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著者	Nohara Katsuhito, Narukawa Masaki, Hibiki Akira
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Center for Data Science and Service Research
Graduate School of Economic and Management
Tohoku University
27-1 Kawauchi, Aobaku
Sendai 980-8576, JAPAN

Estimating the value of coral reefs in Kume Island, Japan, using a contingent behavior method: A Poisson-Inverse Gaussian approach with on-site correction

Katsuhito Nohara[a,*], Masaki Narukawa[b] and Akira Hibiki[c]

[a]*Hokusei Gakuen University,* [b]*Okayama University, and* [c]*Tohoku University*

Abstract

Coral reefs face a critical crisis because of rising ocean temperature, human resource use, run-off of red soil, among others. Since the recreational and tourism value of reef, in particular, have great potential, the degradation of reef quality may have a great effect on the tourism industry of Okinawa Prefecture, which largely depends on it. This study employs a contingent behavior approach to estimate the effect of reef extinction on recreational demand for Kume Island, Okinawa, Japan. Moreover, the Poisson-Inverse Gaussian model with correction for on-site sampling issues proposed in this study can potentially derive more accurate estimates of consumer surplus. The results show that the CS losses in the case of coral reef extinction become about 627.78 million yen per year.

Keywords: *Contingent behavior, Coral reef*; *Count data model*; *On-site sampling*; *Poisson-Inverse Gaussian model*; *Random-effects model*

1. Introduction

Currently, coral reefs worldwide are facing serious threats. The Paris Agreement proposed to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels. However, even if we can achieve that target, 70 to 90 percent of coral reefs are projected to decline with high statistical confidence by the middle of this century (IPCC, 2018). The Okinawa Prefecture has 80 percent of the coral reefs of Japan. However, they now tend to decrease because of factors including coral reefs bleaching, primarily due to climate-induced ocean warming, feeding damage by acanthaster, and run-off of red soil. (Hongo and Yamano, 2013). The Ministry of the Environment started an investigation of the coral reef communities in 2017 to capture their condition by using images from an artificial satellite and results from a field study. In 1991, the area covered by more than 50 percent of coral reefs filled 5.5 percent of all the area in the surrounding waters of Ishigaki Island and Iriomote Island. However, from the recent investigation, its coverage reduced by approximately 0.1 percent. A

* Corresponding author at: School of Economics, Hokusei Gakuen University, 2-3-1 Ohyachi-Nishi, Atsubetsu-ku, Sapporo, 004-8631, Japan. *E-mail address*: noahra@hokusei.ac.jp

supplementary investigation in 2018 concluded that coral reefs bleaching occurred at all observation spots (https://www.env.go.jp/press/105494-print.html). However, in 2010, the World Wildlife Fund (WWF) reported that a diver and fisherman had discovered a new coral reef community in Kume Island (https://www.wwf.or.jp/activities/achievement/3434.html). Although its scholarly value is remarkably high, it might disappear due to ocean warming or other external factors. As coral reef bleaching occurs in many other remote islands of the Okinawa Prefecture, it seems to be an urgent issue to conserve coral reefs in Kume Island even if those conditions are not terrible at present.

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 point out that coral reefs have multiple ecosystem functions which support tourism benefits such as the generation of fine sand beaches, the maintenance of islands, protection from storm, and the production of seafood (Perry et al., 2015; Kench, 2014; Perry et al., 2011; Ferrario et al., 2014; Cabral and Geronimo, 2018). The tourism or recreation value of coral reefs in the world have the highest potential net benefits, and the net present value includes the value of fisheries, coastal protection, and biodiversity (Cesar et al., 2003; van Beukering et al., 2011). Therefore, the degradation of coral reefs would seriously affect the tourism industry. According to the Okinawa Prefectural Government[1] in 2016, a ripple effect on other industries of the tourism industry will be approximately 1.14 trillion yen. As the Okinawa Prefecture largely depends on the tertiary industry, the detriment to the tourism industry would lead to a sluggish regional economy.

