Tohoku University Research Center for Policy Design Discussion Paper

TUPD-2024-009

Using contingent behavior analysis to estimate benefits from coral reefs in Kume Island, Japan: A Poisson-inverse Gaussian approach with on-site correction

Katsuhito Nohara
College of Tourism, Rikkyo University
Graduate School of Economics and Management, Tohoku University

Masaki Narukawa
Faculty of Humanities and Social Sciences, Okayama University

Akira Hibiki
Graduate School of Economics and Management, Tohoku University

May 2021
Revised September 2024

Using contingent behavior analysis to estimate benefits from coral reefs in Kume Island, Japan: A Poisson-inverse Gaussian approach with on-site correction

Katsuhito Nohara*[1], Masaki Narukawa[2], and Akira Hibiki[3]

Abstract

Coral reefs face a critical crisis worldwide because of rising ocean temperature, excessive use of resources, and red soil erosion. As reefs have great recreational and tourism value, the degradation of their quality may have a significant effect on tourism. This study employs a contingent behavior approach to estimate the effect of reef extinction on the recreational demand for Kume Island, Okinawa, Japan. We propose a Poisson-inverse Gaussian (PIG) model with correction for on-site sampling issues to derive a more accurate estimate of consumer surplus. The results show that the annual consumer surplus per person trip is 5,898 yen (US$ 49.15 in 2015 currency) according to the random-effects PIG model.

Keywords: *Contingent behavior; Coral reef; Economic valuation; On-site sampling; Poisson-inverse Gaussian model; Random-effects model*

1. Introduction

In Japan, there are 34,700 hectare (ha) coral reefs, and Okinawa Prefecture has 80% of them. However, they now tend to decrease because of factors, including coral reef bleaching, primarily due to climate-induced ocean warming, feeding damage by Acanthaster, and red soil erosion (Hongo and Yamano, 2013). The Ministry of the Environment started an investigation of coral reef communities in 2017 to evaluate their condition using artificial satellite images and field studies. In 1991, the area covered by more than 50% of coral reefs filled 5.5% of the area in the surrounding waters of Ishigaki and Iriomote Islands. However, the 2017 investigation revealed that its coverage declined from 5.5% in 1991 to 0.1%. A supplementary investigation in 2018 concluded that coral reefs bleaching occurred at all observation spots (https://www.env.go.jp/press/105494-print.html).

The factors influencing the destruction of coral reefs mentioned above have affected the condition

---

[1] College of Tourism, Rikkyo University, Saitama and Research Cenger for Policy Design, Tohoku University, Miyagi, Japan

[2] Faculty of Humanities and Social Sciences, Okayama University, Okayama, Japan

[3] Research Cenger for Policy Design and Graduate School of Economics and Management, Tohoku University, Miyagi, Japan

*Corresponding author

1-2-26 Kitano, Niiza-shi, Saitama, 352-8558, Japan

E-mail address: noharak@rikkyo.ac.jp

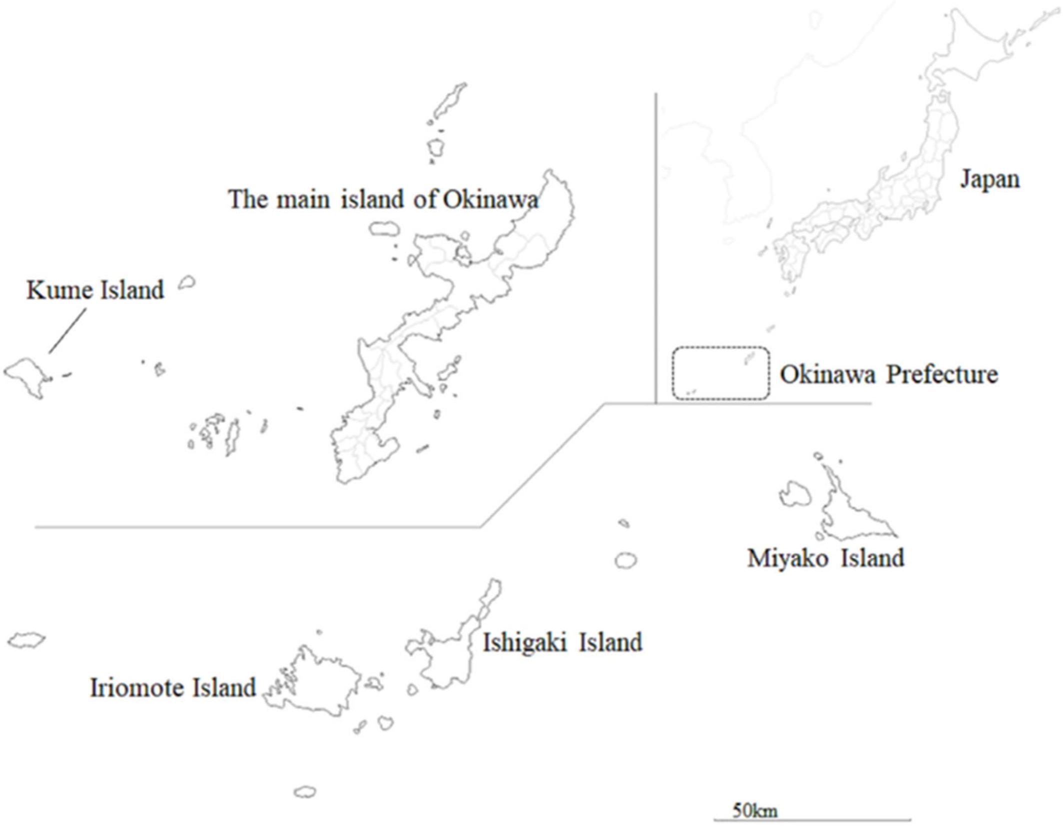

Figure.1 Location of Kume Island

of coral reefs in Kume Island, which was the study location selected for this study (Figure 1). Kume Island is located approximately 90 km west of the main island of Okinawa and is blessed with numerous natural resources that yield many potential ecosystem services. As pointed out by Masucci et al. (2019), although Kume Island has rich marine biodiversity and many endemic species, many factors, such as coastal modifications, red soil runoff by agriculture, and climate change, have affected coral reefs on Kume Island. In light of this situation, many studies have investigated the status of coral reefs in Kume Island and highlighted its critical situation (Omija et al., 1998; Kimura et al., 2011; Fujita et al., 2012; Yamano et al., 2015, and Masucci et al., 2019).

As previously indicated, although Kume Island has substantial natural resources, some of its coral reefs may face the threat of loss. In general, coral reefs provide many ecological goods and services, such as food provision, shoreline protection, erosion regulation, biogeochemical cycling, and tourism and recreational opportunities (Elliff and Kikuchi, 2017; Robles-Zavala and Reynoso, 2018). Additionally, many studies have pointed out that coral reefs have multiple ecosystem functions that support tourism benefits, such as the generation of fine sand beaches, maintenance of islands, protection from storms, and the production of seafood (Perry et al., 2015; Kench, 2014; Perry et al., 2011; Ferrario et al., 2014; Cabral and Geronimo, 2018). Therefore, the degradation of coral reefs may

Table 1 The number of tourists for 30 years in isolated islands of Okinawa Prefecture

Island name	1985	2015	The rate of increase (%)
Ishigaki	250,072	11,477,964	4489.86
Miyako	122,715	511,665	316.95
Kume	81,268	102,797	26.49
Iriomote	71,405	380,573	432.98
Ie	58,000	135,739	134.03

seriously affect the tourism industry of Kume Island in the future. Nevertheless, tourists who visit Kume Island are scanty compared to other isolated islands of the Okinawa Prefecture, such as Ishigaki and Miyako Islands. Table 1 shows the top five most visited isolated islands in 1985 and the corresponding number of tourists in 1985 and 2015, as obtained from the Okinawa Prefectural Government (2018). It indicates that the state of coral reefs is not necessarily correlated with the number of tourists because it has increased in Ishigaki and Iriomote Islands. This might imply that most tourists do not have enough knowledge about the importance of coral reefs in maintaining marine ecosystem services, particularly tourism. As evidence, according to a public opinion poll conducted by the Cabinet Office (2014), most people do not recognize the ecosystem services of coral reefs such as recreation or tourism as cultural services; only 19% do. As shown in Table1, although the increasing rate of tourists in the past 30 years in Kume Island is of the lowest value among the isolated islands, it is substantial to examine how these reef conditions can be maintained due to their significance. As mentioned earlier, the coral reefs around Ishigaki Island are deteriorating, and it is possible that the number of tourists to Kume Island, where beautiful coral reefs exist and are easily accessible from the main island, will increase in the future. Therefore, in order to sustainably use the coral reefs in Kume Island, it is important to estimate their economic value by focusing on the use value of coral reefs, which tourists are particularly likely to recognize through their leisure activities.

