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Spatial Hedonic Analysis to support Tourism-sensitive Tsunami Mitigation Planning

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Abstract

The construction of protective infrastructure such as seawalls and the designation of land-use and building regulation zones are commonly recommended strategies for tsunami and sea-level rise oriented mitigation in coastal areas. While the effectiveness of these strategies are undoubted, in regions where coastal tourism is the primary industry, the implementation of such strategies have been low due to fear of negative economic impact related to loss of coastal view and accessibility. Therefore, this paper examines the influence of coastal amenities to hotel room rates alongside other attributes through hedonic analysis. Specifically, it investigates whether rooms with coastal views, accessibility to beaches, and safety due to sea walls or dikes are priced higher than other rooms, in order to quantify the associated values of Japanese coastal areas where tourism is a key economic driver. Subsequently, it suggests geographical market boundaries to guide the management and risk-mitigation of coastal areas. Findings reveal that: Semi-parametric Geographically Weighted Regression (S-GWR) results can accurately identify both stationary and non-stationary relationships present between the dependent and explanatory variables; view of the sea and other environmental attributes have significant influence on hotel room pricings; and tsunami mitigation strategies which can have long-term implications should be adopted in a manner sensitive to the tourism industry.

Keywords: OLS; GWR; hedonic; tsunami; disaster mitigation; spatial planning; tourism; SDGs

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1. Introduction

The construction of protective infrastructure such as seawalls or coastal levees and the designation of land-use and building regulation zones in coastal areas, which are tsunami-prone or at risk from sea-level rise, is a commonly recommended strategies to ensure disaster risk reduction. While the effectiveness of these strategies are undoubted, residents often still remain wary of such strategies, especially in regions where coastal tourism is the primary industry, and even more so, where the areas are rurally located. Fear that such policies will cause less people to come in (as tourists/residents) and more people to move out result in political tensions between the municipality (seeking to maximize the safety of the whole community) and the residents (seeking to minimize their economic losses which may result from such a designation); hindering the implementation of any long-term risk reduction strategies that may affect building development.

The aim of this paper is to understand the value of coastal environmental features which may be affected if the aforementioned types of policies are enacted. To this extent, a hedonic pricing model is employed in analyzing hotel room rates given its effectiveness in determining the value of non-market attributes (such as environmental amenities) on market prices. Multiple hedonic models (ranging from Ordinary Least Square (OLS) to Geographically Weighted Regression (GWR)) are employed to reveal fixed and spatially varying attributes in the study region, and the consequent implications for multi-regional and region-specific tsunami countermeasures are identified. The intention of this work to aid in an evidence-based consensus-building and decision-making process for risk mitigation which not only focuses on the risk exposure factor but is also sensitive to the long-term economic concerns of the region.

The remainder of this paper is structured as follows: Section 2 links this study with the existing literature on coastal hazard mitigation and hedonic pricing; while section 3 describes the data and analysis methodology. In section 4, we describe and evaluate the three hedonic models including OLS and GWR. Section 5 summarizes the study presented in this paper.

2. Literature review

As recent tsunami and hurricane disasters have repeatedly demonstrated, development in at-risk areas only exacerbate the vulnerability to future disasters. Thus, the land-use planning strategies to mitigate the risk of such areas have been categorized into four categories: 1) protect (includes building new defensive structures); 2) accommodate (altering existing assets to reduce vulnerability); 3) avoid (not placing assets in at-risk areas through zoning and building regulations); and 4) retreat (relocating existing assets to safer areas) (Butler et al., 2016; Eichhorst et al., 2011; Macintosh et al., 2015). Of the four, avoid and retreat strategies are likely to have the highest impact, and are therefore commonly recommended measures for coastal areas with risk of tsunami or sea-level rise (Eisner, 2005). Yet, as Butler et al. (2016) report, they are also the most under-utilized strategies, especially in already built-out areas.

To overcome this issue, governments across the world are enacting statutes that enable the designation of special zones to restrict development in certain at-risk areas (Bhattacharya et al., 2017; Horney et al., 2017). Japan is no different. After the Great East Japan Earthquake in 2011, an Act on Promotion of Tsunami Countermeasures was brought into effect for the coastal region of Japan, which calls for designation zones employing a combination of soft measures (such as evacuation plans) and hard measures (such as land-use and building regulations) in addition to protective infrastructural measures (such as coastal levee building) (Bhattacharya et al., 2017). However, thus far the adoption rate of the more stringent measures (such as land-use and building regulations) are very low due to community concerns over the economic impact of such measures (Bhattacharya et al., 2017). A big part of the concern is owing to the high dependence on the tourism industry in these at-risk coastal regions, which may be affected by such regulations in different ways. Several prior studies have already highlighted the value of sea view for the housing market and the hotel industry in coastal regions of Europe (Espinet et al., 2003; Fleischer, 2012; Latinopoulos, 2018). As such, the loss or deterioration of coastal views and reduction in beach accessibility due to increase in seawall/levee height and coverage or implementation of building restriction zones, could potentially decrease the attractiveness of properties and hotels that currently boast these amenities. Hence it is imperative to: 1) identify the attributes that are likely partial price determinants; 2) establish whether the trends observed in prior studies are also true for Japan; 3) quantify the economic values of relevant attributes which may be affected in mitigation policy implementation; and 4) formulate appropriate risk mitigation strategies that are sensitive to resulting economic effects. All of these four objectives are covered in this paper.

Since its establishment based on the theoretical work by Lancaster (1966) and Rosen (1974) , the hedonic pricing model approach has come to be widely used across different disciplines. The theoretical framework based on the utility-maximizing approach allows the derivation of implicit attribute prices for multi-attribute goods under conditions of perfect competition through decomposition of a composite good's prices, into a function of homogenous attributes (or characteristics) (Andersson, 2010). The approach is particularly useful in real-estate studies for quantifying the value of structural, environmental and locational amenities of a place which are otherwise not explicitly quantifiable (Xiao, 2017). Although hotel markets are equally appropriate for hedonic analysis they are not as popular owing to the difficulties in attaining price records (Andersson, 2010). However, with the recent development of internet-based travel agencies and web scraping tools, exhaustive data on room rates and hotel characteristics are available to be further combined with GIS-based locational and environmental information for a comprehensive hedonic analysis on hotel room prices. Consequently, the price of a room (Y_i) can be defined by a set of attributes as follows:

$$Y_i = f_i(S_i, E_i, L_i, T_i) \tag{1}$$

Where S_i, E_i, L_i, and T_i represent the room/hotel characteristics and services, environmental, locational, and seasonality attributes, respectively. While numerous previous studies have considered the implicit prices of locational and environmental amenities from hotel room prices (Andersson, 2010; Fleischer, 2012; Kim et al., 2020a; Latinopoulos, 2018), there are only limited number of studies which relate hotel prices to hazard mitigation planning (Hamilton, 2007) and even those are conducted using the OLS linear regression method, which assumes that a spatially constant relationship exists between dependent and independent variables which may not necessarily be true for the entire region of study (Kim and Nicholls, 2016; Xiao, 2017). Thus, to comprehend the spatial effects present, aspects such as spatial dependence (or spatial autocorrelation) and spatial heterogeneity (or spatial non-stationary) must also be investigated.

Following the First Law of Geography by Tobler (1970) which states that "everything is related to everything else, but near things are more related than distant things," spatial characteristics often exhibit local homogeneity as hotels in the same neighborhood are likely to share similar developmental requirements and building characteristics, and also share the same location amenities such as restaurant and malls –resulting in spatial dependence (Zhang et al., 2011). A special case of spatial dependence is spatial heterogeneity which considers the non-stationarity (or spatially varying relationship) between variables that cannot be accounted for by a global (OLS) model (Getis, 1994); leading to inaccurate regressions results when employing non-spatial regression methods (Anselin, 1988). Accordingly, GWR which extends the traditional OLS regression model by including spatial data (by assigning geographical weights) and examining the local regression coefficients is suggested for measuring and modeling spatial non-stationarity (Fotheringham et al., 2002). Furthermore, since it is not necessary that all variables have non-stationary propertied over space, a mixed model which accounts for both fixed and varying variables - a semi-parametric GWR (S-GWR)- can yield more accurate and meaningful results (Latinopoulos, 2018; Nakaya, 2008).