A large number of studies have attempted to estimate the monetary value of coral reefs in several parts of the world by using non-market valuation methods. The travel cost method (TCM) using revealed preference (RP) data is one of the widely accepted techniques to assess the value of outdoor recreational activities. However, it is difficult to estimate the difference in consumer surplus (CS) when the quality of the environment has changed. Therefore, combining contingent behavior (CB) classified as stated preference (SP) data with TCM (TCM + CB) has recently been attempted. The CB model 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). TCM+CB is often applied to quality changes to estimate benefits which includes sports fishing, recreational fishing, coastal wetland, swimming, cave diving, and winter outdoor recreation (Alberini et al., 2007; Prayaga et al., 2010; Pueyo-Ros et al., 2018; Deely et al., 2019; Lankia et al., 2019; Morgan and Huth, 2011; Filippini et al., 2018). Apart from these, some studies are adopting TCM + CB to valuate coral reefs. Bhat (2003) estimates the recreational benefits if the quality of coral reefs is improved by the so-called gamma distributed Poisson random-effects model in TCM + CB, which indicates that the number of

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[1] Okinawa Prefectural Government, http://www.pref.okinawa.jp/site/chijiko/kohokoryu/foreign/english/index.html, Accessed date: 16 April 2018.

trips will increase by about 43 percent and the change in CS per person will be US$3,080 under the scenario of 100 percent improvement of coral quality. Folkersen et al. (2018) employ TCM + CB to estimate the effect of deep sea mining on future trip demand in Fiji, although they focus on the number of planned future trips with and without deep sea mining. This approach means that irrespective of whether degradation of coral reefs would occur, the recreational use-value of coral reefs is limited to diving and snorkeling. However, Kragt et al. (2009) estimate the effects of Great Barrier Reef degradations on trip demand by using only CB data in a negative binomial random-effects model. Although almost all of the previous studies estimate the effects of environmental improvements on trip demand, they assess 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 decline in reef quality. Following their approach, we use only CB data by asking respondents about their future trips under the scenario of both its current state and extinction. Note that this study focuses on not the improvement of reef quality but the extinction of coral reefs because of two reasons. First, for example, they argue that using the number of planned trips at current and degraded reef quality is more suitable in the case of Great Barrier Reef quality decline, from which they consider an 80 percent 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 percent loss on their future trips even if they are shown pictures. Second, we pay much attention to the fact that coral reefs were imminently threatened with extinction in the past, and this situation is worsening year by year. For instance, multiple events of coral bleaching have been recorded in most regions since the mass bleaching event of 1998, which cause a 100 percent coral depletion in some regions.[2] Given the state of recent coral reefs, such a scenario is not unrealistic. Furthermore, the extinction of coral reefs does not necessarily induce zero recreation demand, although it may affect water quality and landscape. According to a public opinion poll carried out by the Cabinet Office (2014), for example, most people do not recognize the ecosystem services of coral reef such as recreation or tourism included in cultural services; only 19 percent do. Meanwhile, in Japan, the recreational value of coral reefs has been little investigated. Oh (2004) and Tamura (2006) estimate the non-use values of coral reefs in the Kerama Islands and around the Akajima sea area by using CVM, respectively. The problem seems to lie in the fact that there are no studies on estimating the effects of the decline in reef quality on future recreational demand in Japan.

It should also be emphasized that the 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) have not estimated the value of coral reefs directly, they adopt a pooled TCM + CB model which cannot capture individual-specific effects in count data. Despite that, Bhat (2003) collects the data through an on-site survey; however, an estimation problem related to the sampling is not dealt with. Statistical analysis of such on-site count data should be

[2] United Nations Environment Programme, Coral Reef Unit, http://coral.unep.ch/Coral_Reefs.html, Accessed date: 16 April 2018.