The remainder of this paper is organized as follows. In the next section, we introduce some previous studies. Section 3 explains the data collection process. Section 4 proposes an estimation approach based on the PIG model for an on-site survey. Section 5 provides the estimation results and welfare estimates related to the loss of reef quality. Section 6 summarizes the conclusions and provides the scope for future research.

2. Review of the literature

2.1 Travel cost method and contingent behavior

The travel cost method (TCM) using revealed preference (RP) data is a widely accepted technique for assessing the value of outdoor recreational activities. Contingent behavior (CB), which asks individuals to state their intended visit frequency if environmental quality changes under a hypothetical situation (Lienhoop and Ansmann, 2011; Pueyo-Ros et al., 2018), allows us to evaluate the changes in environmental quality (Englin and Cameron, 1996). Therefore, combining CB classified as stated preference (SP) data with TCM (TCM + CB) has recently been attempted. TCM+CB is often applied to estimate benefits, including sports fishing, recreational fishing, coastal wetlands, urban park, swimming, cave diving, and winter outdoor recreation (Bertman et al., 2020, Alberini et al., 2007; Prayaga et al., 2010; Pueyo-Ros et al., 2018; Deely et al., 2019; Mäntymaa et al., 2021, Lankia et al., 2019; Morgan and Huth, 2011; Filippini et al., 2018).

Apart from these, some studies have adopted TCM + CB to evaluate coral reefs. Bhat (2003) estimates the recreational benefits if the quality of coral reefs is improved using the random-effects Poisson-gamma model in TCM + CB, which indicates that the number of trips will increase by approximately 43%, and the change in CS (Consumer Surplus) per person will be US$ 3,080 under the scenario of 100% improvement in coral quality. Folkersen et al. (2018) employ TCM + CB to estimate the effect of deep-sea mining on future trip demand in Fiji, using the number of planned future trips with and without deep-sea mining. However, this approach means that irrespective of whether the degradation of coral reefs occurs, the recreational use-value of coral reefs is limited to diving and snorkeling. In addition, Kragt et al. (2009) estimate the effects of Great Barrier Reef degradation on trip demand using only CB data or in the panel data model. Although almost all previous studies have estimated the effects of environmental improvements on trip demand, they have also assessed the effects of environmental degradation on recreational demand. That is, they use the number of future trips as SP data under the hypothetical scenario of a decline in reef quality. Following their approach, we use only CB data by asking respondents about their future trips under both scenarios (i.e., the current state and the extinction scenario) as including trip demand at the current state of reef quality in the dependent variable might result in biased welfare effects.

Our study focuses not on the improvement of reef quality but the extinction of coral reefs for two reasons. First, Kragt et al. (2009) argue that using the number of planned trips at current and degraded reef quality is more suitable in the case of the Great Barrier Reef quality decline—from which they consider an 80% reduction of coral reefs as a hypothetical scenario. However, it seems difficult for respondents to imagine the effects of reef degradation, such as an 80% loss on their future trips, even if they are shown pictures. Second, we pay considerable attention to the fact that coral reefs were imminently threatened with extinction in the past, and this situation has worsened every year. For instance, multiple coral bleaching events have been recorded in most regions since the mass bleaching event of 1998, which caused 100% coral depletion in some regions (UNFCCC; 2018). Given the state of recent coral reefs, our scenario is more realistic. Furthermore, although the extinction of coral reefs may affect the water quality and landscape, it does not necessarily induce zero recreation demand. As mentioned above, the reason is that most people do not grasp the relation between the existence of coral reefs and the tourism benefits they enjoy. Therefore, an analysis using CB data under our scenario is feasible. Meanwhile, in Japan, the recreational value of coral reefs has been little investigated. Oh

(2004) and Tamura (2006) estimated the non-use values of coral reefs in the Kerama Islands and around the Akajima sea area using CVM (Contingent Valuation Method). Imamaru et al.(2020) used a discrete choice model to estimate the value of coral reefs in Japan as a whole, focusing on differences in the type of coral reef information presented to respondents. Their study is challenging and interesting, but it is different from this study because of using CVM through a web based survey. To our knowledge, there are no studies estimating the effects of the decline in reef quality on future recreational demand in each region of Japan.

2.2 Statistical method

From the viewpoint of a statistical approach, it should also be emphasized that previous studies estimating the value of coral reefs have not considered the possibility of employing a more suitable statistical approach. For example, although Prayaga et al. (2010) and Pueyo-Ros et al. (2018) do not estimate the value of coral reefs directly, they adopt a pooled TCM + CB model that cannot capture individual-specific effects in count data. Moreover, despite the fact that Bhat (2003) collects data through an on-site survey, an estimation problem related to the sampling is not addressed. Indeed, statistical analysis of such on-site count data should be controlled for truncation and endogenous stratification, as advocated by Shaw (1988), who addresses these issues in the Poisson regression model. As pointed out by Haab and McConnell (2002), the Poisson regression model is subject to the potential misspecification of assuming equidispersion. Therefore, if overdispersion is recognized, the negative binomial model is more suitable for trip count data. Kragt et al. (2009) analyze CB data using the random-effects negative binomial model; however, their model is not adjusted for on-site sampling. To collect data through an on-site survey, even if only CB data are used in the estimation, it must be corrected for the aforementioned issues. Furthermore, as argued by Guo and Trivedi (2002), Sarker and Surry (2004), and Cameron and Trivedi (2013), the capability of the negative binomial model to capture overdispersion will be limited and inadequate if the data have a distribution with a long tail. Therefore, a reliable statistical inference cannot be made. Willmot (1987) and Dean et al. (1989) consider the Poisson-inverse Gaussian (PIG) model to be an easier and more usable parametric model because, in an analysis of insurance data, it reflects more long-tailed count data than the negative binomial model, even with the same number of parameters. Additionally, Guo and Trivedi (2002) apply the PIG model to an analysis of patent data.

As this study uses trip number data from an on-site survey, our estimation approach is based on the PIG model and incorporates Shaw's (1988) correction for on-site sampling issues. Moreover, to analyze the CB data, we expand it into a random-effects model that can use pseudo-panel data, as in Beaumais and Appéré (2010). Although Narukawa and Nohara (2018) propose an estimation approach for panel count data truncated at zero to utilize TCM + CB, they assume that the data are collected via a web-based off-site survey. However, our approach is clearly different from theirs, as we consider the

PIG model adjusted for an on-site survey. To our knowledge, this is the first attempt to construct a PIG approach using on-site sampling data. This study estimates the changes in consumer surplus in a Kume Island trip resulting from a decline in reef quality using the PIG approach while controlling for on-site sampling in CB.