This paper utilizes both OLS and S-GWR regression techniques to conduct a thorough hedonic pricing analysis of hotel room rates along the Pacific coast of Japan which has high tsunami risk from the expected Nankai Trough megathrust.

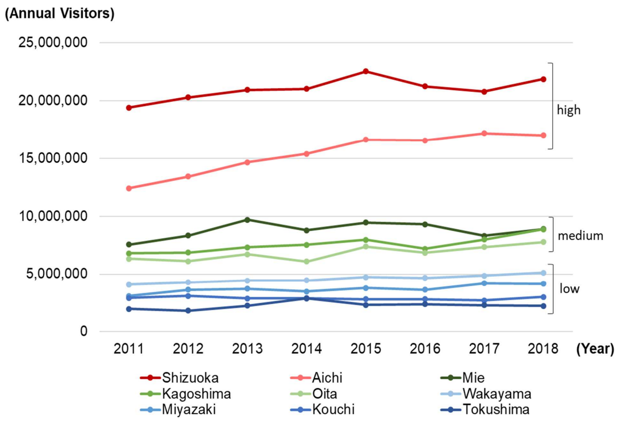


Figure 1: Tourist accommodation statistics by prefecture (created based on data from Japan Tourism Agency, MLIT, 2011-2018)

3. Methodology

3.1. Study area

The coastal region on the Pacific coast of Japan from Kanto to Kyushu facing the Nankai trough, which runs across 9 prefectures (i.e. Kagoshima, Miyazaki, Oita, Kouchi, Tokushima, Wakayama, Mie, Aichi, Shizuoka) is the selected study area for this research. In the event of the offshore Nankai Trough earthquake, the majority of these coastal municipalities are expected to experience tremors up to seismic intensity (Japan Meteorological Agency JMA) scale 7 and upper 6, and cause 1015km^2 of land to be inundated. The extent of the estimated inundation can be seen in Figure 2 along with the currently existing seawalls (only vertical coastal levees have been considered here as they are the most prominent protection measure and directly influence the coastal view). The maximum estimated wave heights for each prefecture are: Kagoshima (13m), Miyazaki (17m), Oita (15m), Kouchi (34m), Tokushima (24m), Wakayama (20m), Mie (27m), Aichi (22m), and Shizuoka (33m) (MLIT, 2012).

The same high risk coastal zone also encompasses many popular tourism destinations in Japan. The trend of yearly tourists to each prefecture over the years (Japan Tourism Agency, MLIT, 2011-2018) is graphed in Figure 1 and consequently divided into three demand categories: high (red), medium (green), and low (blue). It is apparent that Aichi and Shizuoka prefectures have a much higher proportion of tourists annually compared with other prefectures, and Aichi in particular, shows the highest growth rate of incoming tourists over the years. It should be noted that this data is in regards to the tourism in the whole prefecture and not limited to the coastal zone as more detailed data could not be obtained.

Table 1 Contribution of the accommodation and restaurant industry to the prefectural GDP (in percentage %) (created based on data from (Cabinet Office Government of Japan, 2011-2017))

Prefecture	2011	2012	2013	2014	2015	2016	2017
Shizuoka	2.52	2.35	2.36	2.35	2.25	2.43	2.43
Aichi	2.20	1.96	1.91	1.93	1.79	1.97	1.95
Mie	2.27	2.12	2.14	2.24	2.06	2.20	2.21
Kagoshima	2.94	2.88	2.87	2.95	2.90	3.09	3.02
Oita	2.60	2.51	2.60	2.58	2.59	2.98	3.00
Wakayama	2.73	2.66	2.72	2.78	2.70	2.91	3.03
Miyazaki	2.94	2.70	2.72	2.65	2.66	2.90	2.85
Kouchi	3.52	3.41	3.60	3.58	3.51	3.63	3.71
Tokushima	2.16	2.07	2.08	2.13	2.14	2.42	2.38
Average	2.65	2.52	2.56	2.58	2.51	2.73	2.73

In addition, Table 1 shows the contribution of the ‘Accommodation and restaurant industry’ (as categorized by the statistical report) to the total GDP of each prefecture for 2011-2017 (Cabinet Office Government of Japan, 2011). In general, these values show an increasing trend across almost all prefectures reaffirming the growth and contribution of this sector to the overall GDPs. When observed in terms of the above-mentioned demand categories, the most recent values (from 2017) show most medium and low demand prefectures to have a higher percentage contribution to the prefectural GDP (>2.5%) from this sector (with the exception of Mie and Tokushima) compared to the high demand categories (<2.5%). This indicates that tourism is an important factor of consideration even in medium to low demand regions. Thus, the implications of this for disaster mitigation planning lie in the fact that all coastal municipalities of the study region need to be cautious in their decision making for disaster mitigation strategies, as negative impact on the tourism industry is likely to greatly affect the future tourism growth in these regions.

It is also worth mentioning that tourism development policies linked with infrastructural development does not always give high priority to coastal landscape planning, resulting in irreversible land use changes due to the promotion of mass tourism in many areas, which can adversely affect the aesthetic value of the existing natural environment (Latinopoulos, 2018) as well as increasing the disaster exposure risk of the region. Hence, it is important to consider a holistic planning strategy which balances both tourism and disaster mitigation, especially in rural coastal destinations whose economy is mainly reliant on tourism. Achieving this entails answering the following questions: (a) What landscape and locational factors are important for coastal tourism? (b) How can the knowledge of its spatial variability (or lack thereof) inform the type of disaster mitigation strategies to be employed?

3.2. Variable definition and data collection

The hotel room pricing data for this study was obtained from an online hotel reservation site database (www.hotels.com) using web scraping. This particular site was chosen based on preliminary investigation on the prevalence of Japanese accommodation listings among 12 different travel booking sites. One main data source was chosen to ensure uniformity and collection of substantial detail on the attributes of the hotels and rooms, however, to compensate for incomplete entries of certain attributes (namely, room size and view type) 2 other sites (www.rururbu.travel and www.ikyu.com) which enlist more details on Japanese domestic listings were used. Previous studies utilizing hedonic pricing approach for hotel tourism have used similar data search methodology (Andersson, 2010; Fleischer, 2012; Kim et al., 2020a; Latinopoulos, 2018). Data extraction for all locations were carried out on the same date (21 December, 2019) for a given date (21 January, 2020) to avoid price differences arising from market fluctuations, and allow the identification of room prices under the same demand conditions; consequently, excluding the seasonality parameter from the econometric analysis (as shown in equation 1). It should be noted that the data acquisition was before the onset of COVID-19 which would have significantly impacted the hotel prices throughout the region in the following months. This implies that our data is reflective of the regular pricing of the hotels and not affected by the market conditions of the COVID-19 crisis. At the same time, since the data is representative of the typical low season in Japan, selection bias risk was low due to greater availability of hotel samples whilst also allowing a baseline definition for the influence of the considered parameters for pricing as the data represents the minimum range of prices that people are willing to pay for hotel rooms in the selected region.

As per the data collection method, the online prices can effectively approximate the expected prices to be incurred by the customers thereby reflecting the implicit prices of the room attributes (Andersson, 2010; Latinopoulos, 2018; Rigall-I-Torrent et al., 2011). Since hotels have different environmental features around them, they provide different views and accessibility features to their customers, who are thus likely to be sensitive to the differentiating characteristics of their hotels and rooms (Latinopoulos, 2018). This can affect their willingness to pay for features such as a *greater* accessibility from hotel or a *better* view from room (Wong and Kim, 2012). The question is therefore, whether the implicit values of these attributes varies within the study area.