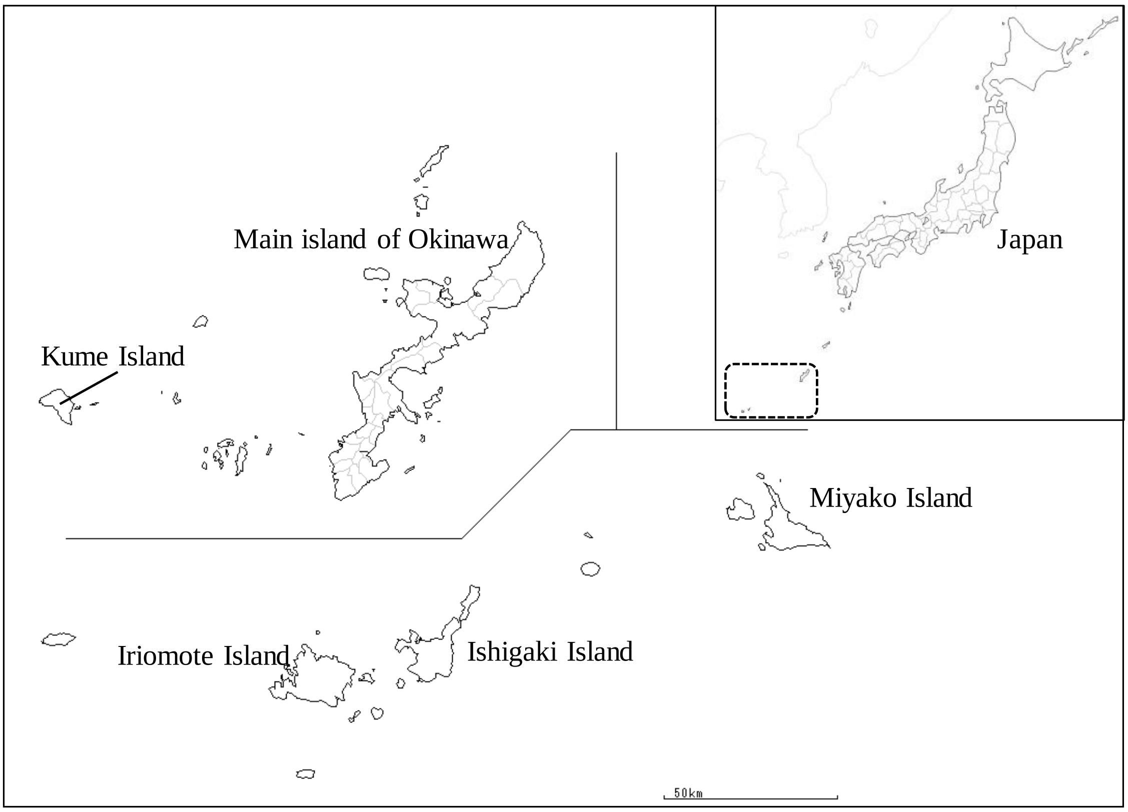
controlled for truncation and endogenous stratification, as advocated by Shaw (1988), who addresses these issues in the Poisson regression model. As stated above, Kragt et al. (2009) analyze CB data by a negative binomial random-effects model; however, their model is not adjusted for on-site sampling. As far as collecting data through an on-site survey, even if only CB data is used in the estimation, it must be corrected for its issues. In addition, as argued by Guo and Trivedi (2002), Sarker and Surry (2004), and Cameron and Trivedi (2013), the capability of negative binomial to capture overdispersion would be limited and inadequate if the data has a distribution with a so-called long (heavy) tail. Therefore, a reliable statistical inference cannot be made. However, 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. Guo and Trivedi (2002) apply the PIG model to an analysis of patent data. Since this paper uses trip number data from an on-site survey, our estimation approach is based on the PIG model and add 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) have recently proposed an estimation approach to panel count data (truncated at zero), to utilize TCM + CB, they presume that the data are collected via a web-based off-site survey. Our approach is clearly different from theirs since we consider the PIG model adjusted for an on-site survey. To our knowledge, this is the first attempt to construct the PIG approach using on-site sampling data, which is another contribution of this study.

This study estimates the changes of consumer surplus in the Kume Island trip resulting from a decline in reef quality using the PIG approach while controlling for on-site sampling in CB. The remainder of this study is composed as follows. In the next section, we explain the data collection procedure. Section 3 proposes the estimation approach based on the PIG model for an on-site survey. Section 4 provides the estimation results and the welfare estimates related to loss of reef quality. Section 5 concludes and presents the topics for future research.

2. Survey design and data

2.1 Data collection

Kume Island is located about 90 km west from the main island of Okinawa (Fig.1) and blessed with a richness of natural resources that yields much potential ecosystem services. However, not so many tourists visit as compared to other isolated islands of the Okinawa Prefecture, such as Ishigaki Island or Miyako Island. However, the rich natural resources have been largely preserved and



Source: http://www.craftmap.box-i.net/ken.php

Fig. 1 Location of Kume island

untouched due to the absence of large-scale development in Kume Island. Table 1 shows the top five most visited isolated islands in 1985 and the corresponding number of tourists in 1985 and 2015, which is obtained from the Okinawa Prefectural Government (2018). Although the increasing rate of tourists in the past thirty years in Kume Island is of least value among the isolated islands, many tourists will likely be attracted to Kume Island in the near future because there remain precious reefs as stated in Section 1.

Our survey was conducted for a week in September 2015 at the Kumejima airport; it included weekdays and weekend.[3] The sample was randomly selected at the airport, as well as from limited visitors who had come from other prefectures to end their trips in Kume Island. We presented photographic material to respondents, which was provided by a scientist, Dr. Hiroya Yamano, to help respondents comprehend the condition of the reef going extinct. We obtained 302 respondents, but not all were used for analysis due to missing information. Thus, 168 respondents were included in the empirical analysis of this study. The information was gathered by distributing a survey questionnaire to visitors who came on a trip to Kume Island. The questionnaire included accompanying persons and

[3] The survey questions used in this study are available upon request.