3. Survey design and data

3.1 Data collection

Our survey was conducted for one week, including weekdays and the weekend, in September 2015 at Kumejima airport. We approached Japanese people who came to the airport and asked them which prefectures they came from and whether their purpose of visiting Kume Island was to enjoy a trip. If they were tourists and had already finished their trips on Kume Island, we continued the interview survey. In total, 342 individuals fulfilled the requirements that they were tourists and came from other regions at the airport, 302 of whom (88.3%) filled out the questionnaire.[4] The questionnaire included accompanying persons and their age, activities enjoyed during the trip, interest in natural resources on Kume Island, visit duration, travel mode, several demographic characteristics, and the number of trips planned for the next ten years given both the current reef quality and the extinction scenario. It was expected that these variables would significantly affect the visitors' trip frequencies. We presented a photographic material to respondents, which was provided by a scientist, Dr. Hiroya Yamano, to help respondents comprehend the condition of reef extinction. We obtained 302 responses, but not all were used for analysis because of partial missing information, such as non-response and writing errors (51 individuals), which we could not recognize at the time of the survey. Additionally, we removed group travelers who did not pay for all of their travel costs and those who were sightseeing while on business (23 individuals). Furthermore, respondents who aimed for multi-purpose trips in Okinawa Prefecture (i.e., respondents who stayed at sites more than one night) were also excluded from the analysis (26 individuals) because this study employed a single-site TCM. Thus, finally, 202 respondents were included in our empirical analysis.

We divided activities in Kume Island into two categories. The first category included activities not related to coral reefs that tourists could actually experience in Kume Island—sightseeing, playing golf, ecotourism, dining, attending weddings, visiting beauty salons, and participating in traditional events. The second category included activities directly and indirectly related to coral reefs (e.g., sea bathing, snorkeling, diving, glass boat, sea kayak, and fishing). Subsequently, we asked tourists to choose the marine activities they had experienced during this trip. Concerning CB questions, Kragt et al. (2009) and Folkersen et al. (2018) ask respondents about the planned trips for the next five years under a hypothetical scenario. However, we set the period to the next ten years because it would be

[4] About 25% of tourists use a ferry and 75% of them use an airplane to come to Kume Island (Kume Island Tourism Association; 2015).

Table 2 Definition of variables used in the model

Variable	Definition	Mean	SD
Visit_SP0	Number of planned recreational trips to Kume Island in the next ten years at the current reef quality	3.847	3.530
Visit_SP100	Number of planned recreational trips to Kume Island in the next ten years at the degraded reef quality (100 percent loss)	1.149	2.587
TC	Per-person travel costs to access Kume Island (¥10,000)	8.863	2.318
SP100	Dummy variable denoting trip counts elicited through a contingent behavior question	–	–
Income	Household income (¥1,000,000)	5.334	3.842
Education	Dummy variable = 1 if the respondent has graduated from the university	0.589	0.493
Accompany	Number of accompanying persons	1.713	1.541
Alone	Dummy variable = 1 if the respondent takes a trip alone	0.079	0.271
Naha stay	Dummy variable denoting stay at Naha city (yes = 1)	0.163	0.371
Days	Trip length in Kume Island	3.604	1.125
Activities			
Leisure	Dummy variable = 1 if the respondent experiences marine leisure during the trip	0.842	0.366
Diving	Dummy variable = 1 if the respondent experiences diving during the trip	0.163	0.026
Fishing	Dummy variable = 1 if the respondent experiences fishing during the trip	0.069	0.255
Interest			
Reef	Dummy variable = 1 if the respondent is interested in coral reef	0.723	0.449
Species	Dummy variable = 1 if the respondent is interested in marine species	0.693	0.462
Insects	Dummy variable = 1 if the respondent is interested in endemic insects in Kume Island	0.064	0.246
Landscape	Dummy variable = 1 if the respondent is interested in landscape of Kume Island	0.822	0.384
Prior experience			
P_Snorkeling	Dummy variable = 1 if the respondent has prior experience of snorkeling	0.772	0.420
P_ Diving	Dummy variable = 1 if the respondent has prior experience of diving	0.454	0.499
P_Fishing	Dummy variable = 1 if the respondent has prior experience of fishing	0.361	0.482

unrealistic for the extinction of coral reefs to occur in such a short term in light of the past bleaching events. In addition, it can be said that our relatively longer hypothetical term excludes scenario bias generated by an unrealistic storyline. Table S1 in the Appendix shows the results of a survey of tourists visiting Kume Island conducted by the Okinawa Prefectural Government in 2015, compared to the data we used for our estimates. The Okinawa Prefectural Government (2015) conducted a questionnaire survey on Kume Island from July to September; thus, the values were not necessarily close to the data in this study because of differences in the survey period. However, the values were relatively close regarding the respondents' residence, length of stay, number of visits, and activities on Kume Island. However, this study had more respondents with lower incomes and younger respondents who visited with friends than the Okinawa Prefectural Government (2015).

Based on the above survey design and the collected data, the variables used in our analysis are summarized in Table 2. In general, the recreation benefits of the quality changes were measured as CS, which is the area between the RP and SP trip demand curves (Whitehead et al., 2000). In other words, respondents provided the actual number of trips (the observed behavior data) under the current reef quality and the planned reef visits (the contingent behavior data) based on a hypothetical reef quality scenario. However, as discussed by Bockstael et al. (1989) and Kragt et al. (2009), the incorporation of the actual number of trips in the recreational demand function could result in biased estimates of CS. Thus, we estimated CS using the number of planned trips under the current reef quality and the scenario of coral reef extinction as dependent variables in the subsequent empirical model. Note that it might be a strong assumption that all the independent variables will remain constant over this time period. However, it is difficult to estimate the future income or travel costs of respondents. Therefore, it would be correct regarding our estimation as an upper bound of surplus.

3.2 Travel costs

The travel costs were computed as the round-trip costs from origin to destination. Specifically, we calculated them by summing 1) the costs of transport from the nearest public office to the nearest airport and 2) the airfares for traveling from that airport to the Kumejima airport. First, when respondents used their own car between their house and the nearest airport, the costs were defined as the petrol cost at that time (135 yen/L), according to the Price Survey of Oil Products, published by the Agency for Natural Resources and Energy (2015). For fuel consumption, the average runnable distance per liter was (26.1 km/L) for passenger cars using petrol, based on the List of Vehicle Fuel Consumption published by the Ministry of Land, Infrastructure, Transport, and Tourism (2015a). If respondents used the highway for time savings, we assumed that they referred to Drive Plaza[2] to infer their costs. The distance from a respondent's house to the nearest airport was calculated using Google Maps.[3] When the respondents used rental cars between their house and the nearest airport, we estimated the cost as the sum of the price of the rental car and the petrol cost. The rental car fee was calculated using the price list of the nearest rental car shop from a respondent's house, assuming that the price of a rental car is the one-way car rental fee.[4,5] When respondents used taxi services or public transportation between their house and the nearest airport, the cost was calculated by summing each fee from the appropriate internet site.[6,7] Subsequently, airfares from the nearest airport to the Kumejima airport were calculated using the Airplane Passenger Survey published by the Ministry of Land, Infrastructure, Transport and Tourism (2015b). We adopted the discount that most passengers utilized at each air route. The opportunity cost of time between the respondents' houses and Kumejima

[2] Drive Plaza. Available from: http://www.driveplaza.com/dp/SearchTop.
[3] Google Maps. Available from: https://www.google.co.jp/maps.
[4] Nippon Rent-a-car. Available from: https://www.nrgroup-global.com/en/
[5] Niconico Rent a car. Available from: https://niconicorentacar.jp/
[6] TaxiSite. Available from: http://www.taxisite.com/ (in Japanese)
[7] Google Maps Transit. Available from: http://maps.google.com/landing/transit/index.html

airport was considered to be one-third of the wage rate, following many previous studies.