The data collection on rooms was not restricted to hotels that offer sea view, as that could have led to a de facto significant value of the sea view. Instead, the hotel rooms sampled in this study were selected on the basis of: (a) their existence within the coastal zone, which was restricted to 3km distance from the coast and at an elevation lower than 300m in order to limit the concerned market segment to only coastal tourism; their information availability for the view type of the room (i.e. garden-view, mountain-view, river-view, lake-view, city-view, sea-view, etc.); (c) the rooms considered were available for booking on the date concerned. These conditions ensure that the sampled data set is within a range which has the potential to offer sea view and better beach accessibility as attributes to the customers for decision making. Furthermore, to achieve a meaningful interpretation of the associated local coefficient value of the sea view and simultaneously compare it with all other views, a dummy variable was used to differentiate rooms that offered a sea view from other view types on the basis that in these coastal regions, the view of the sea would be considered a priori as superior to other view types. These conditions are consistent with the prior study of Latinopulous (2018) and the resulting hotel room data points can be seen in Figure 3.

The explanatory variables in the study were selected based on their inclusion in previous studies, concern of our present study, and data availability. Based on the aforementioned pre-conditions, 2813 rooms were considered from 382 hotels across the region. For hotels with more than one view type available, the median price for each view type was obtained, resulting in the final selection of 478 rooms. The distribution of the rooms across the different prefectures are presented in Table 2.

Table 2 Distribution of observed data by region

Prefectures	Hotels	Rooms	Selected rooms based on the view type characteristics
Kagoshima	67	470	84
Miyazaki	9	73	10
Oita	47	528	71
Kouchi	22	136	26
Tokushima	14	125	16
Wakayama	35	297	43
Mie	34	198	43
Aichi	29	179	34
Shizuoka	125	807	151
Total	382	2813	478

All raw and processed data for the analysis, as well as other statistical data used in this paper are presented in the accompanying Data-in-Brief article.

Initially, 22 attributes were considered a priori as factors that may affect the price of rooms; while the majority of the factors consisted of the hotel and room amenities, other factors were associated with the environmental and locational characteristics. The variety of attributes considered and the attained sample size ensure that the room choice represents a choice of attributes for the tourists. The descriptive statistics for these attributes have been summarized in Table 3.

3.3. Data analysis

Figure 3: Area of study and location of sampled hotels

Table 3

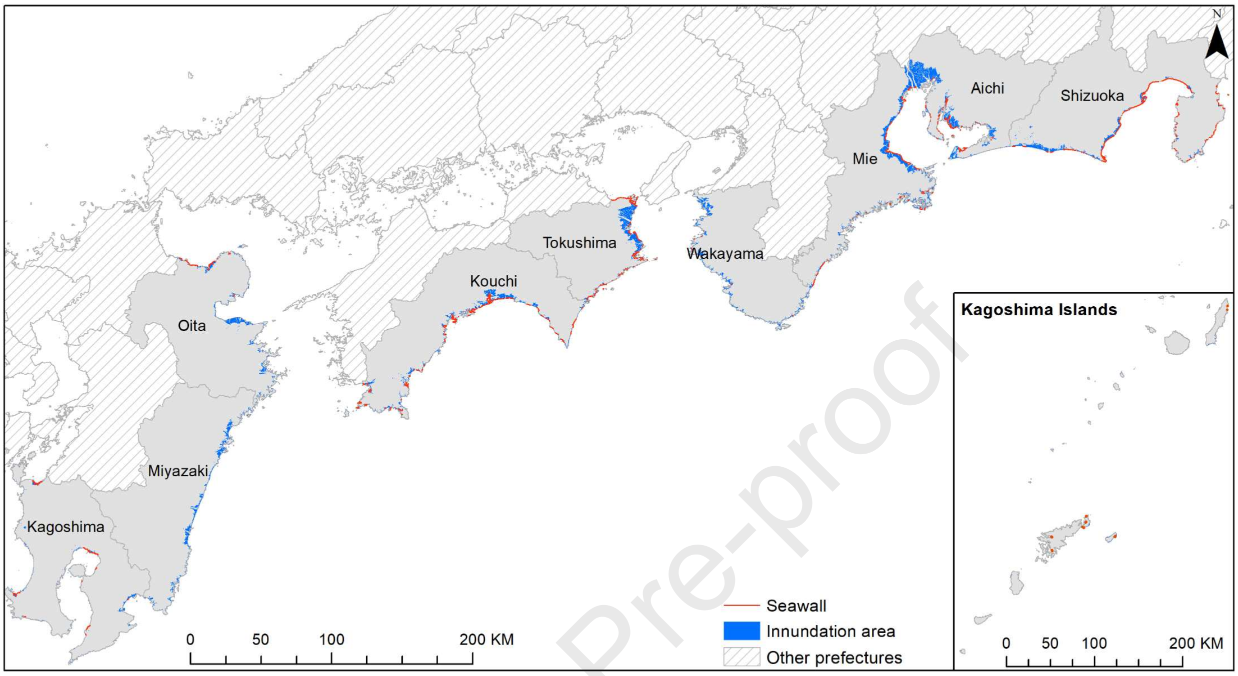
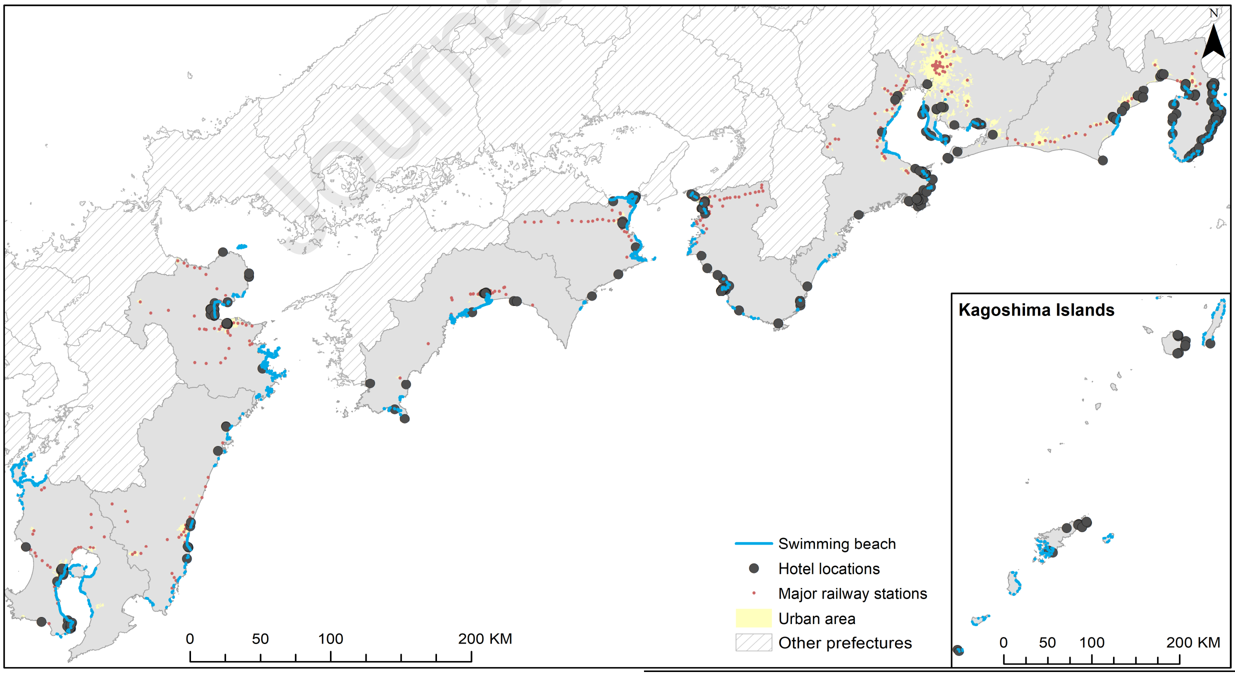


Figure 2: Estimated inundation area for Nankai trough induced tsunami and current seawall structures (based on MLIT data)