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

their age, activities enjoyed during the trip, the interest for natural resources in Kume Island, the visit duration in Kume Island, travel mode, several demographic characteristics, and the number of trips planned for the next ten years at the current reef quality given the extinction of coral reef. It was expected that these variables would affect visitors' trip frequency significantly. Moreover, we gathered data on whether visitors had stayed at Naha city to locate the main destination of the trip. Since there were no direct flights between Kume Island and other domestic regions, and all visitors had to transit at Naha airport, we can exclude the possibility of a substitute recreation site affecting the demand for Kume Island and apply the framework of a single-site demand function. Although 19 percent of respondents made a stop in Naha city and all of them had an overnight stay there, their length of stay at Kume Island was greater than that of Naha city. 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 its period to the next ten years because it would be unrealistic for the extinction of coral reefs to occur in such a short term.

From 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 are measured as CS, which is the area between the RP trip demand curves and the SP trip demand curves (Whitehead et al., 2000). In other words, respondents provide 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. However, as discussed by Bockstael et al. (1989) and Kragt et al. (2009), since incorporating the actual number of trips in the recreational demand function would result in biased estimates of CS, it seems more appropriate for its estimation to employ the difference between the planned recreational demand at the current reef quality, as well as the degraded reef quality. Thus, we estimate CS by using the number of planned trips at the current reef quality and at the extinction of coral reefs as dependent variables in the subsequent empirical model.

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;	3.417	3.287
Visit_SP100	Number of planned recreational trips to Kume Island in the next ten years at the degraded reef quality (100 percent loss)	0.452	1.866
TC	Per-person travel costs to access Kume Island (¥10,000)	7.017	1.525
SP100	Dummy variable denoting trip counts elicited through a contingent behavior question		
Income	Household income (¥1,000,000)	5.500	3.864
Education	Dummy variable = 1 if the respondent has graduated from the university	0.601	0.491
Accompany	Number of accompanying persons	2.571	1.610
Alone	Dummy variable = 1 if the respondent takes a trip alone	0.083	0.277
Kume 1	Dummy variable = 1 if the respondent experiences marine leisure during	0.845	0.363
Kume 2	the trip	0.143	0.351
Kume 3	Dummy variable = 1 if the respondent experiences diving during the trip	0.006	0.077
	Dummy variable = 1 if the respondent participates in activities in a natural		
Interesting 1	environment during the trip	0.637	0.482
Interesting 2	Dummy variable = 1 if the respondent is interested in coral reef	0.673	0.471
Interesting 3	Dummy variable = 1 if the respondent is interested in marine species	0.054	0.226
	Dummy variable = 1 if the respondent is interested in endemic insects in		
Interesting 4	Kume Island	0.821	0.384
Naha stay	Dummy variable = 1 if the respondent is interested in landscape	0.185	0.389
Days	Dummy variable denoting stay at Naha city (yes = 1)	3.690	1.137
Experience 1	Trip length in Kume Island	0.976	0.153
	Dummy variable = 1 if the respondent has prior experience of marine		
Experience 2	activities except for diving	0.446	0.499
Experience 3	Dummy variable = 1 if the respondent has prior experience of diving	0.054	0.226
	Dummy variable = 1 if the respondent has prior experience of activities in a natural environment		

2.2 Travel costs

The travel costs are computed as the round trip costs from origin to destination. Specifically, we calculated them by summing up 1) the costs from the nearest public office to the nearest airport and 2) airfares 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) which corresponds to the Price Survey of Oil Products published by Agency for Natural Resources and Energy (2015).[4] The average runnable distance per liter (26.1 km/l) of passenger cars using petrol, based on the List of Vehicle Fuel Consumption published by Ministry of Land, Infrastructure, Transport and Tourism (2015a),[5] was adopted for the calculation of fuel consumption. If respondents used the highway for time savings, we assumed that they referred to Drive Plaza[6] to infer their cost. The distance from a respondent's house to the nearest airport was calculated using Google Maps.[7] When the respondents used rental cars between their house and the nearest airport, we regarded that costs as the sum of the price of a rental car and the petrol cost. The rental car fee was calculated by using the price list of the nearest rental car shop from a respondent's house. We assumed that the price of a rental car is the one-way car rental fee.[8,9] When respondents used taxi services or public transportation between their house and the nearest airport, the cost was calculated by summing up each fee from the appropriate internet site.[10,11] Second, airfares from the nearest airport to the Kumejima airport were calculated by using the Airplane Passenger Survey published by the Ministry of Land, Infrastructure, Transport and Tourism (2015b).[12] We adopted the discount which most passengers utilized at each air route. The opportunity cost of time between respondents' house and Kumejima airport was considered to be one-third of the wage rate following many previous studies.

