Global Ecology and Conservation 21 (2020) e00899

Contents lists available at ScienceDirect

Global Ecology and Conservation

journal homepage: http://www.elsevier.com/locate/gecco

Original Research Article

Spatial tradeoff between biodiversity and nature-based tourism: Considering mobile phone-driven visitation pattern

Yoon Jung Kim [a], Dong Kun Lee [b], Choong Ki Kim [c, *]

[a] Korea Environment Institute (KEI), Sejong, 30147, Republic of Korea
[b] Department of Landscape Architecture and Rural System Engineering, CALS, Seoul National University, Seoul, 08826, Republic of Korea
[c] Division for Natural Environment, Korea Environment Institute (KEI), Sejong, 30147, Republic of Korea

ARTICLE INFO

Article history:
Received 19 August 2019
Received in revised form 23 December 2019
Accepted 23 December 2019

Keywords:
Nature-based tourism
Cultural service
Protected area management
Spatial trade-off
Ecosystem services
Bayesian network

ABSTRACT

Nature-based tourism contributes to the conservation of biodiversity by offering financial stability and enhancing visitors' interest in nature, and thus has become an increasingly important issue in managing protected areas. However, unsustainable tourism can adversely affect biodiversity due to increased human traffic, and can devastate a wilderness area. Although the demand for nature-based tourism is on the rise, monitoring tourist's spatial visitation pattern and its characteristics in protected areas is extremely rare. Therefore, this study quantified the spatial visitation pattern of tourists in protected areas in an innovative way by using mobile phone information and evaluated the trade-off between conservation requirements and visitation preferences to offer insights into biodiversity conservation. To clarify the causal relationship between tourism and biodiversity by considering various biodiversity factors at the species and landscape levels, we applied a Bayesian network approach reflecting multi-causality. This study showed significant spatial causality between biodiversity and tourism preference, particularly with respect to biodiversity at the species level. Supporting artifacts in protected areas were not affected in such a relationship. This study highlighted the necessity to monitor 133 protected areas on Jeju Island that were identified as visitation hotspots. The methodology and its applications described in this study may offer insights into the improvement of tourism management and the conservation of biodiversity in protected areas.

1. Introduction

The concept of multifunctional landscapes, which assumes that the landscape offers more than a single ecosystem service, has attracted much attention (Brandt et al., 2000; Gonzalez-Redin et al., 2016). Within the framework of a multifunctional landscape, an increase or decrease in different ecosystem services, such as nature-based tourism and biodiversity, may interfere with the supply of others (Hall, 2010; Qiu and Turner, 2013; Vallet et al., 2018), because it can involve complex interactions (Bennett et al., 2009; Lester et al., 2013; Power, 2010; Viglizzo and Frank, 2006; Wang et al., 2017; Yang and Yang, 2014). In this respect, the management of protected areas (PAs) often requires the fulfillment of multiple or conflicting objectives, and this is coupled with a rapid increase in nature-based tourism (Balmford et al., 2009; Manning et al., 2017; Muñoz

* Corresponding author.
E-mail addresses: kimyj@kei.re.kr (Y.J. Kim), dklee7@snu.ac.kr (D.K. Lee), ckkim@kei.re.kr (C.K. Kim).

https://doi.org/10.1016/j.gecco.2019.e00899
2351-9894/

et al., 2019). In fact, tourism in modern PAs has received much attention due to its known benefits for income and livelihood, although early management objectives generally tended to focus on conservation of the wilderness (Muñoz et al., 2019).

However, the number of beneficiaries of nature-based tourism can directly or indirectly affect the conservation status of a species or ecosystem (Filby et al., 2014; Pérez-Jorge et al., 2017; Ranaweerage et al., 2015). Negative effects on wildlife may increase when repeated short-term behavioral impacts accumulate due to human activities, thus reducing the intactness of the ecosystem (Christiansen et al., 2013). Moreover, whether the benefits of tourism outweigh the costs to the environment remains a question (Ziegler et al., 2019). Hence, management decisions on PAs often involve a trade-off between two values and conflicting goals, i.e., conserving the wilderness or promoting visitation. Clearly, to avoid a negative impact of tourism on the ecosystem, monitoring of visitation density in every area of a PA is necessary to perform suitable visitation management (Hadwen et al., 2007). Establishing proactive management strategies by identifying hotspots with high visitation density is important to perform targeted monitoring and management of such hotspots (Hadwen et al., 2007). However, even though unsustainable tourism can be a major source of environmental depletion, visitation management is often conducted without considering the number of tourists (Kurniawan et al., 2016). In this context, attention to possible conflict areas between two ecosystem services, tourism and biodiversity, is required in PA management by identifying the density of visitors to configure the sustainability of tourism and reduce future environmental losses (Cord et al., 2017; Vallet et al., 2018).

One of the main challenges in determining visitation density and performing subsequent management is the acquisition of data that reveals overall spatial visitation patterns. Multiple destinations must be reflected, and intensive visitor surveys should be carried out to identify tourist destinations (Hanson, 1980; Heberling and Templeton, 2009; Heikinheimo et al., 2017; Sessions et al., 2016). However, field-based visitor counts are generally limited in coverage and do not consider every inner location of a PA. It is often hard to demonstrate the relationship between visitation and a particular location with existing field data, which represents point samples rather than landscape data (Hadwen et al., 2007; Wood et al., 2013). It is hard to find aggregated data on visitor count on a large scale due to its high cost and labor-intensive features (Kim et al., 2019; Schägner et al., 2017). In this regard, there was even a single session of the IUCN World Conservation Congress 2016 titled “Visitors count! – Count visitation! Tourism in protected areas …” (Schägner et al., 2017).

To resolve such issues, an alternative methodology for the analysis of visitation patterns using big data from mobile phones and social media has recently gained attention (Fisher et al., 2019; Kim et al., 2019; Ploetz and Smoreda, 2017; Salas-Olmedo et al., 2018; Sessions et al., 2016; Wood et al., 2013). Using this methodology, coordinate information revealing peoples’ visits to multiple sites has been applied to identify spatial visitation preferences reflecting a diverse range of visitors. Such emerging innovative approaches using new forms of big data make it possible to observe where people go and to identify the biodiversity attributes that face spatial trade-offs with high visitation density. To evaluate the intersection between highly preferred areas for both nature-based tourism and biodiversity value, an understanding of the complex underlying causal relationships is required. Indicators of biodiversity can vary greatly due to the multifaceted characteristics of nature (Gaston and Biodiversity, 1996). Different aspects, such as species diversity and functional traits, can be quantified to evaluate the importance of biodiversity (Santini et al., 2017). Moreover, regarding spatial scale, biodiversity attributes such as gamma diversity (regional biodiversity) and alpha diversity (species assemblage) can be inspected (Socolar et al., 2016). Furthermore, as PAs generally contain impervious areas including convenience facilities and roads, the consideration of the distribution of such features is required, since the coverage of impervious areas within PAs can be used to determine ecological value (Creech and Williamson, 2019). Hence, multiple attributes related to biodiversity importance need to be reflected in the analysis.

Therefore, this study aimed to identify place-based information on frequently visited hotspots and inspect the trade-off between visitation preference and biodiversity importance in PAs. A Bayesian network (BN) was applied to inspect multiple causalities reflecting multiple biodiversity attributes, since a Bayesian network approach is well known for its ability to show direct and indirect causalities (Barton et al., 2012; Mccann et al., 2006). Specifically, visitation densities in PAs were evaluated using mobile phone-based telecommunications information. The association between high visitation density and biodiversity attributes was evaluated to elucidate management priority issues that may show a potential conflict between the two values. To the best of our knowledge, such a comparison of visitation patterns and biodiversity features in PAs using big data has not previously been performed. It is expected that this study will offer insights into the sustainable management of PAs to promote synergies between tourism and biodiversity conservation.

2. Methods

2.1. Study site

The study site was located within inland PAs on Jeju Island, which is in the southern region of the Republic of Korea. This site was designated as a UNESCO World Natural Heritage site because it features outstanding biodiversity and has a high tourism value. Among the official PAs in Jeju, we confined our study to 66 inland PAs, with a total area of less than 25 km^2.