Descriptive statistics of dependent and independent variables



Variable (Category)	Description	Mean	Min	Max

Price[a]	Room price (¥/night)	22372	4545	159473
Star_rating	Star rating of the hotel (1-5 rating scale)	3.16	0	5
Room_size	Size of room in (sqm)	29.8	3	173
Suite	Dummy: = 1 if room is of suite type	0.04	0	1
Deluxe	Dummy: = 1 if room is of deluxe type	0.04	0	1
Superior	Dummy: = 1 if room is of superior type	0.06	0	1
Standard	Dummy: = 1 if room is of standard type	0.38	0	1
Villa	Dummy: = 1 if room is of villa type	0.01	0	1
Open-air_bath	Dummy: = 1 if room has an open-air bath	0.06	0	1
Onsen	Dummy: = 1 if hotel offers onsen spa	0.49	0	1
Parking	Dummy: = 1 if free car parking is available for guests	0.90	0	1
Review rating	Average customer rating (0-10 scale)	8.05	0	10
Refund	Dummy: = 1 if booking is able to be cancelled free of cost	0.92	0	1
Breakfast	Dummy: = 1 if breakfast is included in room price	0.73	0	1
Dinner	Dummy: = 1 if dinner is included in room price	0.19	0	1
Non smoking	Dummy: = 1 if it is a non-smoking room	0.70	0	1
Wi-Fi	Dummy: = 1 if Wi-Fi is available at hotel/room for free	0.96	0	1
Pool	Dummy: = 1 if swimming pool is available	0.24	0	1
Seaview	Dummy: = 1 if room provides full or partial seaview	0.51	0	1

Table 3 *(continued)*

Variable (Category)	Description	Mean	Min	Max
D_beach	Distance (in meters) to the nearest swimming beach	4117	0.19	32472
D_station	Distance (in meters) to the nearest station	17635	45.8	508705
D_bus-stop	Distance (in meters) to the nearest bus-stop	3751	25	20693
D_coast	Distance (in meters) to the coast	747.8	0.18	2990
Elevation	Elevation (in meters) above sea level	32	0.1	280.5
Urban area	Dummy: = 1 if hotel is located in urban area	0.42	0	1

[a] Dependent variable.

The data analysis was conducted using various software programs including SPSS (version 26.0), ArcGIS (version 10.5.1), GEODA (version 1.14.0), RStudio (version 1.2.5033), and GWR4 (version 4.0).

After acquiring the relevant GIS-based data, basic analysis was carried out to attain distances to environmental features such as the coast and beaches in addition to finding out the likely inundation depths at the hotel locations and the vicinity to seawall (coastal levee) structures. Having attained data for all variables considered, descriptive analysis was conducted in terms of numeric description (e.g. mean, standard deviation, and correlation coefficient) as shown in Tables 3 and A1. Based on the correlation matrix (Table A1), variables that displayed especially weak (non-significant) correlation with the dependent variable (i.e. Deluxe, Superior, Villa, Refund, Wi-fi) were eliminated from the consequent multiple regression analysis to keep the focus on the variables that mattered.

An Ordinary Least Squared (OLS) multiple regression analysis was performed to investigate the relationship between the hotel room price and the hotel and environmental attributes. Based on relevant tests, a semi-logarithmic linear model was selected as the most appropriate functional form for the hedonic analysis (i.e. providing better model fit). This is in accordance with previous hedonic studies (Espinet et al., 2003; Latinopoulos, 2018; Rigall-I-Torrent et al., 2011; Thrane, 2007) which make similar choices owning to greater explanatory power, goodness-of-fit, and ease of interpretation. Hence, in this model, the dependent variable is the natural logarithm of the room price for one night ($\ln(Y_i)$ –equation (2)) which means that the effect of local b_i-coefficients to the price of rooms can be interpreted as (a) $100 * \beta_j$-for the estimated percentage change in the room price when a continuous regressor changes by one unit; and (b) $[exp(\beta_j) - 1] * 100$ for dummy variables.

$$\ln(Y_i) = a + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i \tag{2}$$

where Y_i is the hotel room price at point i (where i denotes the number of hotels (i = 1 to n)); a is the intercept term; X_j denotes the *j* characteristics of the hotel rooms (j = 1 to k attributes); β_j is the associated coefficient; and ε_i is the random error (Zhang et al., 2011).

Furthermore, to investigate the possibility of spatial variation, the OLS regression is repeated with the inclusion of prefectural dummy variables before employing a Semi-parametric Geographically Weighted Regression (S-GWR) using GWR4 (Nakaya et al., 2009) to explore the important local variations. As opposed to a Geographically weighted regression (GWR) model where all regression coefficients are assumed as non-stationary, a S-GWR model allows the inclusion of global effect variables where appropriate (i.e. when the effect of the variable is independent of location), thus representing a mixed spatial model. Therefore, the S-GWR model is expressed as follows:

$$\ln\big(Y_i(x_i, y_i)\big) = a(x_i, y_i) + \sum_{j=1}^{k} \beta_j X_{ij} + \sum_{j=r+1}^{l} \beta_j(x_i, y_i) X_{ij} + \varepsilon_i \tag{3}$$

where a and β coefficients have a location specific relationship as represented by the (x_i, y_i) coordinates. Though different spatial kernel functions can be used in GWR and S-GWR models, due to the variation in the density of data points across the study region, an adaptive bi-square spatial kernel function was employed for S-GWR analysis (Fotheringham et al., 2002). The S-GWR model is calibrated iteratively by means of estimating global and local parameters repeatedly until some convergence condition is satisfied. In this case, the corrected Akaike Information Criterion (AICc) for a given bandwidth size is minimized according to the procedure proposed by Brunsdon et al. (1999). To confirm that every local variable is significantly varied across space, the Geographical variability test for these local coefficients is implemented in GWR 4.0. In addition, the local parameter estimates and significant T-values from the S-GWR model were interpolated using natural neighbor interpolation in GIS and presented as continuous surface maps.

Finally, combining the spatial model results, a map to help prioritize the adoption of different region-specific mitigation strategies was produced.

4. Results

The regression analysis results (presented in Table 4) for: (a) the global OLS model (Model 1), (b) the global OLS model with regional dummies (Model 2), and (c) the S-GWR model (Model 3) are discussed in the following sections.

4.1. Model 1 –Global OLS model

The OLS results show most of the selected attributes to have significant impact on room rates (1^{st} column in Table 4). While considerable number of hotel characteristics (such as *Star_rating*, *Suite*, *Standard*, and *Breakfast*) show similar positive association with room price as observed in previous studies outside of Japan (Andersson, 2010; Israeli, 2002; Latinopoulos, 2018), few additional characteristics particular to Japan were found to have more significant effect on the price in our study. Particularly, rooms that offer attached open-air bath with hot spring water (*Open-air_bath*) or rooms in hotels with common hot spring bath area (*Onsen*) are priced 51.5% and 11.2% higher, respectively, than rooms in hotels that have only regular shower and bathtubs.

Out of the locational and environmental characteristics considered, the *seaview* and urban variables had a significant impact on room prices. Rooms that offered *seaview* as opposed to any other view types were priced 11.4% higher while rooms that were positioned in an *Urban_area* are rated 12.6% lower than similar rooms in hotels with natural surroundings. The only other locational characteristic that exhibited some (10%) statistical significance on the price was the *D_station* variable which surprisingly showed a positive association with room price meaning increasing distance from station resulted in highly priced rooms. However, this makes sense when the locations of the major railway stations are considered (Figure 2) with respect to the hotel rooms. Most stations are not as close to the coastline as they are usually connected to the transportation infrastructure that is in the interior. This in combination with the fact that rooms prices increase the closer they are to the coast (shown by the negative association of *D_coast*), indicates that for coastal tourism, accessibility to public transportation is not a priority as most tourists are domestic (more than 80% in each of the study area prefectures according to the tourism statistics of 2018 from Japan Tourism Agency, MLIT) and travel by car (Suzuki and Takemura, 2017).

Multicollinearity is a main concern in using the hedonic pricing approach. Thus the correlation among the independent variables was explored in the correlation matrix (Table A1) where correlation coefficients were found to be relatively low (<0.50); well below the threshold value of 0.70 used in previous studies (Latinopoulos, 2018) to consider the potential existence of multicollinearity. Furthermore, for the highest correlation found between the variables *D_beach* (18) and *D_station* (19) (R = 0.48), we attempted to confirm the potential presence of multicollinearity by calculating the variance inflation factor (VIF). The VIF values ranged from 1.052–1.640, well below the generally considered thresholds in the range of 5-10, indicating that multicollinearity was not a serious problem in the model.

