Mobile phone network data reveal nationwide economic value of coastal tourism under climate change

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ABSTRACT
The technology-driven application of big data is expected to assist policymaking towards sustainable development; however, the relevant literature has not addressed human welfare under climate change, which limits the understanding of climate change impacts on human societies. We present the first application of unique mobile phone network data to evaluate the current nation-wide human welfare of coastal tourism at Japanese beaches and project the value change using the four climate change scenarios. The results show that the projected national economic value loss rates are more significant than the projected national physical beach loss rates. Our findings demonstrate regional differences in recreational values: most southern beaches with larger current values would disappear, while the current small values of the northern beaches would remain. These changes imply that the ranks of the beaches, based on economic values, would enable policymakers to discuss management priorities under climate change.

1. Introduction

Climate change adaptation is essential for sustainable development (Sanchez Rodríguez, Úrge-Vorsatz, & Barau, 2018; Scott & Becken, 2010); however, limited fine-grained projection of impacts on human societies has prevented adaptation policymaking (Ford et al., 2016). The recent development of new technologies to collect large volume, variety, and velocity of data streams—big data—has substantial potential to enhance climate change adaptation (Faghmous & Kumar, 2014; Ford et al., 2016; Illiiva & McPhearson, 2018; Jagadish, 2015). Historically, climate change literature has utilized big data to understand climate systems and dynamics (Faghmous & Kumar, 2014; Manogaran & Lopez, 2018); however, big data applications that address human dimensions in the light of climate change have been limited (Ford et al., 2016). A series of critical studies used Twitter data to demonstrate the polarized perceptions concerning climate change, and the spatiotemporal differences in opinions (Jang & Hart, 2015; Kirilenko & Stepchenkova, 2014; Roxburgh et al., 2019). Lu and his colleagues also utilized activated records of mobile phones, that is, calls, text messages, and data downloads, to identify human migration and mobility patterns driven by climate-related impacts in Bangladesh (Lu et al., 2016). Those findings provided new insight into human attitudes and behaviours concerning climate change at fine spatiotemporal scales; however, they have been overrated as per active mobile phone usage in terms of times and spaces, since such data sources depend heavily on people’s active behaviours such as tweets and calls. However, few monetary evaluations of human welfare using big data have been documented, which could hinder discussions of policy priorities within resource constraints (Woodruff & Stults, 2016).

By using unique mobile phone network data, together with overcoming the above challenges, a monetary evaluation of current and future fine-grained human welfare associated with coastal tourism at the national scale in Japan is first undertaken by combining a traditional valuation method with beach loss projections under climate change. Recent climate policies require alignment of local adaptation measures with global mitigation efforts by policymakers (Rogelj et al., 2016; Swart & Raes, 2007) to consider priority settings across the nation, especially within resource constraints. Thus, the monetary evaluation of
human welfare of unpriced services supports policy decision-making by providing a standardized objective basis (Bateman et al., 2013; Strand et al., 2018). Among a variety of ecosystem services, coastal tourism is an ideal example for the application of the approach presented in this study, since tourism provides substantial benefits to people; however, it is one of the services that are the most vulnerable to climate change, primarily because of sea level rise (SLR) (Nicholls & Cazenave, 2010).

Japan is geographically diverse from north to south and is composed of a variety of islands; thus, it provides not only unique biodiversity but also substantial ecosystem services (Fujikura, Lindsay, Kitazato, Nishida, & Shirayama, 2016; Fukumoto, 1989; Kuniki, 2012; Yamamoto et al., 2017). In Japan, coastal tourism as represented by bathing beaches has been historically recognized for over 100 years, and about a hundred million people enjoy coastal tourism annually over a thousand beaches across Japan (Oguchi, 1985). In recent years, the Japanese coastal ecosystem — which is the backbone of coastal tourism — has been facing the risk of climate change impacts (Kumagai et al., 2018), corresponding to the global phenomenon (IPCC, 2018; Nicholls & Cazenave, 2010). Japan was regarded as a roughly medium-ranked country concerning vulnerability of beach tourism (Perch-Nielsen, 2010). However, despite the apparent necessity of climate change adaptation in coastal tourism, there has been minimal research on coastal tourism in Japan (Andrea Ghermandi & Nunes, 2013; Kato & Horia, 2018). In particular, coarse-scale analysis has failed to discuss priority settings.