3. Model estimation

3.1 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

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

where $\boldsymbol{\beta}$ is the parameter vector. If y_i is independently Poisson distributed with the above mean

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[4] Agency for Natural Resources and Energy., 2015. The Price Survey of Oil Products. http://www.enecho.meti.go.jp/statistics/petroleum_and_lpgas/pl007/results.html#headline4, Accessed date: 22 February 2018.

[5] Ministry of Land, Infrastructure, Transport and Tourism., 2015a. The List of Vehicle Fuel Consumption. http://www.mlit.go.jp/jidosha/jidosha_fr10_000031.html, Accessed date: 22 February 2018.

[6] Drive Plaza. http://www.driveplaza.com/dp/SearchTop, Accessed date: 22 February 2018.

[7] Google Maps. https://www.google.co.jp/maps, Accessed date: 21 February 2018.

[8] Nippon Rent-a-car. https://www.nrgroup-global.com/en/, Accessed date: 21 February 2018.

[9] Niconico Rent a car. https://niconicorentacar.jp/, Accessed date: 21 February 2018.

[10] TaxiSite. http://www.taxisite.com/ (in Japanese), Accessed date: 22 February 2018.

[11] Google Maps Transit. http://maps.google.com/landing/transit/index.html, Accessed date: 22 February 2018.

[12] Ministry of Land, Infrastructure, Transport and Tourism., 2015. Airplane Passenger Survey, http://www.mlit.go.jp/koku/koku_tk6_000001.html (in Japanese). Accessed date: 22 February 2018.

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 expression is a generalization of the standard Poisson regression model, although specifying $g(\nu)$ is necessary to obtain the explicit form of the density. The most popular example is to assume that ν follows a gamma distribution; that is, the mixed Poisson distribution (2) is the Poisson-gamma mixture, which leads to the well-known negative binomial model.

This study considers the PIG model of Dean et al. (1989), in which ν follows an inverse Gaussian (IG) distribution. Since $\mathrm{E}(\nu) = 1$, the probability density function of an IG distribution is given by

$$g(\nu) = \sqrt{\frac{1}{2\pi\tau\nu^3}} \exp\left(-\frac{(\nu-1)^2}{2\tau\nu}\right),$$

where $\mathrm{Var}(\nu) = \tau > 0$ is a shape parameter and unknown. Thus, we have a Poisson inverse Gaussian mixture as the mixed Poisson distribution (2). From the explicit expression of a PIG distribution shown by Willmot (1987), the conditional probability mass function for the PIG model can be obtained from Equations (3) and (4) below. If $y > 0$,

$$h(y|\mathrm{x}) = \frac{p(0)\lambda^y}{\Gamma(y+1)} \sum_{k=0}^{y-1} \frac{\Gamma(y+k)}{\Gamma(y-k)\Gamma(k+1)} \left(\frac{\tau}{2}\right)^k (1+2\tau\lambda)^{-\frac{y+k}{2}}, \tag{3}$$

whereas if $y = 0$,

$$p(0) = \exp\left(\tau^{-1}\left(1 - \sqrt{1+2\tau\lambda}\right)\right). \tag{4}$$

Note that as the shape parameter $\tau \to 0$, the PIG model approaches the standard Poisson regression model, and, thus, τ is the parameter describing 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

$$h^S(y|\mathbf{x}) = h(y|\mathbf{x})w(y,\lambda), \quad w(y,\lambda) = \frac{y}{\mathrm{E}(y|\mathbf{x})}. \tag{5}$$

Thus, by applying Equation (5), we can construct a log-likelihood function suitable for the on-site sampling data, as shown in Equation (6):

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

$$= \sum_{i=1}^{N} \left\{ \log\frac{\lambda_i}{\Gamma(y_i)} + \tau^{-1}\left(1-\sqrt{1+2\tau\lambda}\right) \log\left(\sum_{k=0}^{y-1} \frac{\Gamma(y+k)}{\Gamma(y-k)\Gamma(k+1)} \left(\frac{\tau}{2}\right)^k (1+2\tau\lambda)^{-\frac{y+k}{2}} \right) \right\}. \tag{6}$$

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

3.2 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 a 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 gamma-distributed Poisson random-effects (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 inverse Gaussian distributed Poisson random effects (RE-PIG) model, which is the expansion of the univariate PIG model. Then, to analyze on-site sampling data, we correct for its sampling effects in a way similar to that given in Section 3.1.