To test for spatial autocorrelation, a Moran's I test (Moran, 1950) using GEODA applying adaptive spatial weights (for nearest 5 neighbors) was performed on the OLS model residuals (Anselin, 2001). The Moran's I statistic was found significant with results of MI = 0.238, z-score = 3.394, $p < 0.001$, meaning that the null hypothesis of no spatial pattern of residuals was rejected, indicating that the coefficients could have been incorrectly specified as a result of non-stationarity. To confirm this, another variation of this OLS model was explored with the inclusion of regional dummies.

4.2. Model 2 -OLS model with regional dummies

Including the regional dummies for prefectures in addition to the attributes considered in Model 1, Model 2 (Table 4, 2nd column) showed improvement in the overall reliability and model fitness with higher adjusted-R^2 values and lower AICc (corrected Akaike Information Criterion) and CV (Cross Validation criterion) estimates.

The hotel attributes and room price relationship mostly remained similar to those of Model 1 with improved statistical significance for *standard* and *non-smoking* rooms. Similarly, higher statistical significance is also exhibited for some of the environmental attributes, namely *D_station* and *D_coast* attributes.

For the regional dummies, 8 prefectures were compared against the 9th prefecture –Shizuoka which had the highest number of sampled observations and is geographically closest to the capital Tokyo. All three prefectures considered in the Kyushu region displayed negative association with room price, with Oita having the only statistically significant result in the region which exhibited that rooms in *Oita* prefecture were rated 12.5% lower than similar rooms in Shizuoka. In the Shikoku region, Kouchi prefecture showed statistically significant results indicating that rooms in *Kouchi* were rated 23.3% higher than similar rooms in Shizuoka. All considered prefectures in the Kansai and Chubu regions exhibited positive association and statistical significance on the price with rooms in *Aichi*, *Mie*, and *Wakayama* prefectures being priced 20.6%, 21.5%, and 21.8% higher, respectively, than similar rooms placed in Shizuoka prefecture. Though there were statistically significant results, the fact that such results could not be attained for all the considered prefectures implies that spatial heterogeneity of hotel room prices may not be able to be captured through the OLS model. Thus a GWR or S-GWR analysis might help capture the spatial variations within each region.

4.3. Model 3 -Semi-parametric GWR model

Results from both of the OLS models (Model 1 and 2) indicated a necessity to switch to the local modeling framework, and since an S-GWR model allows the inclusion of global (fixed) effect variables as well as local (varying), this was conducted to find the optimal

Table 4
Hedonic equation estimates of OLS- and GWR-based models

	Model 1 –Global OLS		Model 2 –OLS with Regional-dummies		Model 3 –Semi-parametric GWR				
					Non-stationary variables				Stationary variables
	Coefficients	Std. Error	Coefficients	Std. Error	Lwr(25th) Quartile	Mean	Median	Upr (75th) Quartile	Coefficients
Intercept term	8.237***	0.149	8.169***	0.147	6.965	7.904	8.350	8.640	
Room/Hotel Characteristics									
Star_rating	0.262***	0.038	0.259***	0.038	-	-	-	-	0.285***
Room_size	0.010***	0.001	0.009***	0.001	0.006	0.009	0.007	0.012	
Suite	0.174*	0.105	0.109	0.104	-	-	-	-	0.168*
Standard	-0.048	0.040	-0.200***	0.053	-	-	-	-	-0.134***
Open-air_bath	0.515***	0.081	0.502***	0.080	-0.122	0.286	0.595	0.799	
Onsen	0.112***	0.040	0.132***	0.041	0.001	0.128	0.086	0.170	
Review_rating	0.009	0.011	0.012	0.010	-0.021	0.051	0.011	0.141	
Breakfast	0.124***	0.043	0.140***	0.043	-0.002	0.088	0.151	0.215	
Dinner	0.580***	0.050	0.559***	0.050	-	-	-	-	0.522***
Non_smoking	0.086**	0.042	0.121***	0.045	-	-	-	-	0.038
Environmental Characteristics									
Seaview	0.114***	0.042	0.117***	0.041	-	-	-	-	0.097**
D_beach	2.00E-06	0.000	0.000	0.000	-	-	-	-	0.000
D_coast	-3.70E-05	0.000	0.000	0.000	-2.04E-04	-5.80E-05	-5.00E-05	5.50E-05	
Elevation	5.89E-04	0.000	0.001*	0.000	-6.07E-04	1.07E-03	2.57E-04	3.39E-03	
Other Locational Characteristics									
D_station	0.000001*	0	0.000**	0.000	-1.00E-06	6.00E-06	2.00E-06	1.30E-05	
Urban_area	-0.132***	0.045	-0.064	0.048	-0.171	0.007	0.085	0.155	
Regional Dummies									
Tokushima			0.166	0.110					
Wakayama			0.218***	0.079					
Oita			-0.125**	0.058					
Miyazaki			-0.206	0.127					
Mie			0.215**	0.088					
Kouchi			0.233**	0.096					
Kagoshima			-0.030	0.061					
Aichi			0.206**	0.084					
N	478		478		478				
Adjusted R^2	0.661		0.676		0.713	0.764	0.743	0.825	
CV	0.153		0.148		0.128				
AICc	452.642		440.309		368.197				

*, **, *** = Statistically significant at the 0.1(10%), 0.05(5%), and 0.01(1%) level.