Here, to evaluate the current human welfare of coastal tourism and project the economic value under climate change, we integrate unique mobile phone network data into a traditional travel cost method (TCM) (Freeman III, Herriges, & Kling, 2014; Parsons, 2017). The data comprise statistics of the estimated population in each 500-square-metre grid and rarely depend on mobile phone users’ intentions since the statistics are derived from hourly operational data (Terada, Nagata, & Kobayashi, 2013). The high spatiotemporal evaluations with standardized measures are acknowledged to provide a nationwide seasonal comparison of coastal tourism values across Japan — that is, 536 beaches in summer and winter (Fig. 1A; for details, see Appendix Table 1) — and enable integration of the estimated values with spatial projections of climate change-driven beach loss (Udo & Takeda, 2017). The data contain information on phone users’ designated residential areas; this key feature helps to uncover human welfare in monetary terms based on consumer theory (Freeman III et al., 2014; Parsons, 2017). Using all the estimates across Japan, as provided in Appendix Table 2, the projection values can be updated when highly reliable climate change-driven environmental data are available and contribute to adaptation policymaking.

1.1. Big data application in tourism

The technology-driven application of big data has received significant attention in tourism. A recent review article categorized the relevant tourism literature into three categories by significant data sources: user-generated data, device-generated data, and transaction data (Li, Xu, Tang, Wang, & Li, 2018). The article found that almost half of the existing literature used user-generated data, including social media and crowdsourced data. In particular, in the context of nature-based tourism, most existing literature used social media and crowdsourced data. Wood, Guerry, Silver, and Lacayo (2013), for example, estimated visitation rates at global recreational sites by using Flickr photo data and found that the data provided a good proxy for empirical visitation rate. Tenkanen et al. (2017) used Instagram and Twitter in addition to Flickr and implied that social media activity was highly associated with park popularity; however, they found differences between social media types, which highlights importance of careful considerations to apply such data for visitor monitoring. These findings suggest that applications of social media and crowdsourced data contribute to development of new visitor monitoring systems in recreational sites. Also, applications of the data can contribute to better understanding of tourists’ interests and preferences. Kim, Kim, Lee, Lee, and Andrade (2019) identified spatial visitation patterns in ASEAN Heritage Parks and explored tourism attractions by using Flickr data. A. Hausmann et al. (2017) used Instagram in an attempt to understand the factors that would attract tourists to protected areas and then reported that charismatic species were not the main attractors in African countries. Yoshimura and Hiura (2017) used Maximum Entropy Modeling Software (MaxEnt) with geotagged photos on Flickr to understand the current landscape values and potential supply of ecosystem services. van Zanten et al. (2016) quantified landscape values across Europe using three social media platforms: Flickr, Instagram, and Panoramio. Anna Hausmann et al. (2018) compared the findings from both Flickr and Instagram and a traditional survey (face-to-face interviews); consequently, they noted that using social media could be a reliable alternative to a traditional survey to understand tourists’ preferences for biodiversity.