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. Similar to Section 3.1, we assume that the conditional mean, which is denoted by λ_{ij} and satisfies $\mathrm{E}(\mu_{ij}|\lambda_{ij}) = \lambda_{ij}$, can be described as follows:

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

The characteristic feature of this specification is that v_{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, by expanding Equation (2) in Section 3.1 to the present context, the conditional probability density function of the RE-PIG model is given by

$$h(\boldsymbol{y}|\tilde{\mathbf{x}}) = \int_0^\infty \prod_{j=1}^{J} \frac{\exp(-\mu_j)\, \mu_j^{y_j}}{y_j!} g(v)dv = \prod_{j=1}^{J} \frac{\lambda_j^{y_j}}{y_j!} \int_0^\infty \exp(-v\, \lambda_J^*) v^{y_J^*} g(v)dv,$$

where $y_J^* = \sum_{j=1}^{J} y_j$, $\lambda_J^* = \sum_{j=1}^{J} \lambda_j$, and the subscript i denoting an individual is omitted for notational simplification. Since $g(v)$ is the density function of the IG distribution, it follows from the same argument in Section 3.1 that, after some calculation, we obtain the conditional probability mass function for the RE-PIG model as follows:

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

where $q(0) = \exp(\tau^{-1}(1 - \sqrt{1 + 2\tau\lambda_J^*}))$.

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

$$h^S(\boldsymbol{y}|\tilde{\mathbf{x}}) = \frac{q(y_J^*)\lambda_1^{y_1-1}}{(y_1-1)!} \prod_{j=2}^{J} \frac{\lambda_j^{y_j}}{y_j!}. \tag{7}$$

Hence, we can construct a log-likelihood function from Equation (7) in the same way as in Equation (6) in Section 3.1 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) is restricted to be positive and is mainly determined by only one parameter.

3.3 Empirical model

This section introduces our model for empirical analysis, in which dependent variables are constructed from the CB data only; thus, the proposed estimation approach is also capable of dealing with such a case. Following the variable definition from the on-site survey as described in Table 2, the recreational demand function for Kume Island can be specified as:

$$\begin{aligned}\lambda_{ij} = \exp\big(&\beta_0 + \beta_1 TC_{ij} + \beta_2 Income_{ij} + \beta_4 Education_{ij} + \beta_5 Accompany_{ij} + \beta_6 Alone_{ij} \\ &+\beta_7 Kume1_{ij} + \beta_8 Kume2_{ij} + \beta_9 Kume3_{ij} + \beta_{10} Interesting1_{ij} + \beta_{11} Interesting2_{ij} \\ &+\beta_{12} Interesting3_{ij} + \beta_{13} Interesting4_{ij} + \beta_{14} Naha_{ij} + \beta_{15} Days_{ij} \\ &+\beta_{16} Experiance1_{ij} + \beta_{17} Experiance2_{ij} + \beta_{18} Experiance3_{ij}\big), \qquad j = 1, 2,\end{aligned}$$

which implies that $\mathbf{x}_{ij} = \big(1, TC_{ij}, Income_{ij}, Education_{ij}, Accompany_{ij}, Alone_{ij}, Kume1_{ij}, Kume2_{ij}, Kume3_{ij}, Interesting1_{ij}, \cdots, Interesting4_{ij}, Naha_{ij}, Days_{ij}, Experiance1_{ij}, \cdots, Experiance3_{ij}\big)'$ and $\boldsymbol{\beta} = (\beta_0, \beta_1, \cdots, \beta_{18})'$ in the framework of Section 3.2. Note that $\mathbf{y}_i = (Visit\_SP0_i, Vist\_SP100_i)'$ represents the CB data under the hypothetical scenarios, the current reef condition, and reef extinction (cf. Kragt. et al., 2009). That is, y_1 is subject to the on-site correction because, to collect the data, an on-site survey is employed 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 is 1 from the on-site survey data. However, y_2 indicates CB data in which the hypothetical scenario of coral reef extinction may lead to a decrease in the number of planned trips.

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

$$\Delta\,\mathrm{CS} = \frac{\lambda_2 - \lambda_1}{\beta_1}, \tag{8}$$

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. In the subsequent section, we compute the estimated $\Delta\mathrm{CS}$ 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 (8). 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).

