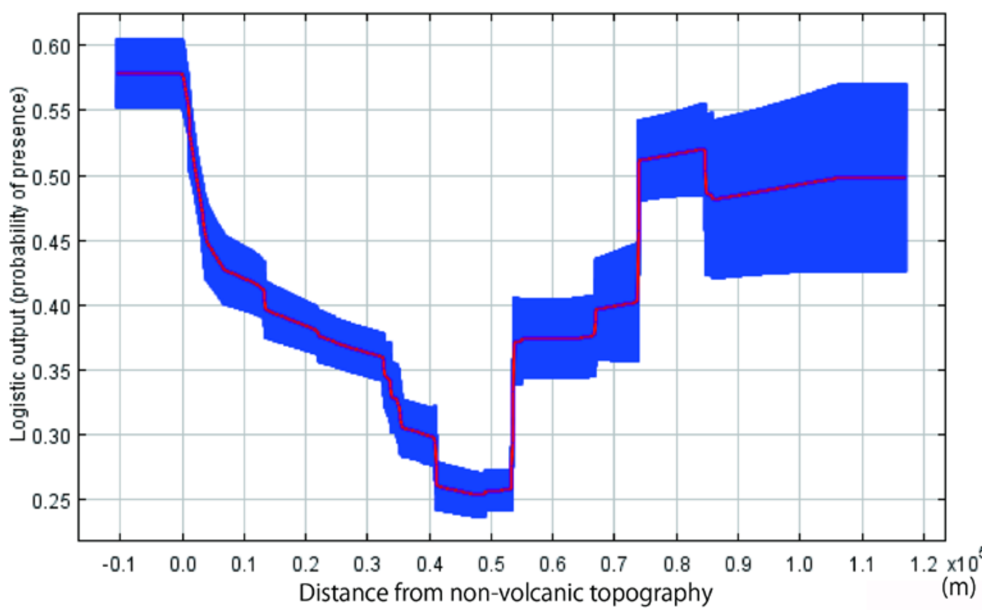
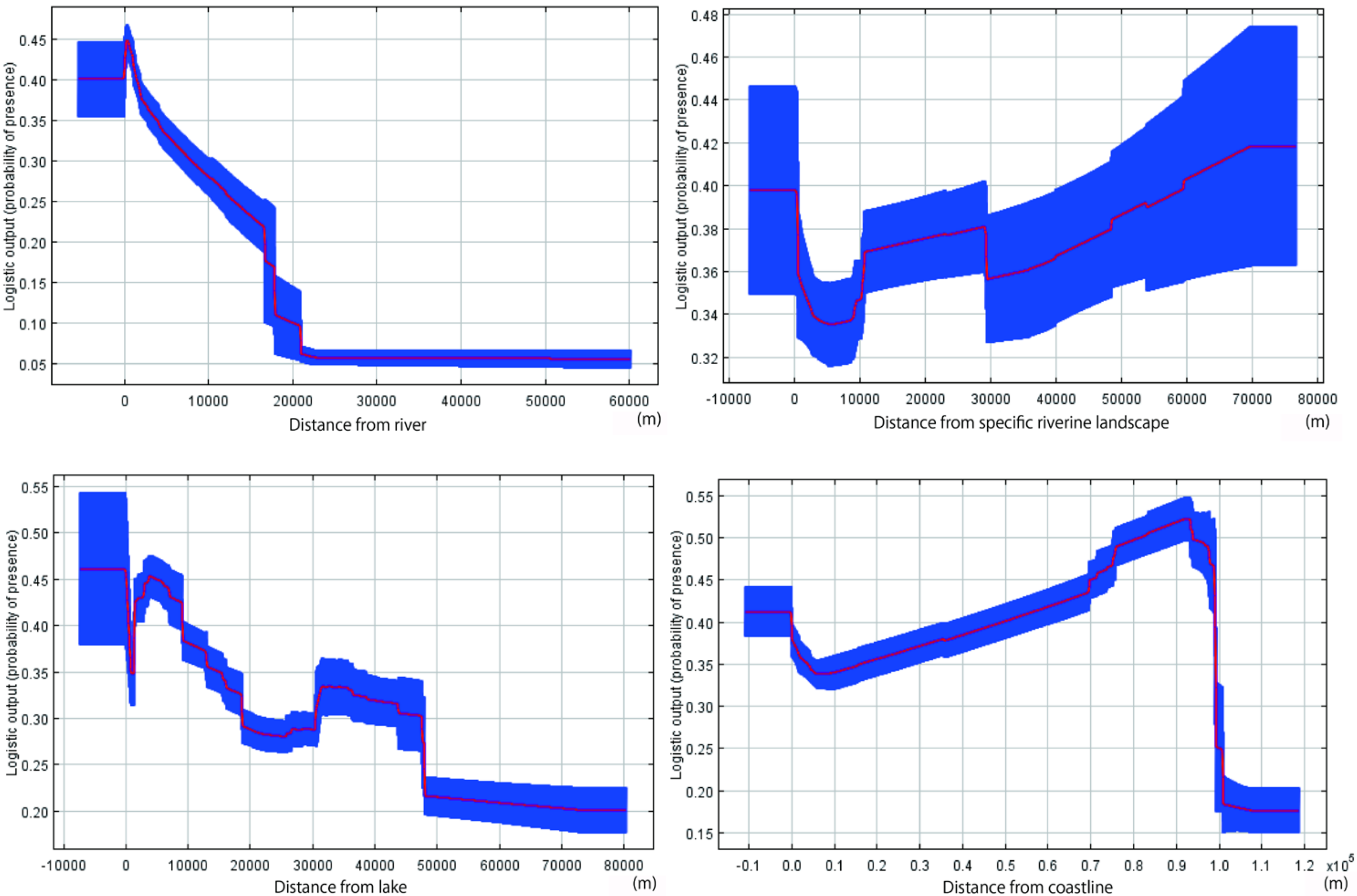
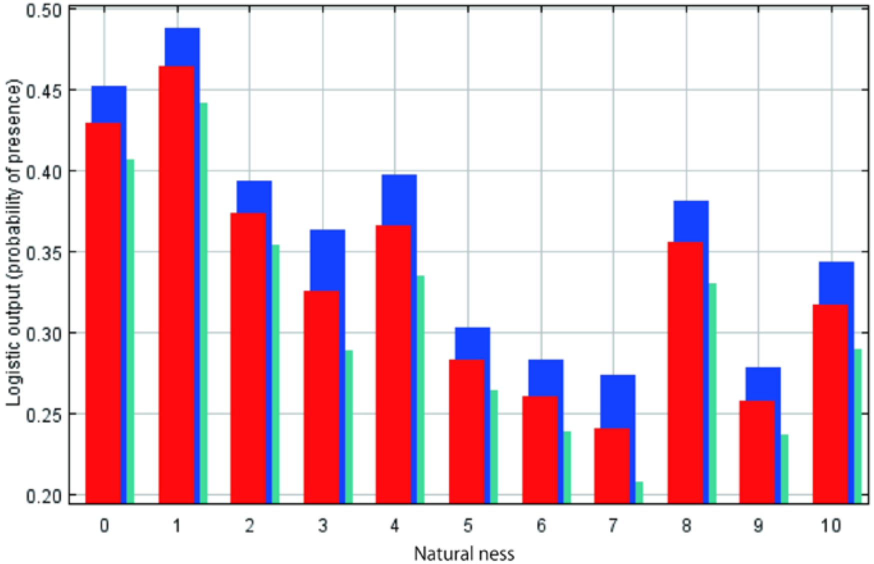



Fig.S4 Response of demand to water body(Continued)



# Fig.S4 Response of demand to naturalness (Continued)




1 Urban area
2 Farmland, Urban and residential district with many trees
3 Nursery garden
4 Secondary short grassland
5 Secondary tall grassland
6 Plantation forest
7 Secondary broad-leaved forest
8 Natural broad-leaved forest
9 Natural mixed forest
10 Alpine heathland and wind-exposed grassland
0 Water body

Fig.S5 ROC curve