Jeju Island was also designated as a World Geology Park in 2010, listed as a Biosphere Reserve in 2002, and has five enrolled Ramsar sites (Schaaf and Rodrigues, 2016). Jeju is the only area in the world where all four internationally designated areas (IDAs) overlap (Schaaf and Rodrigues, 2016). The properties of the four IDAs, including exceptional natural beauty, significant natural habitats, geological heritage, and unique cultural traditions, are all present at the site. Specifically, Jeju contains unique natural resources, including 2,000 subtropical to subpolar species (http://www.jejusi.go.kr).

Jeju Island is one of the most well-known regions for nature-based tourism in the Republic of Korea. In 2016, 2.9 million foreign visitors toured Jeju's 30 major tourist attractions, and a total of 13.7 million visitors visited the island according to Jeju Province's annual statistical yearbook (http://www.jejusi.go.kr). The number of visitors is significantly high compared to Jeju Island's population of 680,000 as of July 2018. Furthermore, the tourism demand for Jeju has shown constant growth from 1980 to 2006 (Seo et al., 2009). The number of foreign visitors to Jeju was 1 million in 2011, increasing to 3.6 million in 2016 (http://www.jejusi.go.kr). The constant increase in the number of visitors has promoted the growth of the regional economy and increased tourism revenue, but issues of environmental sustainability and the carrying capacity of the island have become public concerns.

2.2. Identification of frequently visited areas in PAs

2.2.1. Mobile phone data

To evaluate spatial visitation patterns, mobile phone data from Korea's largest telecommunications company (SKT, http://www.sktelecom.co.kr/en), which includes more than 29 million mobile subscribers, accounting for approximately 50% of the nation's total population, were acquired. Data was downloaded from the National Open Data Portal (data.go.kr). The mobile phone data used in this paper is cell tower-based data that shows the floating population. Specifically, mobile phone-based location data can be classified as active data, recorded even when people do not make phone calls or send text messages, and passive data, collected when an individual makes a phone call or texts (Lee et al., 2018; Xu et al., 2016). The data used in this study is active data because it records a floating population based on the transmitted signals (see Lee et al., 2018). When people move, the corresponding cell tower changes based on the GPS signal of individual devices, and thus the density of the floating population can be estimated without any overlapping calculation (Xu et al., 2016).

Spatial coverage of cell towers without non-service zones should be considered to avoid biases. Hence, in this study, an estimated floating population map based on 300 m $\times$ 300 m grid was applied considering the average coverage of distributed cell towers on Jeju. Non-service zones are nonexistent in Jeju's 5G, Long-Term Evolution (LTE) and Wideband Code Division Multiple Access (WCDMA) networks.

Specifically, information on the number of visitors from outside of Jeju in 2014 was obtained. Since this study was carried out to assess possible conflicts between ecosystem services regarding nature-based tourism and biodiversity, we attempted to only consider tourists. Tourism has been defined as "The activities of persons travelling to and staying in places outside their usual environment for not more than one consecutive year for leisure, business and other purposes not related to the exercise of an activity remunerated from within the place visited" (Peeters et al., 2007). Even though tourism generally includes local residents, it is hard to separate tourists and non-tourists (e.g., commuters). Hence, to better reflect the mobility of tourists but not the daily routines of local people, we focused on people from outside of Jeju. In addition, the majority of tourists in Jeju consisted of visitors from outside, not local residents. According to Jeju Province's annual statistical yearbook, 12.2 million tourists were recorded in 2014, compared to the total number of residents recorded as 600,000 (http://www.jejusi.go.kr).

Although the specific number of visitors cannot be determined, such mobile phone data can distinguish the upper and lower rates of visitation density (Ploetz and Smoreda, 2017). However, in this study, as further verification was required, the official field observation statistics on the number of visitors were compared to the mobile phone data for validation. Monthly surveys are performed to determine the number of visitors to several natural resource tourism amenities on Jeju Island (e.g., national parks and botanical gardens; http://www.jejusi.go.kr). Pearson correlation coefficients and p values were quantified between two datasets, which were the observed total number of monthly visitors and mobile phone-driven floating population.

2.2.2. Visitation density in PAs

To discern frequently visited areas, the upper 20% of visited areas across Jeju were identified as visitation hotspots. Moreover, to distinguish distinct spatial clustering areas with high visitation, Getis-Ord Gi* spatial statistics and Moran's I correlation coefficient were calculated using ArcGIS10.6. Spatial clustering can reflect areas "where observed patterns are not likely the result of random processes or of subjective cartographic design decisions" (Getis and Ord, 1996; Nordling et al., 2017). Regarding the spatial relationship among neighboring features, the Getis-Ord Gi* statistic identifies whether visitation in a given cell is statistically clustered compared to the loss in neighboring cells. Hence, along with the identified upper 20% of visited pixels (300 m $\times$ 300 m), clustered visited areas with a Z score above 1.65, indicating a 90% significance level of the cluster, were considered visitation hotspots. The identified hotspots were masked along the boundaries of the PAs.

Furthermore, as seasonal fluctuations in visitation can affect temporal visitation densities, this study quantified the seasonality of visitation. The Gini coefficient, which is one of the most commonly used metrics in characterizing visitation patterns (Fernandez-Morales, 2003), was calculated to measure the seasonality of visits (eq (1).). Gini coefficient values range from 0 (perfect equality) to 1 (perfect inequality). The higher the value, the greater the inequality between monthly visits. The metric was calculated using the "ineq" package in RStudio (RStudio Team, 2016).

$$G = 1 - \sum_{i=0}^{N}(\sigma Y_{i-1} + \sigma Y_i)(\sigma X_{i-1} - \sigma X_i) \tag{1}$$

σX represents the cumulative number of months in a year and σY represents the cumulative number of visitors in each month (both σX and σY are in fractions). N represents the number of observations.

Regarding visitation hotspots (frequently visited areas) and seasonality, six levels of visitation density were identified. First, the number of visitors from outside of Jeju was divided into three grades: high, middle, and low. For mobile phone data, the number of visitors from outside of Jeju was divided into three levels using the Jenks natural breaks function in ArcGIS10.6, which automatically classifies the data set by inspecting relatively large differences. The approximate number of visitors listed in Table 1 was estimated based on regression analysis of the monthly observed number of visitors to six representative attractions (Bija Forest, Seogwipo Recreation Forest, Jeongbang Waterfall, Jeju Stone Culture Park, Cheonjiyeon Waterfall, and Seongsan Ilchulbong) in Jeju, which showed an R^2 value of 0.69. For visitation seasonality, two grades were identified: low (Gini index < 0.5) and high (Gini index > 0.5). A total of six levels of visitation density were indicated, as shown in Table 1.

2.3. Intersection between visitation density and biodiversity attributes

2.3.1. Indicators of biodiversity

Table 2 lists the indicators reflecting the level of biodiversity that were applied. Since there can be variety of features of biodiversity depending on spatial scale (Gaston and Biodiversity, 1996), it is important to have an understanding of biodiversity features across spatial scales for effective conservation action (Socolar et al., 2016). Therefore, we selected indicators reflecting biodiversity importance considering both species and landscape scale. The values of indicators were quantified for each 300 m $\times$ 300 m grid. As mobile phone information indicated the floating population in 2014, each data was selected and applied regarding the temporal range (Table 2).

Since species information can show the specific spatial distribution of biodiversity (Magurran, 2013), species diversity (B_DIVERSITY) and total number of endangered species (BIRD_n) for birds were evaluated. The Shannon Diversity Index (Spellerberg et al., 2003) was used to quantify B_DIVERSITY. Next, to reflect biodiversity at the landscape level, the landscape metric (SHDI) was calculated using Fragstat3.3. (McGarigal et al., 2002). It quantifies the Shannon Diversity Index (Spellerberg et al., 2003) based on the number of patches across a landscape. When the number of different patch types (e.g., deciduous forest, wetland) increases, the value of SHDI increases. Quantification of SHDI was conducted based on a national land cover map within 22 classes on land cover (egis.me.go.kr). After that, the general characteristics of matureness and size for each PA were considered. Average forest age (FOREST_age), number of years elapsed after designation (PASS_YR), and total area (PA_area) were quantified. Moreover, to better reflect conservation requirements, the management category of the International Union for Conservation of Nature (IUCN) was considered because it can reflect the degree of conservation action required to maintain a wilderness area. (Dudley, 2008). Lastly, the presence of artificial artifacts was quantified as an indicator. The percentage of impervious areas (IMPER.) including residential, commercial and road areas, was considered to reflect the proportion of non-artificial areas. The number of facilities (FACIL) such as convenience stores, restaurants, and accommodation was also considered.