4. Estimation results

We estimate the parameters in the recreational demand function constructed in the previous section by the two types of econometric approaches–the RE-PGM and RE-PIG models with on-site correction. All computations in this section are conducted using Ox (Doornik, 2009). Table 3 reports the estimation results of the empirical model by the two approaches. First, the travel cost coefficients (TC), which is our primary interest, are negative as expected and significant at the 5% level in both approaches. Moreover, both of the likelihood ratio (LR) statistics reject the null hypothesis that all of the coefficients except for the constant are zero at the 1% significance level. Although there are only

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

	RE-PGM		RE-PIG	
Variable	Coeff.	SE	Coeff.	SE
TC	-0.138**	0.061	-0.125**	0.063
SP100	-1.676***	0.125	-1.676***	0.125
Income	0.055**	0.025	0.053**	0.025
Education	-0.468**	0.184	-0.452**	0.187
Alone	1.378***	0.321	1.361***	0.331
Accompany	0.222***	0.059	0.221***	0.054
Kume1	0.591**	0.285	0.545*	0.294
Kume2	0.987***	0.296	0.972***	0.299
Kume3	1.630*	0.963	1.887*	1.071
Interesting1	-0.148	0.190	-0.138	0.194
Interesting2	-0.182	0.205	-0.178	0.208
Interesting3	0.986***	0.357	0.959***	0.362
Interesting4	0.131	0.244	0.139	0.247
Naha stay	0.164	0.234	0.213	0.242
Days	0.086	0.074	0.096	0.078
Experience1	-0.349	0.562	-0.349	0.569
Experience2	-0.225	0.196	-0.232	0.200
Experience3	-0.681	0.431	-0.639	0.443
Constant	-0.647	0.854	-0.367	0.799
α or τ	1.905*	1.047	0.977***	0.281
Log-likelihood	-466.6		-465.2	
LR	318.0***		310.5***	
AIC	973.3		970.5	

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

slight differences in the significance level between the RE-PGM and RE-PIG models, each of the coefficients for SP100, Income, Education, Alone, Accompany, Kume, and Interesting 3 is 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. Further, the coefficients associated with Kume show statistically positive signs, indicating that the experience of activities during the trip has increasing effects on future recreational demand. Since Days and the other dummy variables except for Interesting 3 are not statistically significant in both approaches, visitors' interest regarding natural resources in Kume Island and past experiences about marine activities do not seem to affect their trip decision making. Focusing on the overdispersion parameters, α and τ, we find that they are statistically different from zero at the 10% and 1% levels, respectively, which implies that ignoring unobserved heterogeneity will incur efficiency loss of the estimators and may also make them inconsistent. Thus, it seems that the random-effects model approaches with on-site correction in the framework of pseudo panel data offer more reliable parameter estimates. Next, to compare the performance between the RE-PGM and RE-PIG models, the Akaike information criterion (AIC; Akaike, 1973) for each approach are reported in Table 3. Since the AIC of the RE-PIG model is slightly smaller than that of the RE-PGM model, in addition to the fact that the significance levels of α and τ are largely different from each other, it is conjectured that the former approach is more appropriate to analyzing our on-site sampling data than the latter approach. This conjecture implies that the IG distribution would be able to capture overdispersion or unobserved heterogeneity than the gamma distribution more adequately.

Following Equation (8) and the related discussion in Section 3.3, we can calculate the per-person CS (ΔCS) for ten years in Table 4, where the 90% confidence intervals of the estimates using the Krinsky-Robb procedure (Haab and MacCnonell, 2002; González-Sepúlveda and Loomis. 2011) are also reported. Note that Table 4 includes the estimates obtained by using the RE-PGM and RE-PIG models while ignoring the on-site sampling issues to examine the effects of on-site correction. The estimation results of the empirical model corresponding to Table 3 by these approaches are provided in the Appendix. It is easily seen from the results that the annual CS per-person trip by the RE-PGM

Table 4 Estimation results for CS loss

	RE-PGM	RE-PIG	RE-PGM without on-site correction	RE-PIG without on-site correction
ΔCS (ten years)	3.769	6.107	22.618	25.476
90% CI-LB	1.598	2.864	13.342	13.749
90% CI-UB	13.193	23.042	59.005	68.032

Unit: ¥10,000

model (3,796 yen) is smaller than that by the RE-PIG model (6,107 yen), and, although both of the confidence intervals are asymmetric, the latter has a wider range than the former. We find that a similar tendency also exists in both models without on-site correction. These features seem to reflect the underestimation caused by the inadequacy of the RE-PGM model specification on unobserved heterogeneity as discussed above. Thus, in terms of the model evaluation, it is preferred to adopt the result of the RE-PIG model in the following discussion. For comparison, Kragt et al. (2009) demonstrated that the annual CS per-person trip was 83.5 Australian dollars in their study, though the per-person recreational value of a site quality change using Equation (8) was not explicitly provided. Thus, converting Australian dollars into yen by using the exchange rate at that time, we find that this amount is approximately 7,097 yen, noting that the hypothetical scenarios (the degraded reef quality) are not the same. It is clear from Table 4 that the CS estimates based on the models without on-site correction are considerably larger than those of the corrected models. Given this fact, there is a possibility that Kragt et al. (2009) will overestimate the CS loss because they did not deal with the on-site sampling issues. It is, thus, crucial to measure recreational values via an on-site survey to control for on-site sampling and adequately specify unobserved heterogeneity or overdispersion.

As the total number of visitors to Kume Island in 2015 is 102,797, the CS loss in the case of coral reef extinction become about 627.78 million yen per year based on our RE-PIG estimate. According to the original budget from the Okinawa Prefectural Government of 2015 and 2019,[13] reproduction project for conservation of coral reefs in 2015 includes 233.52 million yen, whereas that amount decreases by 69.3 million yen in 2019. As the original budget in 2015 to protect coral reefs is not enough given our results, it might be necessary to reconsider the optimal allocation of budget and the effective use of it.

5. Concluding remarks

In Japan, coral reefs in the Okinawa Prefecture are seriously damaged, and their distributional area decreases year by year. However, there remains a coral reef community which has remarkably high scholarly value in Kume Island. Thus, this paper focuses on Kume Island and estimates the recreational demand function by using only CB data. Moreover, we propose the 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 and show that the annual CS per-person trip is 6,107 yen by the RE-PIG model. To avoid the overestimation of CS, the comparative study suggests that, choosing the appropriate estimation approach and the correct for on-site sampling issues is a requirement. However, note that

[13] Okinawa Prefectural Government. https://www.pref.okinawa.jp/site/somu/zaisei/17312.html, Accessed date: 30 May 2019.

there is still some room for improving the estimation accuracy because the sample size may be small.

Furthermore, from the estimated CS loss, the coral reef extinction in Kume Island might cause serious economic damage to recreational demand in the Okinawa Prefecture. According to the report about the action plan to conserve coral reef ecosystems in Japan 2016-2020, published by the Ministry of the Environment (2015) in Japan, three priority issues are selected, and one of them is the *promotion of sustainable tourism in coral reef ecosystems*. This report also mentions that coral reef tourism is very popular and is an industry which produces the highest economic value in the coral reef areas. Finally, it concludes that the coral reef will become more and more important in terms of the development of the tourism industry in the region because conservation of the coral reef ecosystem enhances its value as a tourism resource. Thus, it is agreeable that the protection of the coral reef based on economic valuation leads to the desirable promotion of sustainable tourism. Additionally, in Kume Island, the reproduction project for the protection of coral reefs was organized in 2019 to promote sustainable activities which aimed at recuperation from coral reef bleaching or death. The contents of this project include cultivation, monitoring, and enlightening people on coral reefs. It seems valid to presume that our results present the necessity of cost-effective policy measures as soon as possible to support, such as a local project. It is hoped that our study would be of some benefit to the conservation of coral reefs in Kume Island.

From the methodological viewpoint, there is a potential concern that the PIG model with controlling for on-site sampling is extended to latent class or random parameter approaches, which was considered and proposed by Hynes and Greene (2013, 2016) based on the negative binomial model. They applied these approaches to the panel dataset of beach users and showed 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, thus, make it possible to more flexibly cover a wide range of specification on unobserved heterogeneity in a pseudo-panel data and would be of value to the field regarding welfare estimation of recreation, which is scope for future research.

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Appendix

Table A1 Results of RE-PGM and RE-PIG models without on-site correction

	RE-PGM		RE-PIG	
Variable	Coeff.	SE	Coeff.	SE
TC	-0.113***	0.043	-0.100**	0.045
SP100	-2.002***	0.122	-2.022***	0.122
Income	0.039**	0.017	0.036**	0.017
Education	-0.285**	0.125	-0.271**	0.129
Alone	1.094***	0.215	1.055***	0.228
Accompany	0.154***	0.035	0.152***	0.034
Kume1	0.368*	0.191	0.330*	0.198
Kume2	0.657***	0.199	0.641***	0.205
Kume3	1.379**	0.616	1.573**	0.656
Interesting1	-0.136	0.130	-0.120	0.135
Interesting2	-0.126	0.139	-0.127	0.144
Interesting3	0.759***	0.237	0.701***	0.247
Interesting4	0.126	0.167	0.125	0.171
Naha stay	0.164	0.159	0.188	0.166
Days	0.077	0.049	0.082	0.051
Experience1	-0.258	0.381	-0.257	0.393
Experience2	-0.130	0.134	-0.134	0.139
Experience3	-0.617**	0.299	-0.571*	0.310
Constant	0.984*	0.520	0.917*	0.543
α or τ	0.232*	0.051	0.279***	0.068
Log-likelihood	-509.0		-506.4	
LR	512.8***		492.7***	
AIC	1058.0		1052.8	

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

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