Whereas, despite the importance of revealing non-monetary value concerning nature-based tourism to support policymaking, there have been only a few studies exploring the value by employing big data. Flickr geotagged photos were applied to travel cost methods to estimate recreational values in lakes and wetlands (A. Ghermandi, 2018; Keeler et al., 2015; Sinclair, Ghermandi, & Sheela, 2018). Both Keeler et al. (2015) and Sinclair et al. (2018) discussed how improvement in water quality would affect recreational demand in lakes and wetlands. A. Ghermandi (2018) compared estimated recreational benefits with management costs at 74 wetlands. In addition to literature using Flickr data, Kolstoe and Cameron (2017) explored bird watching value using a special online database of bird observation, eBird, developed by Cornell University. Using the rich data set concerning bird watching, they identified willingness to pay of birders for an additional bird species by season. Furthermore, although findings were different from non-monetary value, previous literature attempted to understand value concerning nature-based tourism at conserved lands in Vermont, USA, and coral reef tourism value worldwide by combining Flickr data with tourists’ expenditures (Sontor, Watson, Wood, & Ricketts, 2016; Spalding et al., 2017).

As described above, to the best of our knowledge, literature using big data has limited to applications of social media and crowdsourced data, especially Flickr. Thus, there have been still significant challenges driven by data sources (e.g. sampling bias), as is the case in other tourism and recreation studies (Chua, Servillo, Marcheggiani, & Moere, 2016; Andrea; Ghermandi & Sinclair, 2019; Li et al., 2018). The present study first integrates mobile phone network data into a valuation method. Based on recent review (Li et al., 2018), research using mobile network and roaming data accounted for four percent even in tourism literature, and no studies have applied such data to understand recreational values. Thus, this study tackles the challenges in and contributes to existing knowledge on both tourism and valuation methods in the context of climate change adaptation.

2. Material and methods

2.1. Mobile phone network data

The present study applied mobile phone network data to estimate coastal tourism values associated with coastal beaches across Japan and projected the tourism values under climate change by integrating climate change scenarios. The data were provided by NTT DOCOMO, which is Japan’s leading mobile phone company (Terada et al., 2013). The company had an approximate 45% market share in the 2015 financial year (FY), as reported by the Ministry of Internal Affairs and Communications (MIC). These data represent the estimated population, based on the mobile phone users in each grid (minimum 500-square metres) across Japan, while considering the market share (Terada et al., 2013); thus, it is called Mobile Spatial Statistics (MSS). The data are derived from the operational data of the mobile phone network on an
hourly basis and contain information about the sex, age, and residential area of users. Note that the researchers were only allowed to access the aggregated data in each grid to protect personal privacy; that is, the accessible information was generally limited to the number of users in each grid by hour, and it was not possible to access any individual’s information. In consideration of user privacy, the company also deleted information related to grids with fewer than 10 people. Interested readers are referred to Technology Reports by the company for a more detailed overview of MSS (Okajima, Tanaka, Terada, Ikeda, & Nagata, 2013; Terada et al., 2013). Although the company has applied their data to urban planning in limited instances (Makita, Kimura, Terada, Kobayashi, & Oyabu, 2015; Nagata, Aoyagi, & Kawakami, 2015; Oda- warna & Kawakami, 2015), no studies have attempted to estimate human welfare and economic values.

The present study not only conducted a large-scale assessment but also investigated seasonal differences in tourism values. The authors believe that addressing this knowledge gap enables the identification of seasonal tourism, such as beach bathing, and discussion of management priorities over seasonality. The procedure described in Fig. 1A was used to select 536 beaches all over Japan from the database managed by the Ministry of the Environment (MOE), Government of Japan (https://water-pub.env.go.jp/water-pub/mizu-site/mizu/suiyoku/dataMap.asp).