2.3.2. Distinguishing the intersection by developing BN

Causalities between the identified level of visitation density and biodiversity were identified using a BN. A BN was applied because it (i) clearly indicates causal interactions among multiple spatial features; (ii) shows different magnitudes of direct and indirect impacts by illustrating layered dependencies; and (iii) effectively integrates various types of variables, since considered factors generally consist of both continuous and discrete values (Barton et al., 2012; Gonzalez-Redin et al., 2016; Marcot et al., 2001; Nyberg et al., 2006; Pérez-Miñana, 2016). It is generally hard to identify graphical identification and quantification of multi-causalities among various features based on typical statistical analysis. Typical statistical analysis such as multiple regression focuses on causality between dependent and independent variables. However, BN can be used to quantify not only causality between dependent and independent variables, but also multiple causal relationships among

Table 1
Six levels of visitation density. Based on HT_LV (number of visitors) and GINI (seasonality measured from the Gini index) values, six levels of visitation density were identified. The figure on HT_LV indicates the approximate number of visitors based on mobile phone data.

Level of visitation density	HT_LV		GINI	
1	Low	$n \leq 319{,}200$	Low	Gini<0.5
2	Low		High	Gini $\geq$ 0.5
3	Medium	$319{,}200 < n < 858{,}800$	Low	Gini<0.5
4	Medium		High	Gini $\geq$ 0.5
5	High	$n \geq 858{,}800$	Low	Gini<0.5
6	High		High	Gini $\geq$ 0.5

Table 2
List of indicators reflecting biodiversity. Considering species and landscape scale, various features of biodiversity were evaluated. The table indicates type of indicators, temporal range of data, and source of data.

Name	Description	Type of indicators	Temporal range of applied data	Source of applied data
IUCN	management category of IUCN protected area noting intactness and its conservation importance on wilderness	Discrete	• Acquired in 2018. • Areas that have been designated as protected area for at least seven years were considered.	IUCN, protectedplanet.net
PA_area	size of each protected area	Continuous		IUCN, protectedplanet.net
PASS_YR	elapsed year after designation as protected area	Continuous		IUCN, protectedplanet.net
FOREST_age	average age class of located trees in inner forest	Discrete	• Investigation took place from 2006 to 2010. • Age class of 10-year interval was considered.	Ministry of forestry, 5th national forest survey
BIRD_n	number of endangered bird species	Continuous	• Investigation took place from 2006 to 2013.	Ministry of environment, 3rd natural environment survey
B_DIVERSITY	Shannon species diversity value of bird species	Continuous		Ministry of environment, 3rd natural environment survey
SHDI	Shannon diversity index on land cover patches in landscape level	Continuous	• Generated in 2013.	Ministry of environment, egis.me.go.kr
IMPER.	percentage of impervious areas (e.g. residential, commercial, road areas)	Continuous		Ministry of environment, egis.me.go.kr
FACIL	number of artifact facilities including convenient/restaurant/accommodation	Continuous	• Data that accumulated and verified until 2015 was applied. • New construction is strictly forbidden after designated as protected area.	Jeju, jejusi.go.kr

independent variables (Barton et al., 2012). It also exhibits no 'black-box' problems that can be shown in other machine learning approaches such as random forest (Barton et al., 2012; Breiman, 2001). Therefore, in this study, BN was applied to reflect multi-causalities between demand on tourism and the various biodiversity indicators in Table 2. The BN was created using the "bnlearn" package in RStudio.

BNs can be developed from data-driven learned approaches, with several constraint-based and score-based algorithms. After inspecting the algorithms of hc (hill-climbing), mmhc (max-min hill-climbing), gs (grow-shrink), and iamb (incremental association), the best-fitting algorithm was selected by performing a k-fold cross validation (number fold = 10). The expected loss in constructing the BN in the case of hc was 22.97, which showed the highest accuracy compared to the other algorithms (expected loss = 28.8–29.6). Hence, a hill-climbing (hc) learning algorithm was applied to generate the directed acyclic graph (DAG) among multiple continuous and discrete variables. The hc algorithm is a score-based algorithm used to build data-driven causal networks, which develop the structure of the layered network based on score caching, score decomposability, and score equivalence (Scutari, 2009). A total of 135 iterations were performed to determine the optimal causal structure with a high goodness-of-fit score. To assist the algorithm in finding the most logical and appropriate structure, a whitelisting function was applied to force certain linkages between variables, such that illogical linkages were avoided. Following these principles to construct the BN, (i) six levels of visitation density were distinguished, as shown in Table 1; (ii) the association between biodiversity features and visitation density were listed as a whitelist, since biodiversity metrics (e.g., species diversity) can also be conservation objectives; and (iii) features regarding the impervious rate and number of artifact facilities were not whitelisted, since these are not direct objectives of biological conservation.

To evaluate the model, a conditional independence (CI) test was performed to confirm adequate d-separation. d-separation is a BN logic that indicates CI among multiple nodes. Moreover, to analyze the robustness of the generated BN, 1,000 bootstraps were performed to analyze the stability of the directions of the arcs.

3. Results

3.1. Validation of mobile phone data

In a comparison of mobile phone data with the observed number of visitors, an overall correlation of 0.64 was observed ($p < 0.01$), which indicated a strong positive correlation (Fig. 1). The monthly trends in the observed number of visitors and mobile phone visitor data showed general agreement on seasonal visitation fluctuations (Supp 1). However, for certain natural resources, such as Chunjeyeon Waterfall and Jeolmul Recreational Forest, mobile phone visitation patterns showed more distinct seasonality (Supp 1).

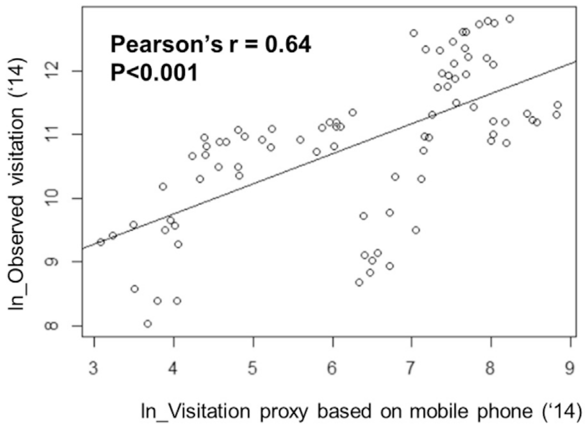


Fig. 1. Reliability of mobile phone-driven data. The graph indicates the correlation between mobile phone-driven floating population and observed numbers of visitors. Values were normalized to ln (annual visitation count).

3.2. Frequently visited areas inside PAs

A total area of 705 km^2, accounting for approximately 38% of Jeju, was distinguished as an area showing distinct telecommunication signals from groups of people (Fig. 2a). This study identified frequently visited areas (visitation hotspots) by determining the upper 20% of visitation density and spatially clustered areas of visitation, as shown in Fig. 2b and c. The areas in the upper 20% of visitation density were widely distributed across Jeju and spatial clustering clearly showed areas with dense visitation. Moran's I analysis also supported the data shown in Fig. 2c, as it validated the highly clustered pattern identified by the Getis-Ord Gi* statistics. The Moran's index value was 0.89 and the Z value was calculated as 249.2 ($p < 0.001$). Visitation hotspots, indicating frequently visited areas, were identified in the PAs by masking the hotspots along the boundaries of the PAs (Fig. 2d). As a result, 47.8% of the 66 PAs analyzed were shown to contain visitation hotspots inside their boundaries. A total of 133 visitation hotspots were present in the areas within the PAs (Fig. 2d).

Overall, seasonality showed high variation for every 300 m grid in Jeju (Supp 2). Compared to non-PAs, high seasonality (Gini index > 0.5) was partially seen in the 133 hotspots identified in PAs (Fig. 3). For instance, PAs such as Seongsan Ilchulbong and Cheonjeyeon Waterfall contained hotspots with high seasonality, and were some of the most frequently visited natural resources (Fig. 3).

3.3. Intersection between frequently visited areas and biodiversity features

A CI test was performed to evaluate the suitability of the BN structure to evaluate the causal relationship between high visitation density and biodiversity attributes. Each linkage exhibited conditional independence, as target parent and child nodes were not correlated without a middle node ($p > 0.1$), thus satisfying the d-separation principles required to construct a BN. The robustness of the BN structure was evaluated by performing 1,000 bootstraps. There were no missing linkages or inverse directions according to this evaluation (Supp 3).