4. Model estimation

4.1 A PIG model with on-site correction

Let y_i and $\mathbf{x}_i = (x_{1i}, \cdots, x_{ki})'$ denote the number of trips by individual i and the k-dimensional explanatory variable vector, which includes a constant, respectively. It, then, follows from the exponential mean specification (Cameron and Trivedi, 2013, p. 71) that the conditional mean of y_i is defined as

$$\lambda_i = \mathrm{E}(y_i|\mathbf{x}_i) = \exp(\mathbf{x}_i'\boldsymbol{\beta}), \ \ i = 1, \cdots, N, \tag{1}$$

where $\boldsymbol{\beta}$ is the parameter vector. If y_i is independently Poisson distributed with the above mean parameter λ_i, Equation (1) is the well-known standard Poisson regression model. However, this specification has the so-called equidispersion property, which means that the conditional variance equals its mean. Thus, to relax this restrictive property, we introduce ν_i, which expresses the unobserved heterogeneity of individuals to Equation (1) as follows: $\mu_i = \lambda_i \nu_i$, where ν_i is independent of y_i, and thus $\mathrm{E}(\mu_i|\lambda_i) = \lambda_i$ because we can assume that $\mathrm{E}(\nu_i) = 1$ without loss of generality. Thus, unobserved heterogeneity is multiplicatively incorporated into the exponential conditional mean. Now, assuming that y_i follows the Poisson distribution of the mean parameter μ_i, and letting $g(\nu_i)$ denote the probability density function of ν_i, the (marginal) probability density function of y_i, which is called a mixed Poisson distribution, is shown as

$$f(y|\mathbf{x}) = \int_0^\infty \frac{\exp(-\lambda\nu)\,(\lambda\nu)^y}{y!} g(\nu)d\nu, \tag{2}$$

where the subscript i for an individual is omitted for notational simplicity. This study focuses on the PIG model of Dean et al. (1989), in which ν in Equation (2) follows an inverse Gaussian (IG) distribution, so that in conjunction with the explicit expression of a PIG distribution shown by Willmot (1987) (see also e.g., Cameron and Trivedi, 2013, Ch. 4.2.6), the conditional probability mass function can be obtained as follows. If $y > 0$,

$$h(y|\mathbf{x}) = \frac{p(0)\lambda^y}{\Gamma(y+1)} \sum_{k=0}^{y-1} \frac{\Gamma(y+k)}{\Gamma(y-k)\Gamma(k+1)} \left(\frac{\tau}{2}\right)^k (1+2\tau\lambda)^{-\frac{y+k}{2}},$$

whereas if $y = 0$, $h(y|\mathbf{x}) = p(0) = \exp\left(\tau^{-1}(1 - \sqrt{1+2\tau\lambda})\right)$. Note that $\mathrm{Var}(\nu) = \tau > 0$ is an unknown shape parameter, and as $\tau \to 0$, the PIG model approaches the standard Poisson regression model, which implies that the parameter τ describes overdispersion.

Since the count data are collected via an on-site survey, there are two problems: truncation and endogenous stratification. This problem exists because non-visitors are excluded, which means that the sample is zero-truncated, and visitors who make frequent trips to the site are covered by oversampling. The endogenous stratification problem is one of the particular forms of the so-called choice-based sampling and causes biased and inconsistent estimators of parameters, which may lead to serious mistakes in the statistical inference. Following Shaw (1988), we derive a probability mass function of the PIG model that allows for on-site sampling. Shaw's correction for the conditional probability density function to control for the effects involved in on-site sampling is given by

$$h^S(y|\mathbf{x}) = h(y|\mathbf{x})w(y,\lambda),\ \ w(y,\lambda) = \frac{y}{\mathrm{E}(y|\mathbf{x})}. \tag{3}$$

Thus, by applying Equation (3), we can construct a log-likelihood function suitable for the on-site sampling data, as shown in Equation (4):

$$\sum_{i=1}^{N} \log h^S(y_i|\mathbf{x}_i;\boldsymbol{\theta}) = \sum_{i=1}^{N} \log\left(\frac{y_i}{\lambda_i} h(y_i|\mathbf{x}_i;\boldsymbol{\theta})\right), \tag{4}$$

where $\boldsymbol{\theta} = (\boldsymbol{\beta}',\tau)'$ is the unknown parameter. Thus, we obtain the maximum likelihood estimators based on the PIG model under on-site sampling.

4.2 Expansion to the random effects model

Given that this study aims to measure the recreational benefits, it is necessary to analyze the TCM + CB data. Thus, it is not desirable to analyze each response from a given individual as univariate count data because ignoring the multivariate dependence will cause an efficiency loss of the estimators and may also affect their consistency. The most natural expansion is to handle it as a multivariate count data, as in Egan and Herriges (2006). However, it is not easy to obtain the estimates because the likelihood function is usually complicated, and its computational burden may be heavy. As an alternative estimation method, their study proposes the use of the seemingly unrelated negative binomial (SUNB) model of Winkelmann (2000) because it avoids computational complexity even though the correlation structure is restrictive. However, Beaumais and Appéré (2010) view multivariate data as a pseudo-panel data. This view implies that the time index of the standard panel data model is regarded as the number of scenarios that accompanies the CB data. Thus, they propose an estimation method invoking the random-effects Poisson-gamma (RE-PGM) model of Hausman et al. (1984), in which each of the random effects is independently and identically distributed as gamma. Following their pseudo-panel approach, we first introduce the random-effects Poisson-inverse Gaussian (RE-PIG) model, which is the expansion of the univariate PIG model and is also proposed by Narukawa and Nohara (2018) for zero-truncated count data. Then, to analyze on-site sampling data, we correct for its sampling effects in a way similar to that given in Section 4.1.

Let y_{ij} be the number of trips in scenario j for individual i, and let $\mathbf{x}_{ij} = (x_{1ij},\cdots,x_{kij})'$ denote the k-dimensional explanatory variable vector, including a constant in scenario j. We first assume that the conditional mean of y_{ij}, which is denoted by λ_{ij} and satisfies $\mathrm{E}(\mu_{ij}|\lambda_{ij}) = \lambda_{ij}$, can be described as follows:

$$\mu_{ij} = \exp(\mathbf{x}'_{ij}\boldsymbol{\beta})\nu_i,\ \ i = 1,\cdots,N,\ \ j = 1,\cdots,J$$

The characteristic feature of this specification is that ν_{ij}, which denotes the heterogeneity of individuals in a scenario, is considered a random effect that is not dependent on scenario j; thus, $v_{ij} = v_i$. Hence, although the random effect is denoted by a random variable that follows a common IG distribution, note that it restricts the correlation structure. The number of trips for each individual is now a multivariate count data; thus, we introduce some new notations: $\mathbf{y}_i = (y_{i1}, \cdots, y_{iJ})'$ and $\tilde{\mathbf{x}}_i = (\mathbf{x}_{i1}, \cdots, \mathbf{x}_{iJ})'$. Then, analogous to Section 2.1 of Narukawa and Nohara (2018), the conditional probability mass function for the RE-PIG model can be derived as

$$h(\boldsymbol{y}|\tilde{\mathbf{x}}) = q(0) \sum_{k=0}^{y_J^*-1} \frac{\Gamma(y_J^* + k)}{\Gamma(y_J^* - k)\Gamma(k+1)} \left(\frac{\tau}{2}\right)^k \left(1 + 2\tau\lambda_J^*\right)^{-\frac{y_J^*+k}{2}} \prod_{j=1}^{J} \frac{\lambda_j^{y_j}}{y_j!} = q(y_J^*) \prod_{j=1}^{J} \frac{\lambda_j^{y_j}}{y_j!},$$

where $q(0) = \exp\left(\tau^{-1}(1 - \sqrt{1 + 2\tau\lambda_J^*})\right)$, $y_J^* = \sum_{j=1}^{J} y_j$, $\lambda_J^* = \sum_{j=1}^{J} \lambda_j$, and the subscript i denoting an individual is omitted for notational simplification.