Two representative time points were first selected from the same fiscal year to estimate coastal tourism in both summer and winter: 13:00 on August 2 (Sunday) in 2015 and 13:00 on January 31 (Sunday) in 2016. To control the impacts of weather and special holidays (e.g. new year) on welfare, Sundays with sunny weather at most Japanese beaches were chosen. Each data point is associated with a 500-square-metre grid for which user information exists, although only aggregated numbers are accessible in consideration of users’ privacy. In this step, the data of whole coastal lines across Japan, considering mobile phone coverage, were included. Then, the data were superimposed on the map of bathing areas in Japan, obtained from the MOE. The process allowed 536 beaches in Japan to be chosen, although the estimation procedure decreased the number of available sites (i.e. applicable sites for TCM) as described in the section Travel cost method. As confirmation, eight adjacent grids were investigated to determine whether there was a mismatch between the selected grid and the actual beach in terms of spatial location; data (grid) were replaced with appropriate data if there were discrepancies. When no appropriate grids were found in the nine grids (e.g. the largest part of the grid was comprised of residential areas), beaches were eliminated from the present research sites.

2.2. Data overview

An overview can be provided of coastal visitors to the 536 beaches, derived from the mobile phone network data pertaining to beaches. The distribution of the average distance of beach users from each beach in summer has a relatively long tail and is more right-skewed, compared to that in winter. The average and median distances in summer are 60.6 and 35.5 km, respectively (SD 160.3); in winter, these values are 23.3 and 12.5 km, respectively (SD 83.3). The summer distribution of the residences of users visiting each beach also has a relatively long tail and is more right-skewed compared to the winter distribution. The average number of cities is 4.0 (SD 8.4) in summer and 1.7 (SD 3.8) in winter. Finally, the summer distribution of the number of users of each beach has a relatively long tail and a more right-skewed shape compared to winter. The average and the median number of users in summer are 194.5 and 79, respectively (SD 386.9), and 120.9 and 48 (SD 244.4), respectively, in winter. The above statistics suggest that human welfare associated with beach recreation in summer tends to be higher than that in winter.

2.3. Travel cost method

This study applied zonal TCM to the above data to estimate the human welfare associated with coastal tourism. Zonal TCM is one of the traditional TCMs for estimating tourism values based on revealed behaviour (Bockstael & McConnell, 2007; Parsons, 2017), and it is still applied continuously to the context of ecosystem services and natural resource management (Jones, Yang, & Yamamoto, 2017; Mayer & Woltering, 2018). However, there have been few applications of big data to TCM, even though the model is more compatible with big data because of its significant advantage of only requiring aggregated data to estimate the tourism values, thereby limiting the extent to which researchers infringe upon peoples’ privacy (Parsons, 2017).

Zonal TCM estimates tourists’ and recreationists’ consumer surplus (CS), which is one of the most common welfare measures in economics (Freeman III et al., 2014), using a demand function derived from the analysis of the relationship between the travel costs incurred to access a recreational site and the visitation rates. The CS is a monetary measure that is defined as the difference between the total amount that visitors are willing to pay for specific goods or services and the total amount that they actually pay. Here, the visitation rate is defined as the ratio of the number of visitors from each city to each recreational zone, divided by the population of each city, which refers to the database organized by the Statistics Bureau of Japan (SBJ: http://www.stat.go.jp/data/jinshu/1/) in the same fiscal year as the MSS.

The travel costs for a round trip were calculated by considering both fuel costs to travel by car and opportunity costs (Adamowicz & Graham-Tomasi, 1991; Freeman III et al., 2014; Mayer & Woltering, 2018; Zhang, Wang, Nunes, & Ma, 2015). The fuel cost calculation was based on the distances between the beaches and visitors’ residences, fuel efficiency, and gas costs. Note that researchers have access to the information on the ratio of visitors’ residential areas in each grid. The distance was calculated by the Open Source Routing Machine OSRM (OSRM: http://project-osrm.org/), which is an application that provides access to the Open Street Map database (Luxen & Vetter, 2011). To calculate the costs of traffic between islands, shipping routes were used and were multiplied by fuel costs in the same way as land routes. Here, both the average fuel efficiency (21.6 km/l) in FY 2015 published by the Ministry of Land, Infrastructure, Transport and Tourism and the average gas costs (1.413 and 1.134 USD/l in summer and winter, respectively) published by the Ministry of Economy, Trade, and Industry were used. As it is widely accepted (Cesario, 1976; Englin & Shonkwiler, 1995; Matthews, Scarpa, & Marsh, 2018; Parsons, 2017), one-third of the average wage of employed people (i.e. “Working households of two or more persons” reported in MIC: http://www.stat.go.jp/data/kakki/time/index.htm) was used to calculate the opportunity costs of travel time. Further, it was assumed that the average driving speed in Japan was 60 km/h to calculate the necessary time to reach each beach from each residential area.