The BN clearly indicated that a low level of biodiversity in PAs was associated with a high visitation density (Fig. 4, Fig. 5, Table 3). In particular, the number of endangered bird species (BIRD_n) and the size of the PA (PA_area) showed the highest conditional density with frequently visited areas (Table 3). Species diversity (B_DIVERSITY) also tended to increase at higher visitation densities. However, patch diversity at the landscape level (SHDI) showed a similar conditional density for all levels of visitation density. PASS_YR, which indicates the number of years that have elapsed since designation as a PA, showed a relatively strong causality at less-visited hotspots.

A conditional probability table (CPT) was obtained to assess discrete biodiversity features (Fig. 5). The CPT indicates the joint probabilities between the level of visitation density in the PA and discrete biodiversity variable values. Both forest and non-forest areas were located in frequently visited areas (level 4–6). Visitation hotspots in PAs with a tree age greater than 20 years were found at visitation density levels of 2, 4, and 6. There was no clear association between visitation density and tree age. However, visitation hotspots with high seasonality (Gini index > 0.5) were generally located in PAs with higher tree ages. Conversely, visitation hotspots without forest areas were shown to have low seasonality for all levels of visitation densities.

IUCN management category I areas, which have high conservation needs and intactness, showed low visitation seasonality (Fig. 5). Level 1 and 2 visitation densities were associated with category I, showing joint probabilities ranging from 20% to 23%. High visitation densities in management category IV, V, and VI areas ranged from 14% to 100%. Overall, the level of visitation density showed an inverse relationship with intactness based on standard IUCN management categories.

We also evaluated whether visitation density was associated with artifacts (e.g., convenience stores) in PAs, but not with biodiversity. Fig. 6 shows how the number of facilities and impervious rate were linked with visitation density and other

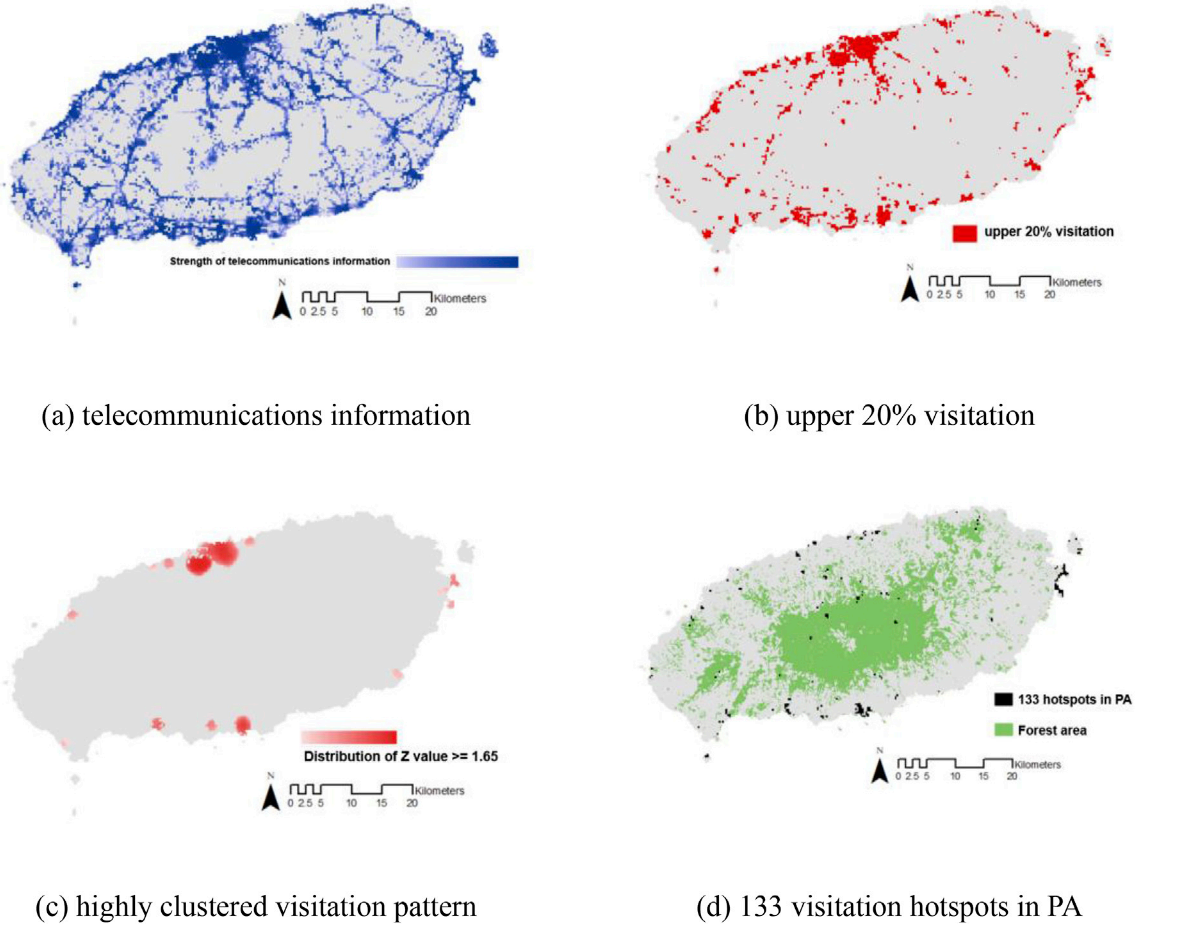


Fig. 2. Distribution of highly visited areas (visitation hotspots) inside PAs. (a) Distribution of mobile phone data (b) Upper 20% of visited areas in Jeju (c) Areas having highly clustered visitation in Jeju (d) 133 identified visitation hotspots based on (b) and (c) inside PAs in Jeju.

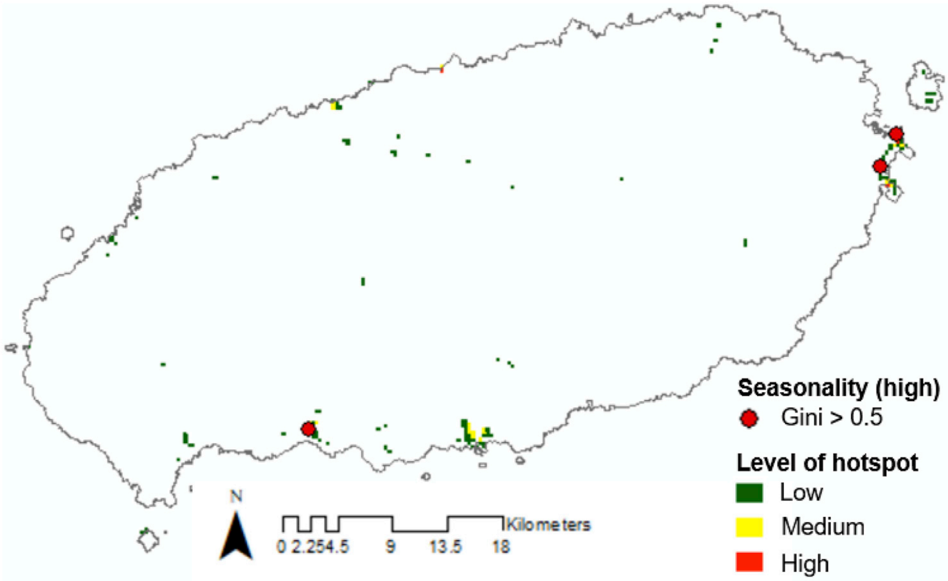


Fig. 3. Identified 133 hotspots in PAs. The level of visitation density (low, medium, high) is presented for 133 hotspots within PAs. The locations showing high visitation seasonality (Gini index > 0.5) are also indicated.