Next, it is necessary to allow for the fact that $\mathbf{y}_i$ is assumed to be collected via an on-site survey. Since there is typically one variable with on-site sampling in $\mathbf{y}_i$, which we set at y_{i1}, it is sufficient to control for the sampling effects only for variable y_1. Thus, considering this point, the conditional probability mass function with on-site correction is written as

$$h^S(\boldsymbol{y}|\tilde{\mathbf{x}}) = \frac{q(y_J^*)\lambda_1^{y_1-1}}{(y_1-1)!} \prod_{j=2}^{J} \frac{\lambda_j^{y_j}}{y_j!}. \tag{5}$$

Hence, we can construct a log-likelihood function from Equation (5) in the same way as in Equation (4) and obtain the maximum likelihood estimators of parameters, which are given by maximizing $\sum_{i=1}^{N} \log h^S(\boldsymbol{y}_i|\tilde{\mathbf{x}}_i; \boldsymbol{\theta})$ with respect to the unknown parameters $\boldsymbol{\theta} = (\boldsymbol{\beta}', \tau)'$. Note that the proposed estimation approach has a similar correlation structure to the SUNB model and the RE-PGM model; thus, the correlation structure among the multivariate count data (that is, the over scenarios) should be positive and is mainly determined by only one parameter, which does not seem restrictive in the context of this study.

4.3 Empirical model

This section introduces our model for empirical analysis, in which dependent variables are written as $\lambda_{ij} = \mathrm{E}(y_{ij}|\mathbf{x}_{ij})$ for $j = 1, 2$ in the framework of Section 4.2 with $\mathbf{y}_i = (y_{i1}, y_{i2})' = (Visit\_SP0_i, Visit\_SP100_i)'$ representing the CB data under the hypothetical scenarios: current reef condition and reef extinction (cf. Kragt. et al., 2009). That is, y_1 is subject to on-site correction because an on-site survey is employed to collect the data, as mentioned in Section 2.1, and it seems natural that the number of visits will not decrease under the current reef quality. The minimum number of planned trips under the current reef quality was 1 from the on-site survey data. However, y_2 indicates the CB data in which the hypothetical scenario of coral reef extinction may lead to a decrease in the number of planned trips. The proposed estimation approach for pseudo-panel data is also capable of dealing with such a case; in other words, it allows for a correlation between the on-site count data

Table 3 Results of RE-PGM and RE-PIG models with on-site correction

	RE-PGM		RE-PIG	
Variable	Coeff.	SE	Coeff.	SE
TC	-0.086**	0.038	-0.085**	0.040
SP100	-0.908***	0.078	-0.908***	0.078
Income	0.071***	0.024	0.072***	0.024
Education	-0.512***	0.174	-0.515***	0.178
Alone	0.685**	0.336	0.656**	0.334
Accompany	0.168***	0.055	0.181***	0.058
Naha stay	0.350	0.234	0.397	0.247
Days	0.038	0.083	0.053	0.085
Leisure	0.443*	0.243	0.423*	0.249
Diving	0.683***	0.262	0.680**	0.266
Fishing	-0.199	0.386	-0.311	0.374
Reef	0.235	0.208	0.254	0.209
Species	-0.425**	0.205	-0.417**	0.210
Insects	0.720**	0.323	0.758**	0.334
Landscape	0.307	0.224	0.306	0.228
P_ Snorkeling	0.299	0.218	0.273	0.225
P_Diving	-0.089	0.191	-0.103	0.197
P_Fishing	0.488***	0.180	0.480***	0.185
Constant	-2.597	1.761	-1.094	0.554
α or τ	12.135	22.079	1.771***	0.456
Log-likelihood	-706.4		-703.9	
LR	215.0***		206.7***	
AIC	1452.9		1447.9	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

y_{ij}. Thus, following the variable definition from the on-site survey as described in Table 3, the recreational demand function for Kume Island can be specified as:

$$\lambda_{ij} = \exp(\beta_0 + \beta_1 TC_{ij} + \beta_2 SP100_{ij} + \beta_3 Income_{ij} + \beta_4 Education_{ij} + \beta_5 Accompany_{ij} + \beta_6 Alone_{ij} + \beta_7 Naha_{ij} + \beta_8 Days_{ij} + \beta_9 Leisure_{ij} + \beta_{10} Diving_{ij} + \beta_{11} Fishing_{ij} + \beta_{12} Reef_{ij} + \beta_{13} Species_{ij} + \beta_{14} Insects_{ij} + \beta_{15} Landscape_{ij} + \beta_{16} P\_Snorkeling_{ij} + \beta_{17} P\_Diving_{ij} + \beta_{18} P\_Fishing_{ij}),$$

$j = 1, 2,$ which implies that $\mathbf{x}_{ij} = (1, TC_{ij}, SP100_{ij}, Income_{ij}, Education_{ij}, Accompany_{ij}, Alone_{ij}, Naha_{ij}, Days_{ij}, Leisure_{ij}, Diving_{ij}, Fishing_{ij}, Reef_{ij}, Species_{ij}, Insects_{ij}, Landscape_{ij}, P\_Snorkeling_{ij}, P\_Diving_{ij}, P\_Fishing_{ij})'$, and $\boldsymbol{\beta} = (\beta_0, \beta_1, \cdots, \beta_{18})'$. Note that $Naha_{ij}$ is a dummy variable coded as '1' if the respondent spent one night in Naha City and '0' otherwise. At the time, there were no direct flights between Kume Island and other areas in Japan, and all tourists had to travel to Naha Airport. However, because those who stayed overnight in Naha City may not have meant that the main destination was

Kume Island, a dummy variable for their stay in Naha was constructed to identify them. Although 16.3% of the respondents stopped in Naha City, and all of them stayed there overnight, the length of their stay at Kume Island was greater than that at Naha City. While we referred to the questionnaire used in this study based on the Okinawa Prefectural Government (2015), some variables were created to align with the main purpose of this study. For example, the "Leisure" variable was created to include other forms of marine leisure activities, such as snorkeling, because tourists engage in various marine leisure activities on Kume Island. On the other hand, since there is a possibility that the experience of marine leisure would influence tourists' demand for Kume Island, we included past experiences not only in Okinawa but also in other parts of Japan. However, to account for the relationship between past marine leisure experiences and demand for Kume Island, we created $P\_Snorkeling$ as a variable representing snorkeling, as this variable accounts for marine leisure activities that are common and conducted easily in both other areas and Kume Island. In addition, because Kume Island has original creatures and places, such as endemic species (Kumejima fireflies) and unique scenery (Hate no Hama), these are also regarded as having a significant impact on demand. Therefore, variables that indicated visitor interest ($Reef$, $Species$, $Insects$, and $Landscape$) were included in the analysis.

From the empirical model as specified above, per-person recreational value of a site quality change is measured as

$$\Delta \mathrm{CS} = \frac{\lambda_2 - \lambda_1}{\beta_1}, \tag{6}$$

where λ_2 is the number of planned trips associated with a change in reef quality (extinction), λ_1 is the number of planned trips under current reef quality, and the coefficient of travel cost is assumed to remain the same after a quality change. As Whitehead et al. (2000) and Beaumais and Appéré (2010) pointed out, if the coefficient of the observed travel cost data does not change after a quality change, the CS can be calculated using Equation (6). In the subsequent section, we compute the estimated ΔCS by replacing λ_1, λ_2, and β_1 with their predicted or estimated values $\hat{\lambda}_1$, $\hat{\lambda}_2$, and $\hat{\beta}_1$ in Equation (6). Note that for the predicted number of the trips, $\hat{\lambda}_j$, the evaluation at the mean of the independent variables is adopted in the same manner as the previous studies (Whitehead et al., 2000).