In the estimations, the log of the visitation rate is the dependent variable, and the travel costs are the independent variables since one of the traditional functional forms of the travel cost was employed, and this was expressed as follows:

\[ LN(VR_{TC}) = a + \beta_{TC} \times Travel\ Cost \]

The employment of a semi-log model is attractive compared with other functional forms, in that the CS per trip per person is estimated from the regression as the negative inverse of the coefficient of the travel cost variable (\( \beta_{TC} \)) (Englin & Shonkwiler, 1995; Zhang et al., 2015). Through this regression process, the present study included 274 estimated values associated with coastal tourism (202 in summer and 72 in winter, presented in Fig. 1B; see also Supplementary materials Appendix Table 2 for more details).

Under the assumption that the daily visitor turnover is low, the authors calculated the coastal economic value per day at each beach by multiplying each estimated CS by the number of visitors in each mesh, 1

1 This paper has converted Japanese yen (JPY) at 100 to the dollar (USD).
2.4. The projections of climate change impacts on coastal values

To project the future economic values at each beach from the estimated current economic values, this study assumed that there were perfect correlations between the loss of coastal values and beach area. To simplify the approach and focus on the data advantage, the present study did not engage with discount rate challenges (Hanewinkel, Cullmann, Schelhaas, Nabuurs, & Zimmermann, 2012; Yamaguchi, 2019). It adopted the projected beach loss driven by SLR between 2081 and 2100, as calculated by Udo and Takeda (2017). To project beach loss for each Representative Concentration Pathway (RCP) scenario (RCP2.6, RCP4.5, RCP6.0, and RCP8.5), they applied the Bruun rule based on the width of each beach across Japan, and used ensemble-mean regional SLR projections using 21 CMIP5 models between 2081 and 2100, relative to the reference period 1986 to 2005 (IPCC, 2013). Although the above predictions have limitations (in part because of several assumptions (Cooper & Pilkey, 2004)), to date, no alternative studies have been conducted to predict future beach loss across Japan. Since the Japanese coastal lines were separated into 77 zones, this study identified the location of each beach in 77 zones and combined the loss rate of each beach with the estimated coastal values (see Appendix Table 1 for details; the published data concerning the 77 zones (Udo & Takeda, 2017) were provided by Dr. Udo). Note that the projected average national and regional beach value loss/remaining rates, as described in Figs. 3 and 4, were calculated using the projected economic values, according to the above process.

3. Results

3.1. Current human welfare and economic values of coastal beaches

Of the 536 potential beaches, the unique TCM detected 274 nationwide coastal tourism values in summer and winter — 202 and 72, respectively (Fig. 1B, see Supplementary materials Appendix Table 2 for more details) — since TCMs are not applicable to a recreational site with few visitors and/or small varieties in visitors’ residences. Thus, seasonal differences in the available sites partially reflect the seasonality of coastal recreational use. Since the estimated human welfare (i.e., consumer surplus $CS$) implies a monetary value per visit per person at each beach, there are substantial spatial-seasonal disparities across Japan (Fig. 2). In addition to those disparities, the mean and median human welfare is 28.23 USD and 8.7 USD, respectively, in summer; the winter values are 10.04 USD and 1.92 USD, respectively.