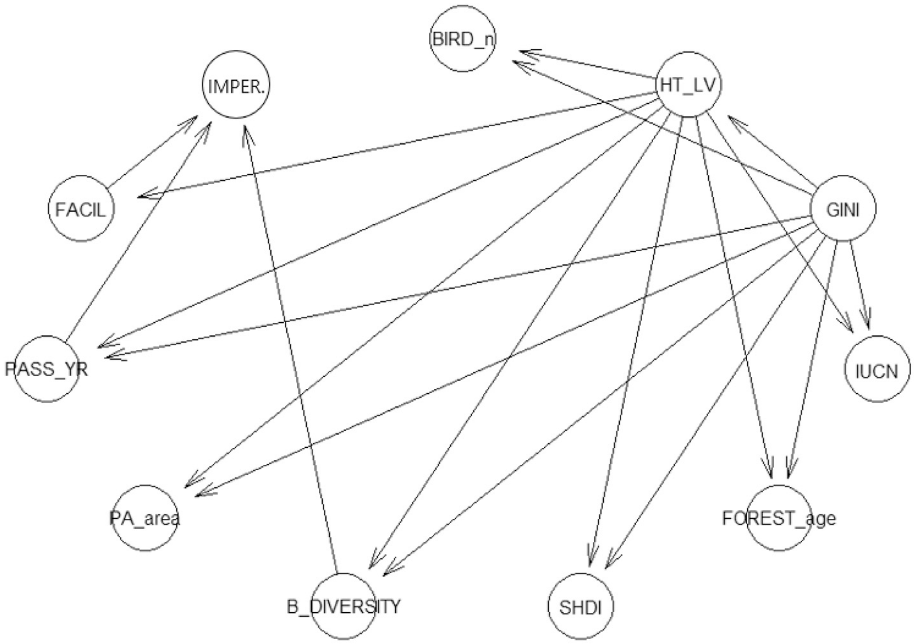


Fig. 4. Bayesian network revealing associations between biodiversity and visitation density. The causal network indicates the association between visitation density and various biodiversity features across 133 hotspots within PAs.B_DIVERSITY: diversity of bird species; SHDI: Shannon diversity index in landscape scale; BIRD_n: number of endangered bird species; PA_area: size of protected area; PASS_YR: elapsed year after the designation as protected area; HT_LV: level of visitation density; IMPER.: percentage of impervious area; FACIL: number of facilities.

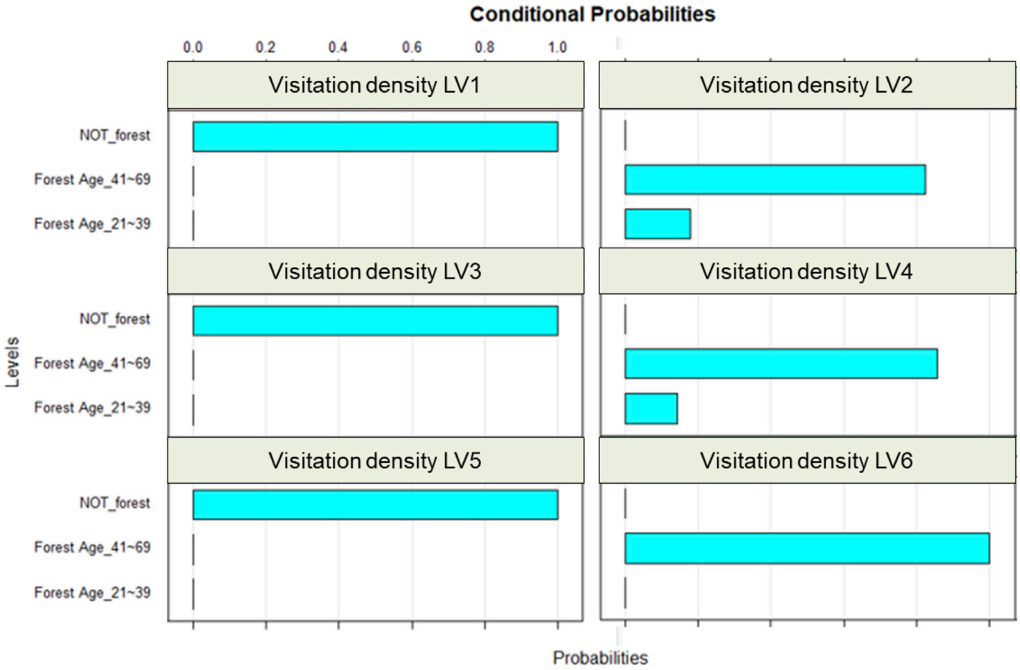
biodiversity features. Generally, the number of facilities, including restaurants, convenience/shopping stores, and accommodation facilities, was directly related to visitation density, indicating higher conditional densities from 22.9 to 31.2, compared to low visitation density (Fig. 6). However, the percentage of impervious areas, including residential areas, roads, and commercial areas, showed an indirect relationship with the distribution of visitation hotspots in PAs. This analysis also showed negative correlations with several biodiversity features, including the number of years as a PA and bird species diversity. In summary, although the number of facilities showed a direct relationship with frequently visited areas in PAs, this study confirmed the existence of a spatial trade-off between biodiversity features and visitation density, as shown in Fig. 6. This is because such artifacts had no positive relationship with the evaluated biodiversity features that demonstrated an individual relationship with visitation density.

4. Discussion

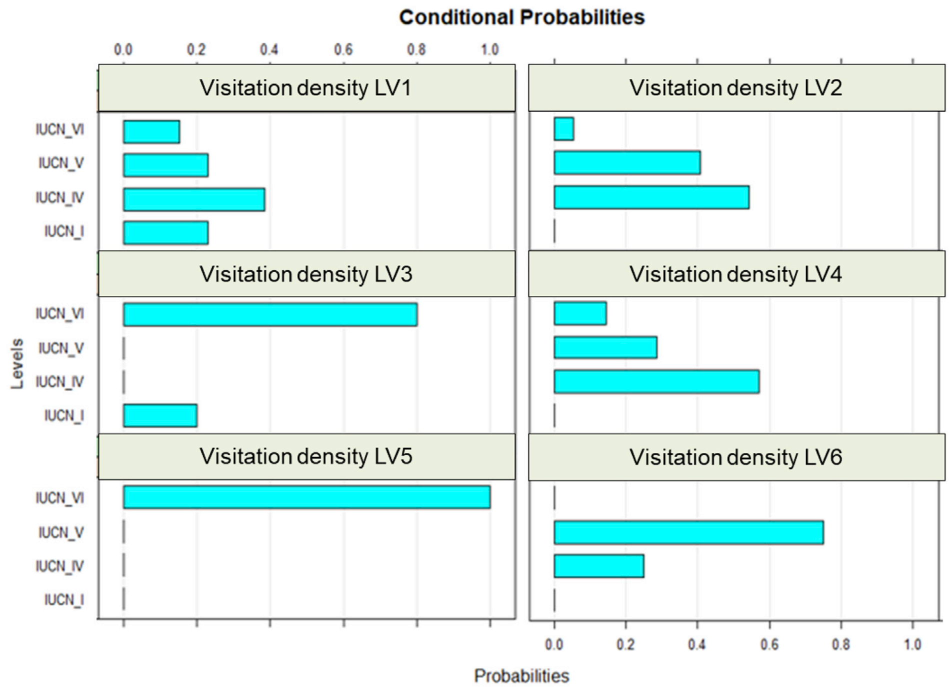
Nature-based tourism is a cultural service that enhances public awareness and financially supports biodiversity conservation (Millennium Ecosystem Assessment, 2005; Steven et al., 2013). However, as human influence is a major threat, it is necessary to monitor the sustainability of visitation patterns, since unsustainable tourism can devastate the natural environment (CBD, 2016; Hall, 2010). Therefore, this study assessed the usefulness of mobile phone telecommunications data to investigate the spatial relationship between visitation preference and various aspects of biodiversity. We showed that visitors from outside of Jeju had clear visitation preferences in PAs, including natural monuments, particular scenic sites, and natural reserves. By identifying the major biodiversity features associated with locations of highest visitation density, this study offered insights into the appropriately prioritized agenda for biodiversity conservation policies.

4.1. Use of mobile phone data to reflect visitation density in PAs

Mobile phone data was effective in showing the overall spatial visitation patterns for a diverse range of PAs of different sizes. The correlation between mobile phone data and observed field data was 0.64 ($p < 0.01$), showing moderate accuracy (Fig. 1). Correlations between this new source of big data and observed field data were generally from 0.6 to 0.9 (Fisher et al., 2019; Kim et al., 2019; Sessions et al., 2016; Wood et al., 2013). Field data is only obtained at limited sites (e.g., ticket booths), so it was not possible to identify the visitation hotspots for every area within the PAs. However, mobile phone data were particularly useful for solving such a problem, because it can reflect where people go most frequently for every area within PAs (Kim et al., 2019). That is, even though such data sources cannot provide the exact number of visitors, they can effectively illustrate overall spatial visitation tendencies and identify areas with high visitation preference.



(a) CPT between average tree age and visitation density



(b) CPT between IUCN management category and visitation density

Fig. 5. Conditional Probability Table considering discrete biodiversity variable and visitation density. The figure indicates the spatial overlap between visitation density and IUCN management category and average tree age in PAs. High joint probability indicates a high degree of spatial overlap. Please see Table 1 for information on level of visitation density.

Table 3
Conditional density among continuous biodiversity features and visitation density. High conditional density indicates a strong causal relationship between two aspects.

	Level of visitation density					
	1	2	3	4	5	6
B_DIVERSITY	0.19	1.02	0.50	1.76	0	2.38
SHDI	1.56	2.25	1.30	2.50	1.20	2.20
BIRD_n	0.38	4.72	0	3.86	0	9.50
PA_area	6.08	5.13	0.36	5.0	0	12.0
PASS_YR	488.38	25.0	38.40	29.86	46.0	15.0

B_DIVERSITY: diversity of bird species; SHDI: Shannon diversity index in landscape scale; BIRD_n: number of endangered bird species; PA_area: size of protected area; PASS_YR: elapsed year after the designation as protected area.

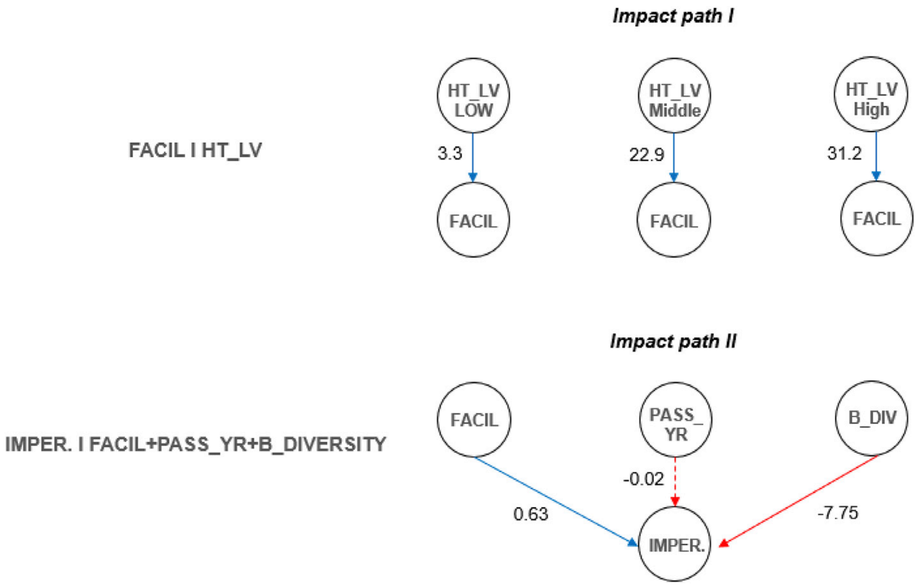


Fig. 6. Impact pathways on artifacts in PAs. Identified conditional densities based on the number of facilities and impervious rate are indicated. Numeric values indicate the degree of conditional density. Red indicates negative causality and blue indicates positive causality between two nodes. The solid line indicates a strong relationship (conditional density > 0.25) and the dotted line indicates a weak relationship (conditional density≤0.25).HT_LV: level of visitation density; IMPER.: percentage of impervious area; FACIL: number of facilities; B_DIVERSITY: diversity of bird species. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

In the upper 20% of visited areas and statistically clustered visitation areas in Jeju, we identified 133 visitation hotspots in PAs (Fig. 2). For the identified hotspots in PAs, we also determined the levels of visitation density to specify areas with relatively high visitation (Table 1). Approximately half of the 66 evaluated PAs were shown to contain visitation hotspots. This result was in accordance with the annual Jeju visitation survey in 2014, which noted that the majority of tourists visited Jeju for scenic beauty (domestic: 47.9%, foreign: 63.3%; Jeju Tourism Organization, https://ijto.or.kr). This survey also indicated that the major tourist attractions in Jeju are natural resources rather than other tourism resources (domestic: 50.2%, foreign: 39.7%; Jeju Tourism Organization). Moreover, we showed that visitation seasonality was generally low in PAs compared to non-PAs, but there were locations with high seasonality in areas within PAs (Fig. 3).

To promote sustainable tourism and conserve natural resources, policy makers need information on the status of supply and demand for nature-based tourism (Arkema et al., 2014; Fisher et al., 2019). As this study showed, the basic step for this requirement is to discern the spatial distribution of visitation density (Önder, 2017). We confirmed that mobile phone data and the methodology described herein can be used to identify the specific areas of PAs that have notable visitation density. Such information can be used to identify prioritized areas that require strict monitoring of carrying capacity.

In regard to field-based surveys, identified visitation density can be jointly applied to increase the effectiveness of PA management. Although visitor counts based on field surveys can generally be carried out for a limited number of visitors compared to mobile phone information, they can be further applied to attest the credibility of mobile phone information (Wood et al., 2013; Kim et al., 2019; Schägner et al., 2017). Moreover, since field-based surveys have the advantage of configuring a perspective-based evaluation that measures visitation satisfaction or reason for visitation, there is a need to coordinate both field-based and mobile phone-based approach (Kim et al., 2019). By applying the two approaches, various perceptions of nature-based tourism can be considered in the management of PAs within the identified visitation density and frequently visited hotspots.

4.2. Spatial trade-off between biodiversity features and visitation density

Considering the data availability in the region, we applied the maximum available number of biodiversity attributes, including IUCN management category; number of endangered bird species; bird species diversity; the size of each PA; Shannon diversity at the landscape level; the average age of forest trees; the number of artifacts, considering impervious areas and the number of facilities; and the years elapsed since designation as a PA. Aspects of biodiversity showing strong causal relationships with high visitation were identified using a BN (Fig. 4). These results indicated that the number of endangered bird species, bird species diversity, and the size of each PA, showed the highest causal relationships with areas showing high visitation density (Table 3). This confirmed that people tended to visit the area within PAs that contain the highest levels of biodiversity. However, matureness or intactness, reflected in the number of years elapsed since designation as a PA; the average age of the trees; and the IUCN management category, were not clearly associated with a higher number of visitors (Table 3, Fig. 5). For instance, in the case of IUCN management categories, hotspots with a large number of visitors (LV 4~LV 6) were shown to be generally located in category IV, V, and VI areas, whereas PAs in IUCN category I showed a lower association with frequently visited hotspots. Meanwhile, the results showed that the number of facilities was directly related to the distribution of medium and high levels of visitors, but the percentage of impervious areas showed an indirect relationship with visitation density (Fig. 6). As there was no clear positive relationship between the location of supporting artifacts and biodiversity features, we pose that biodiversity itself had spatial causality with visitation patterns.

Overall, these results showed that the number of bird species in particular exhibited a causal relationship with visitation density. Increasing the number of species can be a fundamental purpose of biodiversity conservation (Mace et al., 2012). Hence, attentive monitoring of bird habitats, particularly those located in IUCN management category IV, V, and VI areas, is necessary to avoid potential conflicts between nature-based tourism and conservation needs. To maintain sustainable tourism, the promotion of the importance of conservation, sustainable tourism activities, voluntary services to preserve intactness, and frequent monitoring are required (Lozano-Oyola et al., 2012). Furthermore, to maintain the intactness of natural areas, holistic measures such as "telecoupling" (socioeconomic and environmental interactions over distances) should be considered, especially for frequently visited PAs with a high level of species diversity (Chung et al., 2018; Liu et al., 2013). Information regarding such spatial trade-offs can potentially be used to help allocate management resources and focus attention on various biodiversity attributes.

4.3. Limitations and next steps

This study applied mobile phone data from visitors coming from outside of Jeju to distinguish between non-tourists and tourists. However, this study cannot confirm that all such data came only from tourists. Furthermore, mobile phone data is limited in that it cannot provide the actual number of visitors. Hence, merging mobile phone data with data from other sources, such as social media platforms, Twitter and Flickr, may be helpful in increasing the accuracy of these analyses (Fisher et al., 2019; Kim et al., 2019). Moreover, to discern the spatial trade-off relationship between tourism and biodiversity, the inclusion of additional biodiversity elements can offer more specific information on monitoring needs and identify specific troublesome locations. This will support the identification of specific flora and fauna that require prioritized management.