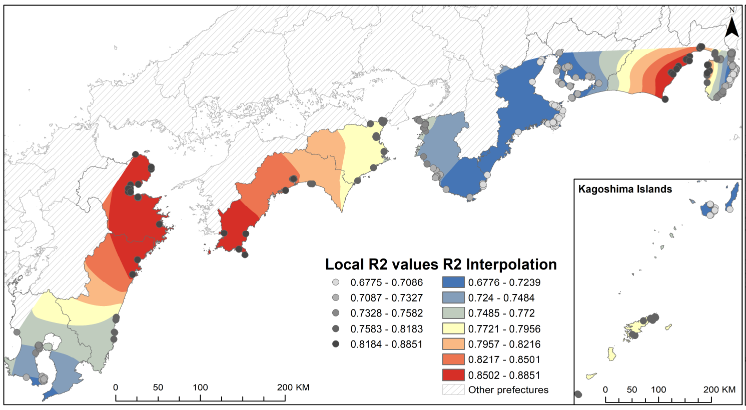


Figure 4: Spatial distribution of local R^2 values

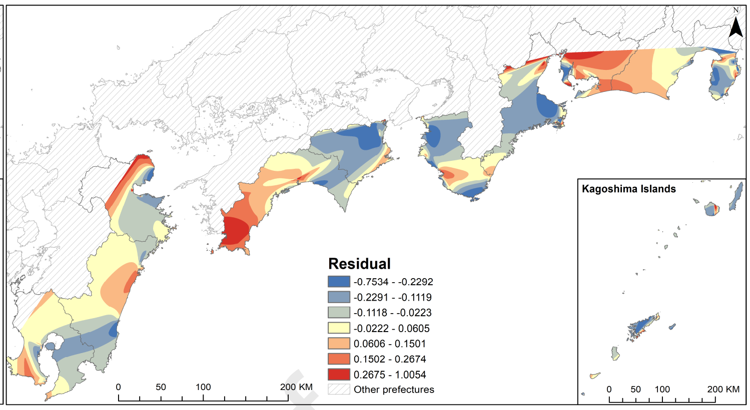


Figure 5: Spatial distribution of residuals

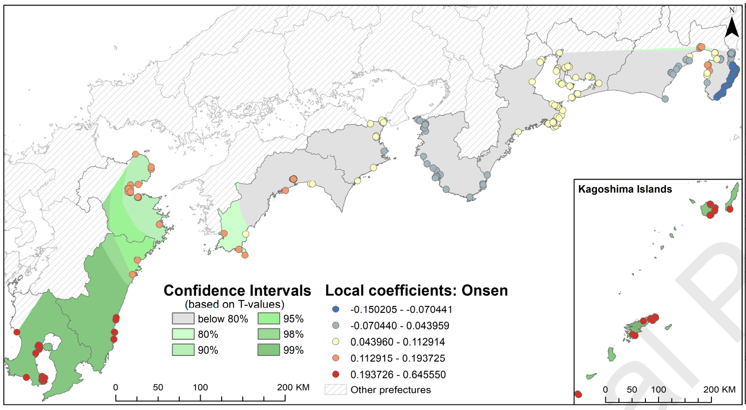


Figure 6: Local model coefficients for *Onsen* variable

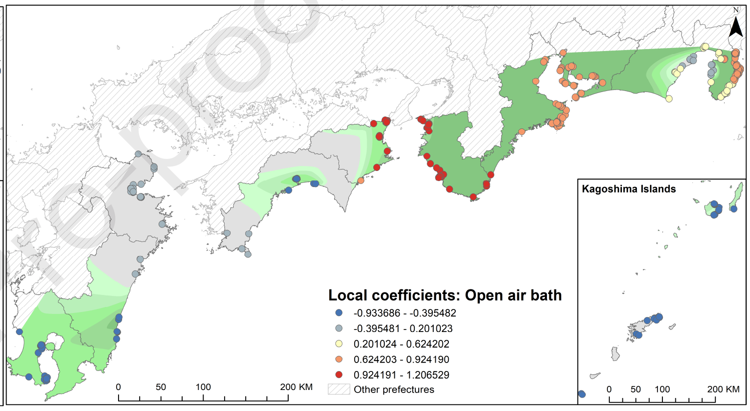


Figure 7: Local model coefficients for *Open-air_bath* variable

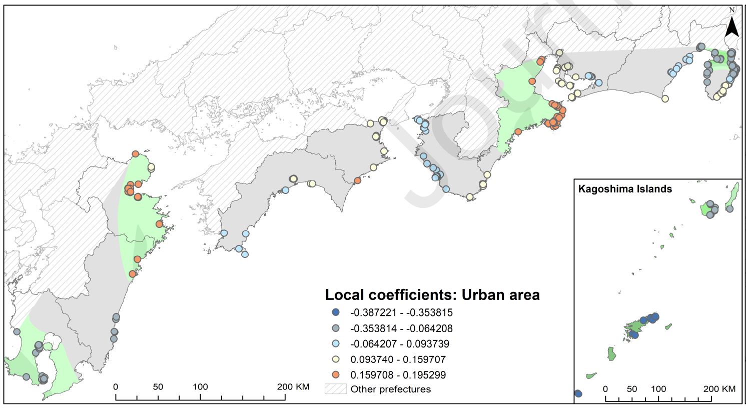


Figure 8: Local model coefficients for *Urban_area* variable

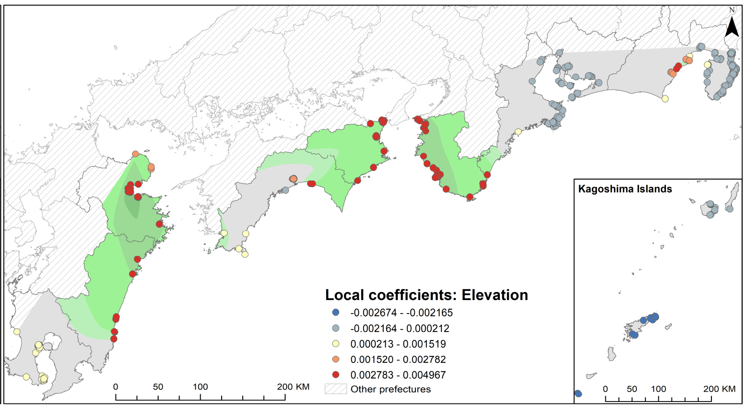


Figure 9: Local model coefficients for *Elevation* variable

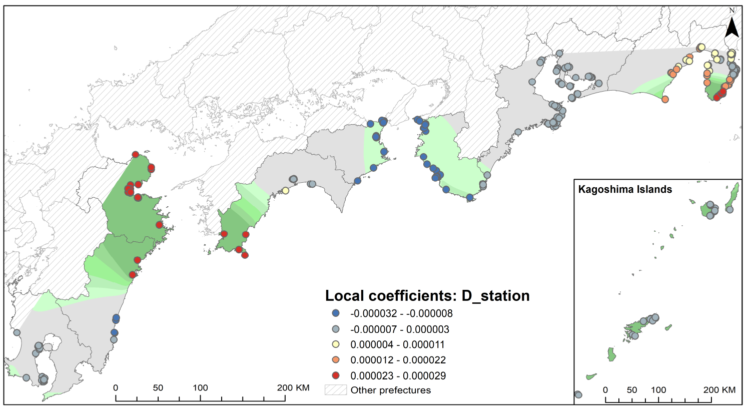


Figure 10: Local model coefficients for *D_station* variable

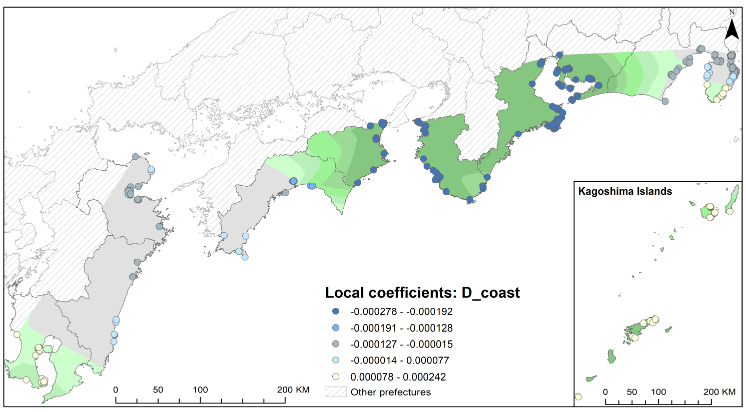


Figure 11: Local model coefficients for *D_coast* variable

combination of global and local variables. GWR 4.0's "L → G variable selection" (local to global) technique and multiple additional iterative runs led to a final model of 9 varying and 7 fixed variables (with a varying intercept term). The non-stationarity of the local variables were confirmed via the following methods: 1) inter-quartile range of local estimates were greater than ±1 standard deviation of the equivalent global parameter signifying non-stationarity (Fotheringham et al., 2002); and 2) a geographical variability test of local coefficients in GWR4 exhibited negative values for Difference (DIFF) of Criterion confirming that the relationship between the local explanatory variables were indeed statistically different across space (Nakaya, 2016). In fact, the DIFF of Criterion values shown in Table 5 showing the difference in model comparison indicator (AICc) between the original GWR model and S-GWR model, indicate that most of the local explanatory variables exhibited a strong evidence of spatial variation (i.e. DIFF of Criterion values are < -2, or > +2 (Nakaya, 2016)).

According to the results of Table 4, the local model of the S-GWR (Model 3 -3rd column) shows significant improvement in terms of significantly higher Adjusted-R^2 values and lower CV and AICc values indicating better goodness-of-fit statistic. Figure 4 shows the interpolated surface (from natural- neighbor interpolation on ArcGIS) of the Adjusted-R^2 values which range from 0.68 to 0.89 – all higher than the Adjusted-R^2 values of the two OLS models; indicating that the local S-GWR model is a significantly better fit for the entire region. Furthermore, the GWR-ANOVA statistic (F-test) as presented in the Analysis of Variance Table 6, indicates a significant performance improvement between the global OLS model (Model 1) and S-GWR model (Model 3) in terms of error variance, statistically significant at the 1% level (F = 3.489).

Figure 5 shows the residual pattern of the S-GWR model, representing the difference between the observed and predicted values of the dependent variable. Positive values of residuals represent regions where the predicted room rates are higher than expected, while the negative values represent regions where the predicted rates are lower than expected. Figure 5 does not show any distinct pattern of over-prediction or under-prediction.