The economic value at each site is calculated by using the estimated welfare and the number of visitors, based on mobile phone network data. Coastal tourism values at each beach per day ranged between 48.65 USD and 361363.64 USD in summer and 16.84 USD to 198421.05 USD in winter, by assuming little visitor turnover per day at each beach. On average, the current economic coastal value in summer (12 thousand USD) was more than double the winter value (5 thousand USD).

3.2. Comparisons between projected physical loss and economic value loss

This study projected economic coastal tourism values under climate change by assuming that those coastal tourism values will be proportionally degraded in the future according to climate change-driven shoreline recession: that is, between 2081 and 2100 (Udo & Takeda, 2017). Compared to the current estimated economic values, the projected economic values are less than a quarter under the RCP2.6 scenario, and they become smaller as the climate scenarios worsen to reach less than one-tenth for the RCP8.5 in both seasons (Fig. 3). Interestingly, the value loss rates are substantially more significant than the physical loss rate (Udo & Takeda, 2017) on a national scale under the four climate change scenarios, when not only all available sites (Fig. 3A) but also corresponding (comparable) sites in summer and winter are considered (Fig. 3B).

3.3. Spatial gradient of change in beach economic values

This study provides further insights into the spatial gradients of the projected economic value loss by considering geographical features from north to south (Fukumoto, 1989). Fig. 4 shows the rate of the remained values by region under climate change compared to each
The findings show that the economic values of the southern region tend to disappear; however, those in the northern region would remain, although most regions would lose most economic values under the RCP8.5 scenario (Fig. 4). The value of the southernmost area (i.e. #11), for example, would completely disappear in all four climate change scenarios, whereas the value of the northernmost area in summer (i.e. #1) would remain — not only at over 50% in the RCP2.6 scenario but also at over 20% in the RCP8.5 scenario.

Fig. 3. The projected remaining physical and economic value rates compared to current situations in summer and winter under the four climate change scenarios. A-B, Comparison with all applicable sites (n = 202 and 72 in summer and winter, respectively (A)), and with consistent sites in summer and winter (n = 64 (B)). In comparison with current situations, the remaining economic value rates are smaller than the corresponding remaining physical rates of beach areas under the four climate change scenarios (RCP2.6, RCP4.5, RCP6.0, and RCP8.5); this implies that the higher-valued beaches have tended to disappear because of sea level rise (SLR).

Fig. 4. Regional comparison of remaining rates concerning economic values in summer and winter. The bar graphs for each region (Fukumoto, 1989) correspond to the remaining rates under the four climate change scenarios (RCP2.6, RCP4.5, RCP6.0, and RCP8.5). The values would decline in the southern region in the future; however, they would remain relatively similar in the northern region.
3.4. Changes in beach ranks based on economic values

Notably, such regional differences in climate change impact result in changes in beach ranks based on economic values. The changes in rank are demonstrated using the RCP2.6 and RCP8.5 scenarios (Fig. 5; see also Appendix Table 2 for each specific economic value). The economic values at southern beaches, which are reddish coloured, tend to disappear; however, the economic values at northern areas will relatively remain even under the RCP8.5 scenario, although most coastal values at beaches will shrink across Japan.

4. Discussion

Big data application is an emerging field in both tourism and climate change adaptation; however, limited applications in economic valuation prevent priority-setting decision-making based on fine-grained evaluations of ecosystem services.

Herein, the first integration of unique mobile phone network data with a traditional economic valuation approach, TCM, enables to estimate fine-scale human welfare and economic values associated with coastal beaches across Japan in summer and winter. The findings show that the present approach would become an alternative measure to the traditional costly and time-consuming valuation methods, since the estimated welfare in this study is of the same order of magnitude as that of previous literature in Japan and other countries (Blackwell, 2007; Ohno, Hayashiyama, Morisugi, & Nohara, 2009; Rolfe & Gregg, 2012; Zhang et al., 2015).