Although such limitations exist, this study provided an innovative methodology to discern the intersection and underlying causal linkages of two ecosystem services, tourism and biodiversity. Our methodology can also be implemented to analyze more specific attributes of cultural ecosystem services such as recreational activities, aesthetics, and spiritual and religious offerings. Information on spatial trade-offs can facilitate the development of prioritized management agendas to inform stakeholders and policy makers to not only conserve biodiversity, but also promote sustainable tourism (Allen, 2015).

5. Conclusions

The demand for nature-based tourism is increasing globally, but there are limited attempts to monitor spatial visitation patterns in PAs and apply these data to biodiversity management. To maintain sustainability in PAs, information regarding tourists' visiting characteristics and their relationship with various aspects of biodiversity is required. Since it was not possible to analyze the spatial patterns of visitors due to limited available field data, this study confirmed the applicability of mobile phone data for evaluating tourism in PAs and gathering insights into potential tourism-biodiversity conflicts. Among the biodiversity attributes evaluated, biodiversity at the species level showed a particularly strong spatial association with frequently visited areas. However, there was a weak association between visitation density and the maturity of the PA. The methodology described in this study can also be applied to other PAs with a high density of tourist visitation. Such efforts to monitor nature-based tourism in PAs can lead to appropriate biodiversity management by offering information regarding the trade-off between biodiversity and tourism.

Acknowledgements

We thank Korea Coast Guard and Ministry of Oceans and Fisheries (KR) for supporting the funding of this research (KCG-01-2017-05: Marine oil spill risk assessment and development of response support system through Big Data analysis, 20170325: Marine ecosystem-based analysis and decision-making support system development for marine spatial planning). We also thank Korea Environment Institute (KEI) for supporting this article through the project 'Planning and operation of support programs for the implementation of the Convention on Biological Diversity'.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gecco.2019.e00899.

References

Allen, K.E., 2015. Trade-offs in nature tourism: contrasting parcel-level decisions with landscape conservation planning. Ecol. Soc. 20, 21. https://doi.org/10.5751/ES-07058-200121.
Arkema, K.K., Verutes, G., Bernhardt, J.R., Clarke, C., Rosado, S., Canto, M., Wood, S.A., Ruckelshaus, M., Rosenthal, A., McField, M., de Zegher, J., 2014. Assessing habitat risk from human activities to inform coastal and marine spatial planning: a demonstration in Belize. Environ. Res. Lett. 9, 114016. https://doi.org/10.1088/1748-9326/9/11/114016.
Balmford, A., Beresford, J., Green, J., Naidoo, R., Walpole, M., Manica, A., 2009. A global perspective on trends in nature-based tourism. PLoS Biol. 7 e1000144.
Barton, D.N., Kuikka, S., Varis, O., Uusitalo, L., Henriksen, J., Borsuk, M., Hera, A. De, Farmani, R., Johnson, S., Dc, J., 2012. Bayesian networks in environmental and resource management. IEAM 8, 418–429. https://doi.org/10.1002/ieam.1327.
Bennett, E.M., Peterson, G.D., Gordon, L.J., 2009. Understanding relationships among multiple ecosystem services. Ecol. Lett. 12, 1394–1404.
Brandt, J., Tress, B., Tress, G., 2000. Multifunctional Landscapes: Interdisciplinary Approaches to Landscape Research and Management. In: Conference material for the conference on "multifunctional landscapes", Centre for Landscape Research, Roskilde October 18-21, 2000. Centre for Landscale Research, Roskilde, pp. 1–264.
Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.
CBD (Convention of Biological Diversity), 2016. CBD/COP/DEC/XIII/3. https://www.cbd.int/decisions/cop/?m=cop-13. (Accessed 12 November 2018).
Christiansen, F., Rasmussen, M.H., Lusseau, D., 2013. Inferring activity budgets in wild animals to estimate the consequences of disturbances. Behav. Ecol. 24, 1415–1425.
Chung, M.G., Dietz, T., Liu, J., 2018. Global relationships between biodiversity and nature-based tourism in protected areas. Ecosyst. Serv. 34, 11–23.
Cord, A.F., Bartkowski, B., Beckmann, M., Dittrich, A., Hermans-Neumann, K., Kaim, A., Lienhoop, N., Locher-Krause, K., Priess, J., Schröter-Schlaack, C., 2017. Towards systematic analyses of ecosystem service trade-offs and synergies: main concepts, methods and the road ahead. Ecosyst. Serv. 28, 264–272.
Creech, T.G., Williamson, M.A., 2019. Ecological and sociopolitical assessment of congressional and presidential designation of federal protected areas. Ecol. Appl. 29 e01888.
Dudley, N., 2008. Guidelines for Applying Protected Area Management Categories. Gland, Switzerland.
Fernandez-Morales, A., 2003. Decomposing seasonal concentration. Ann. Tourism Res. 30, 942–956.
Filby, N.E., Stockin, K.A., Scarpaci, C., 2014. Long-term responses of Burrunan dolphins (Tursiops australis) to swim-with dolphin tourism in Port Phillip Bay, Victoria, Australia: a population at risk. Glob. Ecol. Conserv. 2, 62–71. https://doi.org/10.1016/j.gecco.2014.08.006.
Fisher, D.M., Wood, S.A., Roh, Y.-H., Kim, C.-K., 2019. The geographic spread and preferences of tourists revealed by user-generated information on Jeju island, South Korea. Land 8, 73.
Gaston, K.J., Biodiversity, A., 1996. A Biology of Numbers and Difference. London, UK.
Getis, A., Ord, J.K., 1996. Local spatial statistics: an overview. Spat. Anal. Model. GIS Environ. 374, 261–277.
Gonzalez-Redin, J., Luque, S., Poggio, L., Smith, R., Gimona, A., 2016. Spatial Bayesian belief networks as a planning decision tool for mapping ecosystem services trade-offs on forested landscapes. Environ. Res. 144, 15–26.
Hadwen, W.L., Hill, W., Pickering, C.M., 2007. Icons under threat: why monitoring visitors and their ecological impacts in protected areas matters. Ecol. Manag. Restor. 8, 177–181. https://doi.org/10.1111/j.1442-8903.2007.00364.x.
Hall, C.M., 2010. Tourism and the implementation of the convention on biological diversity. J. Herit. Tour. 5, 267–284.
Hanson, S., 1980. Spatial diversification and multipurpose travel: implications for choice theory. Geogr. Anal. 12, 245–257.
Heberling, M.T., Templeton, J.J., 2009. Estimating the economic value of national parks with count data models using on-site, secondary data: the case of the Great Sand Dunes National Park and Preserve. Environ. Manag. 43, 619–627.
Heikinheimo, V., Minin, E. Di, Tenkanen, H., Hausmann, A., Erkkonen, J., Toivonen, T., 2017. User-generated geographic information for visitor monitoring in a national park: a comparison of social media data and visitor survey. ISPRS Int. J. Geo-Inf. 6, 85.
Kim, Y., Kim, C. ki, Lee, D.K., Lee, H. woo, Andrada, R.I.T., 2019. Quantifying nature-based tourism in protected areas in developing countries by using social big data. Tour. Manag. 72, 249–256. https://doi.org/10.1016/j.tourman.2018.12.005.
Kurniawan, F., Adrianto, L., Bengen, D.G., Prasetyo, L.B., 2016. Vulnerability assessment of small islands to tourism: the case of the marine tourism park of the gili matra islands, Indonesia. Glob. Ecol. Conserv. 6, 308–326. https://doi.org/10.1016/j.gecco.2016.04.001.
Lee, W.K., Sohn, S.Y., Heo, J., 2018. Utilizing mobile phone-based floating population data to measure the spatial accessibility to public transit. Appl. Geogr. 92, 123–130. https://doi.org/10.1016/j.apgeog.2018.02.003.
Lester, S.E., Costello, C., Halpern, B.S., Gaines, S.D., White, C., Barth, J.A., 2013. Evaluating tradeoffs among ecosystem services to inform marine spatial planning. Mar. Policy 38, 80–89. https://doi.org/10.1016/j.marpol.2012.05.022.
Liu, J.Q., Hull, V., Batistella, M., DeFries, R., Dietz, T., Fu, F., Hertel, T.W., Izaurralde, R.C., Lambin, E.F., Li, S., 2013. Framing sustainability in a telecoupled world. Ecol. Soc. 18, 26.
Lozano-Oyola, M., Blancas, F.J., González, M., Caballero, R., 2012. Sustainable tourism indicators as planning tools in cultural destinations. Ecol. Indicat. 18, 659–675.
Mace, G.M., Norris, K., Fitter, A.H., 2012. Biodiversity and ecosystem services: a multilayered relationship. Trends Ecol. Evol. 27, 19–26. https://doi.org/10.1016/j.tree.2011.08.006.
Magurran, A.E., 2013. Measuring Biological Diversity. John Wiley & Sons, UK.
Manning, R.E., Anderson, L.E., Pettengill, P., 2017. Managing Outdoor Recreation: Case Studies in the National Parks. CABI, UK.
Marcot, B.G., Holthausen, R.S., Raphael, M.G., Rowland, M.M., Wisdom, M.J., 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. For. Ecol. Manage. 153, 29–42.
Mccann, R.K., Marcot, B.G., Ellis, R., 2006. Bayesian belief networks : applications in ecology and natural resource management. Can. J. For. Res. 36, 3053–3062.
McGarigal, K., Cushman, S.A., Neel, M.C., Ene, E., 2002. Spatial pattern analysis program for categorical maps. https://www.umass.edu/landeco/research/fragstats/fragstats.html. (Accessed 10 January 2019).

Millennium Ecosystem Assessment, 2005. Millennium Ecosystem Assessment. Ecosyst. Hum. Wellbeing a Framew. Assess. Isl. Press, Washington DC.
Muñoz, L., Hausner, V., Brown, G., Runge, C., Fauchald, P., 2019. Identifying spatial overlap in the values of locals, domestic- and international tourists to protected areas. Tour. Manag. 71, 259–271. https://doi.org/10.1016/j.tourman.2018.07.015.
Nordling, J., Potapov, P., Harris, N.L., Goldman, E., Ansari, S., Gabris, C., Bennett, L., Minnemeyer, S., Hansen, M., Lippmann, M., Raad, M., 2017. Using spatial statistics to identify emerging hot spots of forest loss. Environ. Res. Lett. 12 https://doi.org/10.1088/1748-9326/aa5a2f, 024012.
Nyberg, J.B., Marcot, B.G., Sulyma, R., 2006. Using Bayesian belief networks in adaptive management. Can. J. For. Res. 36, 3104–3116.
Önder, I., 2017. Classifying multi-destination trips in Austria with big data. Tour. Manag. Perspect. 21, 54–58. https://doi.org/10.1016/j.tmp.2016.11.002.
Peeters, P., Szimba, E., Duijnisveld, M., 2007. Major environmental impacts of European tourist transport. J. Transp. Geogr. 15, 83–93.
Pérez-Jorge, S., Louzao, M., Oro, D., Pereira, T., Corne, C., Wijtten, Z., Gomes, I., Wambua, J., Christiansen, F., 2017. Estimating the cumulative effects of the nature-based tourism in a coastal dolphin population from southern Kenya. Deep. Res. Part II Top. Stud. Oceanogr. 140, 278–289. https://doi.org/10.1016/j.dsr2.2016.08.011.
Pérez-Miñana, E., 2016. Improving ecosystem services modelling: insights from a Bayesian network tools review. Environ. Model. Softw 85, 184–201.
Ploetz, T., Smoreda, Z., 2017. Exploring the use of mobile phone data for domestic tourism trip analysis. NETCOM 31–3/4, 335–372. https://doi.org/10.4000/netcom.2742.
Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. Biol. Sci. 365, 2959–2971.
Qiu, J., Turner, M.G., 2013. Spatial interactions among ecosystem services in an urbanizing agricultural watershed. Proc. Natl. Acad. Sci. 110, 12149–12154.
Ranaweerage, E., Ranjeewa, A.D.G., Sugimoto, K., 2015. Tourism-induced disturbance of wildlife in protected areas: a case study of free ranging elephants in Sri Lanka. Glob. Ecol. Conserv. 4, 625–631. https://doi.org/10.1016/j.gecco.2015.10.013.
RStudio Team, 2016. RStudio. Integrated development environment for R, Boston, Massachusetts.
Salas-Olmedo, M.H., Moya-Gómez, B., García-Palomares, J.C., Gutiérrez, J., 2018. Tourists' digital footprint in cities: comparing Big Data sources. Tour. Manag. 66, 13–25. https://doi.org/10.1016/j.tourman.2017.11.001.
Santini, L., Belmaker, J., Costello, M.J., Pereira, H.M., Rossberg, A.G., Schipper, A.M., Ceaușu, S., Dornelas, M., Hilbers, J.P., Hortal, J., 2017. Assessing the suitability of diversity metrics to detect biodiversity change. Biol. Conserv. 213, 341–350.
Schaaf, T., Rodrigues, D.C., 2016. Managing MIDAs: Harmonising the Management of Multi-Internationnaly Designated Areas: Ramsar Sites, World Heritage Sites. Biosphere Reserves and UNESCO Global Geoparks. Gland, Switzerland.
Schägner, J.P., Maes, J., Brander, L., Paracchini, M.L., Hartje, V., Dubois, G., 2017. Monitoring recreation across European nature areas: a geo-database of visitor counts, a review of literature and a call for a visitor counting reporting standard. J. Outdoor Recreat. Tour. 18, 44–55. https://doi.org/10.1016/j.jort.2017.02.004.
Scutari, M., 2009. Learning Bayesian Networks with the Bnlearn R Package VV arXiv preprint arXiv:0908.3817.
Seo, J.H., Park, S.Y., Yu, L., 2009. The analysis of the relationships of Korean outbound tourism demand: Jeju Island and three international destinations. Tour. Manag 30, 530–543. https://doi.org/10.1016/j.tourman.2008.10.013.
Sessions, C., Wood, S.A., Rabotyagov, S., Fisher, D.M., 2016. Measuring recreational visitation at US National Parks with crowd-sourced photographs. J. Environ. Manag. 183, 703–711.
Socolar, J.B., Gilroy, J.J., Kunin, W.E., Edwards, D.P., 2016. How should beta-diversity inform biodiversity Conservation ? Trends Ecol. Evol. 31, 67–80. https://doi.org/10.1016/j.tree.2015.11.005.
Spellerberg, I.F., Ecology, G., Article, O., Zealand, N., 2003. A tribute to Claude Shannon (1916–2001) and a plea for more rigorous use of species richness, species diversity and the 'Shannon–Wiener'Index. Glob. Ecol. Biogeogr. 12, 177–179. https://doi.org/10.1046/j.1466-822X.2003.00015.x.
Steven, R., Castley, J.G., Buckley, R., 2013. Tourism revenue as a conservation tool for threatened birds in protected areas. PLoS One 8 e62598.
Vallet, A., Locatelli, B., Levrel, H., Wunder, S., Seppelt, R., Scholes, R.J., Oszwald, J., 2018. Relationships between ecosystem services: comparing methods for assessing tradeoffs and synergies. Ecol. Econ. 150, 96–106. https://doi.org/10.1016/j.ecolecon.2018.04.002.
Viglizzo, E.F., Frank, F.C., 2006. Land-use options for Del Plata Basin in South America: tradeoffs analysis based on ecosystem service provision. Ecol. Econ. 57, 140–151.
Wang, J., Peng, J., Zhao, M., Liu, Y., Chen, Y., 2017. Significant trade-off for the impact of grain-for-green programme on ecosystem services in north-western yunnan, China. Sci. Total Environ. 574, 57–64.
Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. Sci. Rep. 3, 2976. https://doi.org/10.1038/srep02976.
Xu, Y., Shaw, S.L., Zhao, Z., Yin, L., Lu, F., Chen, J., Fang, Z., Li, Q., 2016. Another tale of two cities: understanding human activity space using actively tracked cellphone location data. Ann. Assoc. Am. Geogr. 106, 489–502. https://doi.org/10.1080/00045608.2015.1120147.
Yang, W., Yang, Z., 2014. Integrating ecosystem-service tradeoffs into environmental flows decisions for Baiyangdian Lake. Ecol. Eng. 71, 539–550. https://doi.org/10.1016/j.ecoleng.2014.07.065.
Ziegler, J.A., Silberg, J.N., Araujo, G., Labaja, J., Ponzo, A., Rollins, R., Dearden, P., 2019. Applying the precautionary principle when feeding an endangered species for marine tourism. Tour. Manag. 72, 155–158.