5. Estimation results

We estimate the parameters in the recreational demand function constructed in the previous section using two types of econometric approaches: the RE-PGM and RE-PIG models with on-site corrections. Table 3 reports the estimation results for the empirical model using the two approaches. First, the travel cost coefficients (TC), which is our primary interest, are negative, as expected, and significant at the 5% level for both approaches. Moreover, both of the likelihood ratio (LR) statistics reject the null hypothesis that all the coefficients except for the constant are zero at the 1% significance level.

Although there are only slight differences in the significance level between the RE-PGM and RE-

Table 4 Estimation results for CS loss

	RE-PGM	RE-PIG	RE-PGM without	RE-PIG without
ΔCS (ten years)	1.232	5.898	34.755	35.689
90% CI-LB	0.063	2.859	20.148	19.559
90% CI-UB	25.792	20.534	94.758	110.872

Unit: ¥10,000

PIG models, all the coefficients for SP100, Income, Education, Alone, Accompany, Leisure, Diving, Species, Insects, and P_Fishing are statistically significant at the 10% or lower levels. In particular, the estimates of SP100 support the anticipation that the number of planned trips at the degraded quality will be less than that at the current quality. Furthermore, the coefficients of leisure and diving on Kume Island are statistically positive, indicating that the experience of marine leisure and diving during a trip increases future recreational demand. As some of the dummy variables regarding activities on Kume Island, tourist interest, and past experiences were not statistically significant in either approach, visitors' interest in the coral reefs on Kume Island and past experiences of marine activities such as diving and snorkeling did not seem to affect their trip decision-making. Additionally, we find that with respect to the overdispersion parameter, τ in the RE-PIG model is statistically different from zero at the 1% level, whereas α, which corresponds to the RE-PGM model, is not even at the 10% level. This implies that ignoring unobserved heterogeneity will incur efficiency loss of the estimators, especially if the IG distribution is not adopted, and may also make them inconsistent. Thus, it seems that the RE-PIG approach with on-site correction within the framework of pseudo-panel data provides more reliable parameter estimates. Next, to further examine the performance of these models, the Akaike information criterion (AIC; Akaike, 1973) for each approach are reported in Table 3. As the AIC of the RE-PIG model is obviously smaller than that of the RE-PGM model, in addition to the fact that α is statistically insignificant in sharp contrast to τ, it is conceivable that the former approach is still more appropriate for analyzing our on-site sampling data. Thus, the IG distribution would capture overdispersion or unobserved heterogeneity more adequately than the gamma distribution.

Following Equation (6) and the related discussion in Section 4.3, we can calculate the per-person CS (ΔCS) for ten years, as shown in Table 4, where the 90% confidence intervals of the estimates using the Krinsky-Robb procedure (Haab and McConnell, 2002; González-Sepúlveda and Loomis, 2011) are also reported. Notably, Table 4 includes the estimates obtained using the RE-PGM and RE-PIG models while ignoring the on-site sampling issues to examine the effects of on-site corrections. The estimation results of the empirical model corresponding to Table 3 using these approaches are provided in Table S2 in the Appendix. The results show that the annual CS per person trip according to the RE-PGM model (1,232 yen (US$ 10.27 in 2015 currency)) is smaller than that of the RE-PIG model (5,898 yen (US$ 49.15 in 2015 currency)). Additionally, although both confidence intervals are asymmetric, the former has a wider range than the latter, in which it is conjectured that the slightly larger upper confidence bound for the RE-PGM model with on-site correction would be due to the insignificance of the overdispersion parameter α. While the tendency of the per-person CS is similar for both models without on-site corrections, their confidence intervals are dissimilar as both the overdispersion parameters α and τ are statistically different from zero even at the 1% level. These features reflect the inadequacy of the RE-PGM model specification for unobserved heterogeneity, as discussed above. Thus, in terms of the model evaluation, it is preferable to focus on the results of the RE-PIG model in the following discussion. For comparison, Kragt et al. (2009) find the annual CS per person trip to be A$ 83.5, although the per-person recreational value of a site quality change using Equation (6) is not explicitly provided. Thus, by converting Australian dollars into yen using the exchange rate at that time, we find that this amount is approximately 7,097 yen (US$ 59.14 in 2015 currency), noting that the hypothetical scenarios (the degraded reef quality) are not the same. Table 4 indicates that CS estimates based on the models without on-site corrections are considerably larger than those of the corrected models. Given this fact, Kragt et al. (2009) might be overestimating the CS loss because they do not address the on-site sampling issues. Thus, it is crucial to measure recreational values via on-site surveys to control for on-site sampling and adequately specify unobserved heterogeneity or overdispersion.

6. Conclusions

In Japan, coral reefs in Okinawa Prefecture are seriously damaged, and their distributional areas decrease every year. However, there remains a coral reef community in Kume Island that has remarkably high scholarly value. In 2009, a dense coral community with approximately 80% cover was discovered in the waters near Kume Island. This is considered to be of high ecological value because of its potential to supply coral larvae to the surrounding waters (WWF, 2010). Thus, this study focuses on Kume Island and estimates the recreational demand function using only CB data. Moreover, we propose a PIG model adjusted for an on-site survey and expand it to the random-effects model as an estimation approach. From the empirical analysis, we estimate the CS losses under the hypothetical scenario of current coral reef quality and extinction, finding that the annual CS per person trip is 5,898 yen by the RE-PIG model. To avoid the overestimation of CS, a comparative study suggests that choosing the appropriate estimation approach and the correction for on-site sampling issues is a requirement.

According to a report on the action plan to conserve coral reef ecosystems in Japan for the period 2016–2020, published by the Ministry of the Environment (2015), three priority issues are selected; one of them is the *promotion of sustainable tourism in coral reef ecosystems*. This report also mentions that coral reef tourism is extremely popular and is an industry that produces the highest economic value in coral reef areas. We find that coral reefs will become increasingly important in terms of the development of the tourism industry on Kume Island, as conservation of the coral reef ecosystem can enhance its value as a tourism resource. Additionally, on Kume Island, a reproduction project for the protection of coral reefs was initiated in 2019 to promote sustainable activities aimed at recuperation from coral reef bleaching or death. The contents of this project include cultivation, monitoring, and enlightening people on coral reefs. Our results present the necessity of cost-effective policy measures to support such local projects as soon as possible.

Although this study provides valuable input in terms of considering the effective policy measures to maintain the quality of Kume Island's coral reefs and can be used to assess the recreational benefits of coral reefs in its protection programs, it has some limitations. First, it is necessary to extend the valuation method to include non-use values to fully consider the total economic value. Second, there is still room for improving the estimation accuracy because the sample size may be small. Third, from a methodological viewpoint, there is a possibility that the PIG model, which controls for on-site sampling, could be extended to latent class or random parameter approaches, as proposed by Hynes and Greene (2013, 2016) based on the negative binomial model. They apply these approaches to a panel dataset of beach users, showing that the unobserved heterogeneity in the framework of their contingent behavior travel cost model can be adequately accounted for even if the data are collected through an on-site survey. These directions may cover a wide range of specifications on unobserved heterogeneity in pseudo-panel data and would be significant to the field regarding welfare estimation of recreation, which can be a scope for future research.

Acknowledgments

This study was funded by the National Institute for Environmental Studies (NIES), JSPS KAKENHI Grant Number JP17K18038 and JP 23K20578, and the Environment Research and Technology Development Fund (JPMEERF20S11821) of the Environmental Restoration and Conservation Agency of Japan.