One of the objectives here is to identify the seasonality of human welfare concerning tourism. The unique approach shows that the average human welfare of coastal tourism in summer is roughly three times that of winter, although there is substantial spatial gradient of human welfare across the nation (Fig. 2). Despite the importance of seasonality in tourism management (Amelung, Nicholls, & Viner, 2007; Atzori, Fyall, & Miller, 2018), it remained a challenge to understand seasonality concerning human welfare because of the limited data availability (Mkwara, Marsh, & Scarpa, 2015). In particular, existing literature using mobile phone data has focused on seasonal changes in population (Ahas, Aasa, Mark, Pae, & Kull, 2007; Deville et al., 2014). Thus, this research contributes to the literature on seasonality in coastal tourism.

Furthermore, it should be emphasized that the above findings are derived from an objective approach in comparison with existing valuation and recent big data approaches (A. Ghermandi, 2018; Keeler et al., 2015; Kolstoe & Cameron, 2017; Parsons, 2017; Sinclair et al., 2018; van Zanten et al., 2016). That is, our estimates rarely rely on preferences of survey samples for participating research and survey efforts of researchers because of non-self-reported data. The advantage enables the identification of objectively spatial and seasonal disparities in human welfare across Japan in summer and winter.

Fig. 5. Change in ranks based on the current and projected economic values under climate change scenarios (RCP2.6 and RCP8.5). (A) Comparison between current values and values under RCP2.6 in summer. (B) Comparison between current values and values under RCP8.5 in summer. (C) Comparison between current values and values under RCP2.6 in winter. (D) Comparison between current values and values under RCP8.5 in winter. The bar charts show the absolute economic values (USD) for each scenario. A broken line identifies zero economic value under each climate change scenario. In this figure, the Japanese yen (JPY) at 100 is converted to the dollar (USD).
welfare across the nation. Sharing findings based on an objective method would be an important first step towards effective actions and policymaking.

Our findings also highlight the importance of monetary evaluations of climate change impacts to enhance adaptation actions. Fig. 3 shows that the higher valued beaches tend to face more severe threats of SLR under climate change. Existing physical evaluations are insufficient to support policymaking. In other words, without considering social-value weights, our society would underestimate the impacts of coastal beach loss caused by climate change. It is recommended that existing ecological and biological evidence concerning climate change impacts be evaluated from a social-value perspective to maintain public support for adaptation actions.

Furthermore, the present study discusses several policy implications concerning climate change by overcoming the lack of interdisciplinary research in tourism (IPCC, 2018). Note that policymakers are charged with deciding where to invest limited resources to address the inevitable impact of climate change and enhance the adaptation measures; however, a lack of large-scale evaluations have limited discussions about management priorities under climate change (Woodruff & Stults, 2016).

As described in Fig. 4, the present nationwide prediction of coastal values shows substantial spatial gradients of climate change impacts, which highlights the importance of tailor-made local adaptation actions. Most interestingly, projected regional differences in climate change impact note that many higher-ranked beaches in the southern region would be ranked the lowest, and vice versa for the northern beaches (Fig. 5). These findings provide concepts for judgement on adaptation policy priorities addressing individual beaches, especially considering resource constraints. One concept is to focus on the current values; that is, current higher-value beaches are prioritized for the implementation of adaptation measures. Another concept is to highlight the values that will remain in the future rather than current values. Targeting future values can economize budgets for adaptation actions, which contributes to sustainable management in the light of cost-effectiveness, although there is substantial uncertainty concerning projections. The selection of values (i.e. current/future) that should be treated as important will be challenging because there is a lack of information to conduct cost-benefit analyses (e.g. nourishment costs) and people’s risk preferences should also be considered (Kubo, Tsuge, Abe, & Yamano, 2019). The latter consideration should also be relevant to the discount rate controversy (Yamaguchi, 2019), although it is beyond the scope of this study. Despite a widespread agreement that coastal tourism has been affected by climate change (IPCC, 2018), studies on the vulnerability of coastal tourism have been limited (Perch-Nielsen, 2010; Scott, Simpson, & Sim, 2012). Although the present findings are based on the loss of beaches under climate change (Udo & Takeda, 2017), evidence from Japan, which is a medium-ranked vulnerability country in the world, would provide an important insight into adaptation strategies of coastal tourism (Perch-Nielsen, 2010).

The present study makes several contributions to tourism management under climate change, and the approach developed here is widely applicable, not only to other climate-sensitive tourism countries. However, this study has some limitations caused by data constraints. First, our findings are based on data collected on Sundays with sunny weather in both summer and winter to focus on coastal use with sunny weather and seasonal change in human welfare of coastal tourism; this procedure prevents insights into weather impacts on coastal tourism. Since tourism is sensitive not only to seasonality and temperature but also to extreme weather events (Pfleiderer, Schleusner, Kornhuber, & Coumou, 2019), insights into weather events should be extended for future analysis (Craig & Feng, 2018; IPCC, 2018). Second, the limited availability of information on users’ behaviours does not allow for a broader insight into general tourism management. For example, the literature showed that vulnerability of coastal tourism could depend on the activity type (Coombes & Jones, 2010), and welfare can change accordingly (Pascoe, 2019). Thus, integrating more detailed user behavioural data can enhance tourism management and climate change adaptation, although user privacy should have high priority. Combining social media data with the present approach can improve the analysis while protecting individual privacy because of the advantages of social media use (Di Minin, Tenkanen, & Toivonen, 2015; Anna Hausmann et al., 2018).

Third, although further challenges concerning privacy remain, integrating personal trip data and individual characteristics into the present approach can improve the estimation of human welfare by using TCM (e.g., Kolstoe & Cameron, 2017; Matthews et al., 2018; Phaneuf & Requate, 2017). For example, differentiating between single-site and multi-site visitors and collecting information on occupation can adjust travel costs. By overcoming the above limitations and investigating further data advantage and validity, the approach presented in this study can be extended to and could contribute to efficient management of climate change.

5. Conclusion

To address increasing threats from climate change, international climate policies require local adaptation based on long-term monitoring in line with a global mitigation effort to address climate change (Rogelj et al., 2016; Swart & Raes, 2007). This study’s first integrated approach, based on unique mobile phone network data, has significant potential to contribute to efficient and objective human welfare monitoring with respect to tourism and recreational services. Automatic data collection using the mobile phone network would provide the same standard over long periods, thus mitigating the existing bias caused by different survey types and efforts (Parsons, 2017) and providing reliable measurements, although access to big data is still controversial and needs public consensus (Ford et al., 2016; Li et al., 2018). In addition to a data collection advantage, the fine-grained projection in this study would be updated once highly accurate forecasts of future physical and biological changes are available. Recent developments in new technologies — for example, remote sensing — have detected notable environmental responses to climate change with high spatiotemporal resolutions, which encourage more extensive integrated research to enhance adaptation policies. Furthermore, other big data sources concerning human behaviour and attitudes can extend the present approach by combining with societies’ interests, which can be distilled from photo and Twitter data (Anna Hausmann et al., 2018; Spalding et al., 2017; van Zanten et al., 2016). The present approach and potential extensions are applicable to a wide variety of climate-vulnerable tourism, from coastal to alpine environments (Fischell, Schuurman, Monahan, & Ziesler, 2015; Liu, Cheng, Jiang, & Huang, 2019), although this study focuses on the risk of SLR in coastal tourism. Globally, climate change-driven ecological and biological shifts have been reported and projected. The application of this approach of detecting national tourism and recreational services in monetary terms can enable policymakers to discuss priorities in strengthening adaptation policies.

Contribution

T.K., H.Y., and T.Y. designed the study. T.K. and S.U. coordinated data compilation, analysis, and graphics. T.K. wrote the manuscript with contributions from S.U., H.Y., T.T., T.Y., and Y.S.

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