In Table 4, the non-stationary variables are represented with their lower- and upper-quartile coefficient values as well as the mean and median coefficients most of which do not resemble their OLS counterpart values. Especially, looking at the inter-quartile range of the local coefficient values of the S-GWR model against the OLS model coefficients, it is apparent that while most regions have positive association with the room price some regions also exhibit negative association with price (considering the lower-quartile coefficients), which the OLS models had failed to capture (e.g. *suite*, *Open-air_bath*, and *breakfast*). On the other hand, the environmental and locational attributes of *D_coast* and *Urban_area* exhibit the opposite case where the OLS had failed to capture the mostly positive relationship (according to the mean/median and upper-quartile coefficients), indicating that in these regions: being located further from the coast or in an urban area can result in higher room price rates.

Table 5

Geographical variability test of local explanatory variables

Variable	F	DOF for	F test	DIFF of Criterion
(Constant)	12.114	4.718	401.981	-63.699661
Room_size	5.208	5.149	401.981	-21.194322
Open-air_bath	6.852	2.822	401.981	-19.107378
Onsen	4.413	4.808	401.981	-14.195106
Review_rating	7.128	4.783	401.981	-31.450232
Breakfast	3.527	5.237	401.981	-6.373324
D_station	3.095	4.311	401.981	-4.138919
D_coast	3.744	4.048	401.981	-7.791025
Elevation	3.250	3.771	401.981	-4.930902
Urban_area	3.006	4.159	401.981	-3.496709

Table 6

GWR-ANOVA (Analysis of Variance) of model performance

Source	SS	DF	MS	F
Global residuals	66.703	461.000		
GWR improvement	25.566	69.705	0.367	
GWR residuals	41.137	391.295	0.105	3.489

One of the greatest advantages of the GWR is its ability to offer informative results beyond global models, especially place-specific local parameter estimates that are visualizable (Brunsdon et al., 1998, 1996). However, as (Matthews and Yang, 2012; Mennis, 2006) argue, the parameter estimates are not meaningful unless their significance (indicated by the t-values of the coefficients) is also presented. Thus, following the approach suggested by Matthews and Yang (2012), thematic maps (Figure 6-11) for the following local explanatory variables have been presented: *Open-air_bath*, *Onsen*, *Elevation*, *Urban_area*, *D_station*, and *D_coast*. T-values for all the maps have been kept constant with increasing shades of green representing increasing significance from 80% confidence interval (t-value <-1.28 or >1.28) to 99% confidence interval (t-value <-2.58 or >2.58). The area in grey is indicative of below 80% confidence interval which means that the attribute being considered has no impact on the room prices in that region (as the parameter estimate is non-significant). This is described in the T-value legend presented in Figure 6. Note that all non-stationary variables presented in Table 4 can be mapped in a similar manner.

Although other hotel characteristics such as *Room_size* and *Breakfast* show above 99% confidence interval significance in a considerable area of the region respectively, due to the focus of this paper being on environmental and locational attributes for hotel pricing, the maps presented here are focused on those relevant attributes with the exception of *Open-air_bath* and *Onsen* as we have identified these to be non-established but important characteristics to Japanese hotels through this paper.

Hot springs are a big part of a tourism culture in Japan and owing to the volatile geological nature of the Pacific coast (which is also the reason for its high tsunami risk), many accommodations boast hot springs as part of their hotel facilities. Thus, characteristics such as *Open-air_bath* (private hot spring bathtub area in addition to regular shower rooms as a room facility) and *Onsen* (bigger common hot spring bath area as a hotel facility) should be considered together. Where statistically significant above a 90% confidence interval, the association with room price is positive with values showing a 20% - 120% range and 18% - 65% range of price increase for rooms with *Open-air_bath* and hotels with *Onsen*, respectively, compared to those without them. Where there is not much impact on price by one variable, there is impact by the other, and therefore these two factors are complimentary to each other –together covering almost all of the region; Kouchi is the only prefecture where neither of these variables are significantly impactful. It should also be noted that in addition to consistently exhibiting a high coefficient factor across all models, in the S-GWR model *Open-air_bath* shows the highest spatial variation in coefficient values with the largest interquartile range of all the local independent variables considered.

According to the results above, of the environmental and geographical attributes, *Elevation* and *Urban_area* are the only two local variables that consider on-site properties rather than proximity (to a certain attribute/characteristic). For *Elevation*, the statistically significant regions across the study area demonstrate only positive association with price (i.e. 0.1% - 0.5% price increase for higher elevations), which could be due to higher elevations providing better room views. While in the case of *Urban_area*, the local coefficient map shows both statistically significant positive association (higher pricing in urban locations in Mie, Oita and northern Miyazaki) and negative association (lower pricing in urban locations of peninsular and island regions of Shizuoka and Kagoshima). These GWR results are valuable as it indicates that urban area locations may result in higher room rates (16.0% - 19.5%) in some regions –an insight that was not perceivable by only looking at the OLS models as they both showed only a negative association.

In terms of proximity related environmental and locational variables, *D_station* and *D_coast*, are locally varying. While the variable coefficient values are too low to be of major significance, in both cases the spatial heterogeneity is clearly observable. For *D_station*, while statistically significant negative association is present in the central region (i.e. the coast of Tokushima, and Wakayama prefectures) and the Kagoshima islands, whilst a positive association is observed in Shizuoka, Oita, and parts of Miyazaki and Kouchi prefectures. Similarly, mapping statistically significant results of *D_coast* coefficients show that increasing the distance from the shore lowers the hotel room rates down to 0.01% - 0.03%

in the central regions of Aichi, Mie, Wakayama, Tokushima and Kouchi; indicating that the closer to the coast the higher the hotel room prices –as observed in previous studies (Fleischer, 2012; Kim et al., 2020b; Latinopoulos, 2018). However, unlike the study of Latinopoulos (2018) in which proximity to coast is essentially a negative global variable, in this study it is a varying coefficient indicating that in some cases (the peninsular and island regions of Shizuoka and Kagoshima prefectures) proximity to coast may also result in lower room prices.

Of particular significance to this study is the stationary environmental variable of *Seaview* which indicates that rooms which offer a sea view, compared to all other view types (including garden view, mountain view, lake view, river view, and city view) is associated with 9.7% higher prices (statistically significant at the 5% level), regardless of the location of the hotel within the study area. This is a distinctive difference from the previous study of Latinopoulos (2018) and perhaps a characteristic of the study region on the pacific coast of Japan. It also has direct implications for the potential tsunami mitigation measures as it means that preventive measures that may obstruct the sea view can result in losses in the accommodation sector of tourism.

The combined spatial model results of variables relevant for tsunami mitigation measures as depicted in Figure 12 are effective in establishing the geographical boundaries within which tourist preference stay homogenous, thereby allowing the identification of region-specific mitigation measures that are sensitive to market trends. Specifically, the map (Figure 12) shows the municipal regions of each prefecture that contain expected inundation areas with and without protection (seawall/levee existence), represented by horizontal hatching and forward-diagonal hatching, respectively. While both types of areas bear some risk, cross hatched region shows higher risk exposure and identify the municipalities that should prioritize risk mitigation infrastructure.

It should also be noted that municipalities with protection measures are not risk free (thus presented here) as it is not apparent whether the pre-existing protection measures are adequate against the currently estimated (since 2011) inundation area and level, which warrants the need for further risk assessment in these regions. Furthermore, among the municipalities highlighted, areas outside of the red colored region signify locations that will not be economically impacted (negatively) by pursuing mitigation measures that include long-term relocation