References

Agency for Natural Resources and Energy. (2015) The Price Survey of Oil Products. Available from: http://www.enecho.meti.go.jp/statistics/petroleum_and_lpgas/pl007/results.html#headline4.

Akaike, H. (1973) Information theory and an extension of the maximum likelihood principle. In Petrov, B.N. & Csaki, F. (eds.), *Second International Symposium on Information Theory*, 267-281. Akademiai Kiado, Budapest.

Alberini, A., Zanatta, V. & Rosato, P. (2007) Combining actual and contingent behavior to estimate the value of sports fishing in the Lagoon of Venice. *Ecological Economics* 61, 530-541.

Beaumais, O. & G. Appéré. (2010) Recreational shellfish harvesting and health risk: a pseudo-panel approach combining revealed and stated preference data with correction for on-site sampling. *Ecological Economics* 69, 2315-2322.l

Bertram, C., Ahtiainen, H., Meyerhoff, J., Pakalniete, K., Pouta, E. & Rehdanz, K. (2020) Contingent behavior and asymmetric preferences for Baltic Sea coastal recreation. *Environmental and Resource Economics* 75, 49-78.

Bhat, M.G. (2003) Application of non-market valuation to the Florida Keys marine reserve management. *Journal of Environmental Management* 67, 315-325.

Bockstael, N.E., McConnell, K.E. & Strand, I.E. (1989) Measuring the benefits of improvements in water quality: the Chesapeake Bay. *Marine Resource Economics*, 6, 1-18.

Cabral, R.B. & Geronimo, R.C. (2018) How important are coral reefs to food security in the Philippines? Diving deeper than national aggregates and averages. *Marine Policy* 91, 136-141.

Cameron, A.C. & P.K. Trivedi. (2013) *Regression analysis of count data*, 2nd ed. Cambridge University Press, New York.

Cesar, H., Burke, L. & Pet-Soede, L. (2003) The economics of worldwide coral reef degradation. *Cesar environmental economics consulting (CEEC)*. Available from: https://www.wwf.or.jp/activities/lib/pdf_marine/coral-reef/cesardegradationreport100203.pdf.

Dean, C., Lawless J.F. & G.E. Willmot. (1989) A mixed Poisson-inverse-Gaussian regression model. *Canadian Journal of Statistics*, 17, 171-181.

Deely, J., Hynes, S. & Curtis, J. (2019) Combining actual and contingent behaviour data to estimate the value of coarse fishing in Ireland. *Fisheries Research*, 215, 53-61.

Egan, K. & Herriges, J. (2006) Multivariate count data regression models with individual panel data from an on-site sample. *Journal of Environmental Economics and Management*, 52, 567-581.

Elliff, C.I. & Kikuchi, R.K. (2017) Ecosystem services provided by coral reefs in a Southwestern Atlantic Archipelago. *Ocean & Coastal Management*, 136, 49-55.

Englin, J. & Cameron, T.A. (1996) Augmenting travel cost models with contingent behavior data. *Environmental and Resource Economics*, 7(2), 133-147.

Ferrario, F., Beck, M.W., Storlazzi, C.D., Micheli, F., Shepard, C.C. & Airoldi, L. (2014) The effectiveness of coral reefs for coastal hazard risk reduction and adaptation. *Nature Communications*, 5, 3794.

Filippini, M., Greene, W. & Martinez-Cruz, A.L. (2018) Non-market Value of Winter Outdoor Recreation in the Swiss Alps: The Case of Val Bedretto. *Environmental and Resource Economics*, 71, 729-754.

Folkersen, M.V., Fleming, C.M. & Hasan, S. (2018) Deep sea mining's future effects on Fiji's tourism industry: A contingent behaviour study. *Marine Policy*, 96, 81-89.

Fujita, Y. & Obuchi, M. (2012) Comanthus kumi, a new shallow-water comatulid (Echinodermata: Crinoidea: Comatulida: Comasteridae) from the Ryukyu Islands, Japan. *Zootaxa*, 3367(1), 261-268.

González-Sepúlveda, J.M. & Loomis, J.B. (2011) Are benefit transfers using a joint revealed and stated preference model more accurate than revealed and stated preference data alone? In J.C. Whitehead, T.C. Haab, and J.Huang (eds.), *Preference Data for Environmental Valuation: Combining Revealed and Stated Approaches*, 289-302. Routledge, New York.

Guo, J.E. & P.K. Trivedi. (2002) Flexible parametric models for long-tailed patent count distributions, *Oxford Bulletin of Economics and Statistics*, 64, 63-82.

Haab, T.C. & McConnell, K.E. (2002) *Valuing Environmental and Natural Resources, The Economics of Non-Market Valuation*. Edward Elgar, Cheltenham, UK.

Hausman, J.A., Hall, B.H. & Griliches, Z. (1984) Econometric models for count data with an application to the patents-R&D relationship. *Econometrica*, 52, 909-938.

Hongo, C. & Yamano, H. (2013) Species-specific responses of corals to bleaching events on anthropogenically turbid reefs on Okinawa Island, Japan, over a 15-year period (1995–2009). *Plos One*, 8, e60952.

Hynes, S. & Greene, W. (2013) A panel travel cost model accounting for endogenous stratification and truncation: A latent class approach. *Land Economics*, 89, 177-192.

Hynes, S. & Greene, W. (2016) Preference heterogeneity in contingent behaviour travel cost models with on-site samples: A random parameter vs. a latent class approach. *Journal of Agricultural and Economics*, 67, 348-367.

Imamura, K., Takano, K. T., Kumagai, N. H., Yoshida, Y., Yamano, H., Fujii, M., Nakashizuka, T. & Managi, S. (2020). Valuation of coral reefs in Japan: Willingness to pay for conservation and the effect of information. *Ecosystem Services*, 46, 101166.

Intergovernmental Panel on Climate Change (IPCC), (2018) Global warming of 1.5°C, summary for policymakers. Available from: https://www.ipcc.ch/sr15/chapter/summary-for-policy-makers/.

Kench, P.S., Owen, S.D. & Ford, M.R. (2014) Evidence for coral island formation during rising sea level in the central Pacific Ocean. *Geophysical Research Letters*, 41, 820-827.

Kimura, T., Shimoike, K., Suzuki, G., Nakayoshi, I., Shioiri, A., Tabata, A., Tabata, Y., Fujita, Y., Zayasu, Y., Yamano, H., Namizaki, N., Yokoi, K., Ogasawara, K. & Yasumura, S. (2011) Large scale communities of Acropora horrida in the mesophotic zone off Kume Island, Okinawa. *The Japanese Coral Reef Society*, 13, 43-45 (in Japanese).

Kragt, M.E., Roebeling, P.C. & Ruijs, A. (2009) Effects of Great Barrier Reef degradation on recreational reef-trip demand: a contingent behaviour approach. *Australian Journal of Agricultural and Resource Economics*, 53, 213-229.

Kume Island Tourism Association. (2015) Kumejima Kanko Toukei Chosa (Tourism Statistical Data in Kume Island). Available from: https://www.kanko-kumejima.com/wp-content/uploads/d98ddeaee3328e0804ed75787348943d-1.pdf (in Japanese).

Lankia, T. & Pouta, E. (2019) Effects of water quality changes on recreation benefits in Finland: Combined travel cost and contingent behavior model. *Water Resource Economics*, 25, 2-12.

Lienhoop, N. & Ansmann, T. (2011) Valuing water level changes in reservoirs using two stated preference approaches: An exploration of validity. *Ecological Economics*, 70, 1250-1258.

Mäntymaa, E., Jokinen, M., Juutinen, A., Lankia, T. & Louhi, P. (2021) Providing ecological, cultural and commercial services in an urban park: A travel cost–contingent behavior application in Finland. *Landscape and Urban Planning*, 209, 104042.

Masucci, G. D., Biondi, P., Negro, E. & Reimer, J. D. (2019) After the long summer: Death and survival of coral communities in the shallow waters of Kume island, from the Ryukyu archipelago. *Regional Studies in Marine Science*, 28, 100578.

Ministry of Land, Infrastructure, Transport and Tourism. (2015a) *The List of Vehicle Fuel Consumption*. Available from: http://www.mlit.go.jp/jidosha/jidosha_fr10_000031.html (in Japanese).

Ministry of Land, Infrastructure, Transport and Tourism. (2015b) *Airplane Passenger Survey.* Available from: http://www.mlit.go.jp/koku/koku_tk6_000001.html (in Japanese).

Ministry of the Environment. (2015) The action plan to conserve coral reef ecosystems in Japan 2016-2020. Available from: https://www.env.go.jp/nature/biodic/coralreefs/pamph/pamph_full-en.pdf.

Morgan, O.A. & Huth, W.L. (2011) Using revealed and stated preference data to estimate the scope and access benefits associated with cave diving. *Resource and Energy Economics*, 33, 107-118.

Narukawa, M. & Nohara, K. (2018) Zero-truncated panel Poisson mixture models: Estimating the impact on tourism benefits in Fukushima Prefecture. *Journal of Environmental Management*, 211, 238-246.

Oh, S. (2004) Economic Valuation of Okinawa's Coral Reefs -Economic Analysis of Unavailable Value by Contingent Valuable Method-, *Journal of Business and Economics*, 32, Okinawa International University, 35-54 (in Japanese).

Okinawa Prefectural Government. (2015) Kanko Tokei Zittai Chosa (Survey of Tourism Statistics in 2015). Available from: https://www.pref.okinawa.jp/_res/projects/default_project/_page_/001/020/281/h27chapter4-k.pdf (in Japanese).

Okinawa Prefectural Government. (2018) Ritou Kankei Shiryo (Statistical material about isolated islands) (in Japanese). Available from: https://www.pref.okinawa.jp/site/kikaku/chiikirito/rito-shinko/h31ritoukannkeisiryou.html.

Omija, T., Nakasone, K. & Kobayashi, R. (1998) Water pollution caused by soil runoff at a coral reef in Shiraho, Ishigaki Island. *Annual Report of the Okinawa Prefectural Institute of Health and Environment*, 32, 113-117.

Perry, C.T., Kench, P.S., O'Leary, M.J., Morgan, K.M. & Januchowski-Hartley, F. (2015) Linking reef ecology to island building: Parrotfish identified as major producers of island-building sediment in the Maldives. *Geology*, 43, 503-506.

Perry, C. T., Kench, P. S., Smithers, S. G., Riegl, B., Yamano, H. & O'Leary, M. J. (2011) Implications of reef ecosystem change for the stability and maintenance of coral reef islands. *Global Change*

Biology, 17(12), 3679-3696.

Prayaga, P., Rolfe, J. & Stoeckl, N. (2010) The value of recreational fishing in the Great Barrier Reef, Australia: a pooled revealed preference and contingent behaviour model. *Marine Policy*, 34, 244-251.

Pueyo-Ros, J., Garcia, X., Ribas, A. & Fraguell, R.M. (2018) Ecological restoration of a coastal wetland at a mass tourism destination. Will the recreational value increase or decrease? *Ecological Economics*, 148, 1-14.

Robles-Zavala, E. & Reynoso, A.G.C. (2018) The recreational value of coral reefs in the Mexican Pacific. *Ocean Coastal Management*, 157, 1-8.

Sarker, R. & Surry, Y. (2004) The fast decay process in outdoor recreation activities and the use of alternative count data models. *American Journal of Agricultural Economics*, 86, 701-715.

Shaw, D. (1988) On-site samples' regression problems of non-negative integers, truncation, and endogenous stratification. *Journal of Econometrics*, 37, 211-223.

Tamura, M. (2006) Toward the Establishment of Strategies for the Sustainable Management of Coral Reefs in Akajima Island; Questioner Survey on Socio-economic Value of Coral Reefs. *Midoriishi* 17, 29-33 (in Japanese).

The Cabinet Office in Japan. (2014) Kankyo Mondai ni kansuru Yoron Chosa no Gaiyo (Summary of a public opinion poll about environmental issues). Available from: https://survey.gov-online.go.jp/h26/h26-kankyou/index.html (in Japanese).

United Nations Framework Convention on Climate Change. (2018) *Yearbook of Global Climate Action 2018 Marrakech Partnership*, Available from: https://unfccc.int/documents/184120.

van Beukering, P., Brander, L., van Zanten, B., Verbrugge, E. & Lems, K. (2011) The economic value of the coral reef ecosystems of the United States Virgin Islands: Final report. IVM Institute for Environmental Studies Report Number: R-11/06., The Netherlands: Amsterdam.

Whitehead, J.C., Haab T.C. & J. Huang. (2000) Measuring recreation benefits of quality improvements with revealed and stated behavior data. *Resource and Energy Economics*, 22, 339-354.

Willmot, G.E. (1987) The Poisson-Inverse Gaussian distribution as an alternative to the negative binomial. *Scandinavian Actuarial Journal*, 1987, 113-127.

Winkelmann, R. (2000) Seemingly unrelated negative binomial regression. *Oxford Bulletin of Economics and Statistics*, 62, 553-560.

WWF Japan (2010) Available from: https://www.wwf.or.jp/activities/achievement/3434.html.

Yamano, H., Satake, K., Inoue, T., Kadoya, T., Hayashi, S., Kinjo, K., Nakajima, D., Oguma, H., Ishiguro, S., Okagawa, A., Suga, S., Horie, T., Nohara, K., Fukayama, N. & Hibiki, A. (2015) An integrated approach to tropical and subtropical island conservation. *Journal of Ecological and Environment*, 38(2), 271-279.

Appendix

Table S1 Comparison of data from the Okinawa Prefectural Government (2015) and this study.

	Survey by Okinawa prefectural government from July to September 2015	Final sample
N	103,551	202
Geographical region		
Hokkaido and Tohoku	0.7%	2.0%
Kanto	57.0%	69.3%
Chubu	7.4%	3.0%
Kinki	17.0%	15.8%
Chugoku and Shikoku	2.2%	2.0%
Kyusyu	1.5%	1.0%
Okinawa	14.2%	6.9%
Age		
20-29	13.7%	35.1%
30-39	23.7%	25.2%
40-49	41.2%	17.8%
50-59	13.7%	11.9%
60-69	7.6%	5.9%
70-79	0.0%	1.5%
Gender		
Male	31.9%	43.6%
Female	68.1%	56.4%
Income		
4 million	15.8%	41.6%
4-6	19.5%	23.8%
6-8	21.8%	16.8%
8-10	17.3%	8.4%
10-15	18.8%	7.4%
15	6.8%	2.0%
Number of visit		
1	65.9%	76.7%
2	14.1%	7.4%
3	3.0%	7.4%
4	3.7%	3.0%
5-9	3.7%	3.5%
10-19	5.9%	1.5%
20	3.7%	0.5%
Accompany		
Alone	8.2%	7.9%
Family	72.4%	42.6%
Friend	11.4%	49.5%
Length of stay in Kume		
2	14.1%	10.9%
3	19.3%	34.7%

4	40.0%	43.1%
5	18.5%	9.9%
6	3.0%	1.0%
7-	0.0%	0.5%
Activities in Kume		
Marine leisure	70.4%	84.2%
Diving	11.9%	16.3%
Fishing	5.2%	6.4%