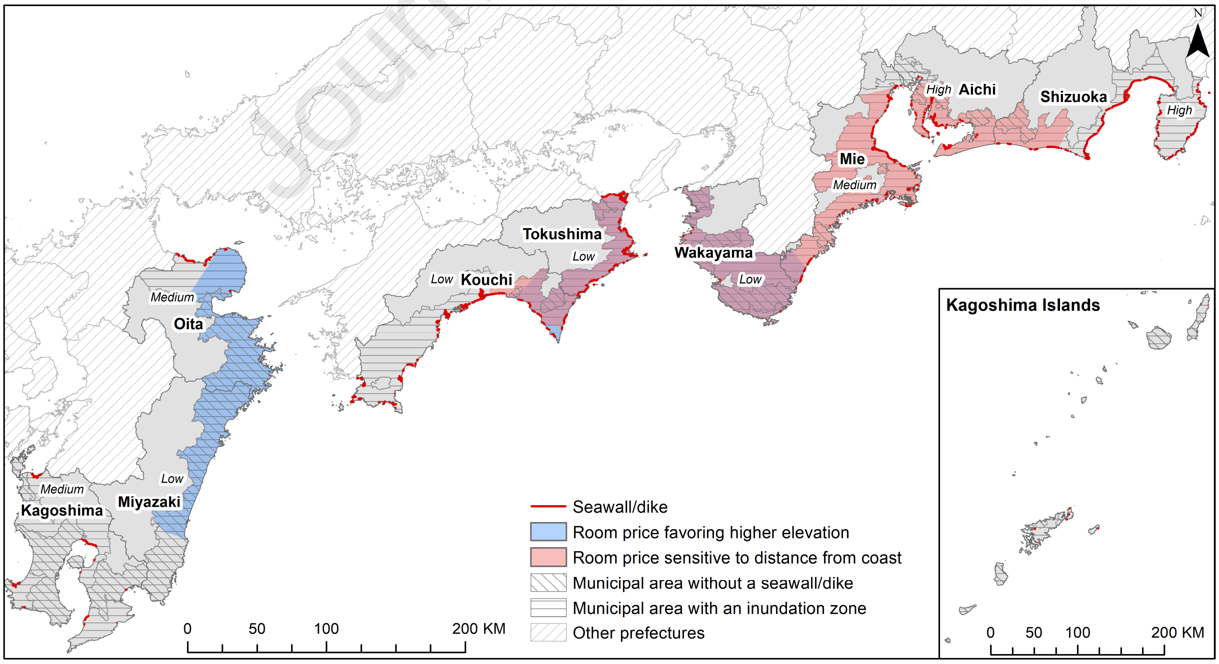


Figure 12: Tsunami risk exposure and potential market sensitivity to mitigation strategies

of buildings to the interior or prohibiting the construction of new properties in close proximity to the coast, as long as the sea view from the rooms can be maintained. However, within the red region, special precautions must be taken in implementing such measures as increasing distance from coast can result in lower room rates. Within this area, the region superimposed with blue (resulting in purple) identifies locations which have an incentive to adopt an alternative mitigation strategy –situating the hotels on higher grounds. This is based on our preceding analysis which showed higher room rates for higher elevations in the blue/purple colored region. Being able to identify such kind of location-specific win-win strategies for tsunami mitigation and profit can be beneficial for the hotel industry, especially in regions with more tourists. Thus, the factors highlighted here should be weighed in consideration with the travel accommodation demand (from Figure 1 -shown in italics in Figure 12) and the hotel sector GDP contribution (from Table 1) of each prefecture, which can suggest the overall economic impact of the adopted strategies.

5. Discussions and Conclusion

This research applied a hedonic pricing model and geographically weighted regression method for investigating the marginal effects of different amenities, and environmental and locational characteristics on room prices whilst also examining their spatial heterogeneity. The results indicated that the relationship between room prices and most of the explanatory variables are spatially variant; implying that a global OLS model on its own would be inaccurate and insufficient for this kind of an analysis. Thus a mixed model analysis using S-GWR which can include both fixed and varying variables is more appropriate to reveal the relationships between the dependent and explanatory variables.

Simultaneously, this work also reveals that in the region considered for the study, not all environmental and locational variables are varying over space. Most significantly, the “view of the sea”, approximated a 9.7% of the average room price in the area of study regardless of the location; indicating that particular caution must be taken to preserve and sustain the hotel room sea views in coastal locations to ensure a positive tourism-based economic growth in these locations. Accordingly, the consideration of alternative coastal protection methods such as offshore embankments, natural and stepped coastal revetments is necessary.

Additionally, adding to the previously established list of hotel attributes typically considered in hedonic studies, this work highlights that hot spring baths (whether in-room or in-hotel –i.e. *Open-air_bath* or *Onsen*, respectively) are important attributes to be considered in the Japanese tourism context.

Furthermore, the results of the analysis as presented in Figure 12 can be useful, not only for marketing purposes as proposed in Latinopoulos (2018) and Kim (2020a), but also for consensus-building on matters of sea-level rise- and tsunami-oriented countermeasures. In particular, the results can allow municipalities to initiate well-informed dialogues with the private sector (i.e. hotel owners) to reach a consensus on mitigation measures that will not harm the long-term tourism-based economic growth of the region. While the need for tsunami mitigation measures are acknowledged for the entire region of consideration, by defining geographical market boundaries of the impact of the environmental characteristics on room prices, the results support the determination of region-specific measures and their prioritization according to tourist demand.

Further research is required for a more thorough consideration of mitigation strategies and quantifying their economic implications in detail such as the overall economic loss of a region attributable to an increase in coastal levee height, or development restriction in near coast locations, and so on, to determine appropriate long-term strategies for these at-risk coastal locations.

Acknowledgments

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Appendix

Table A1: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) Price (log_cost)	1																					
(2) Star_rating	.45**	1																				
(3) Room_size	.55**	.40**	1																			
(4) Suite	.22**	.20**	.37**	1																		
(5) Deluxe	0.02	-0.05	0.06	0.02	1																	
(6) Superior	-0.03	0.03	-0.01	-0.05	-0.05	1																
(7) Standard	-.14**	-0.06	-.21**	-.15**	-.16**	-.19**	1															
(8) Villa	0.03	0.02	.15**	-0.02	-0.02	-0.03	-0.09	1														
(9) Open_air_bath	.36**	.21**	.21**	-0.05	-0.05	-0.02	-.12*	0.05	1													
(10) Onsen	.34**	.14**	.11*	-0.01	-0.01	-0.09	-.10*	-0.07	.23**	1												
(11) Review_rating	0.07	.11*	0.07	0.03	0.02	0	-.10*	0.05	0.03	0.04	1											
(12) Refund	0.05	0.02	0.04	0.01	-0.06	-.10*	0.03	0.03	-0.07	0	-0.04	1										
(13) Breakfast	.23**	.19**	-0.01	-0.01	-0.07	-0.09	0.08	0.03	0.09	.10*	0.02	-0.01	1									
(14) Dinner	.54**	.14**	.14**	0.02	0.01	-0.03	0.05	-0.01	.11*	.27**	0	0	.30**	1								
(15) Non_smoking	.20**	-0.05	.15**	0	0.04	0.01	-.28**	0.03	.10*	.15**	-0.01	-.10*	-0.06	0.04	1							
(16) Wi_Fi	-0.02	0.06	-0.05	0.04	-0.07	0.05	-.12*	0.02	0.05	0.02	0.04	-0.01	-0.05	-.10*	0.04	1						
(17) Seaview	.32**	0.05	.20**	.10*	0.01	-0.01	0.05	-0.08	0.02	.18**	-0.03	0.01	-0.02	.19**	.13**	-0.02	1					
(18) D_beach	-.10*	-.11*	-.10*	-0.06	-0.04	0.03	-0.04	0.06	-0.04	-.27**	-0.02	.09*	-.11*	-.14**	-0.03	0.02	-.11*	1				
(19) D_station	0.07	-0.05	0.09	-0.04	-0.04	.11*	-.11*	0.03	-0.04	-.17**	0.01	0.06	-0.08	-0.07	.12**	-0.02	0.09	.48**	1			
(20) D_coast	-.16**	0.04	-0.03	-0.01	0.02	0	-0.03	-0.06	0.08	-.17**	-0.02	0.01	0.04	-.10*	-.13**	0.01	-.45**	-0.01	-.16**	1		
(21) Elevation	.28**	0.07	.20**	.10*	0.06	-0.01	-.18**	0	.15**	.20**	-.11*	-0.01	0.01	.22**	.20**	-0.06	0.07	-0.05	-0.05	.29**	1	
(22) Urban_area	-.32**	0.01	-.14**	-.09*	-0.02	0.02	-.10*	-0.06	-0.01	-.16**	.10*	-0.05	0.06	-.25**	-.17**	0.06	-.38**	-0.08	-.20**	.36**	-.28**	1

N= 478. *,** = correlation is significant at the 0.05 and 0.01 level (2-tailed), respectively.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: