# Trade-off between benefit from the ocean and flood hazard risk: A spatial multilevel hedonic analysis

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## Abstract

Bayside residential areas, which enjoy scenic ocean view, are very often attractive, and many parsons prefer living in bayside areas. However, many of bayside areas are also flood prone areas. For example, a popular residential area of Yokohama city, Japan, is predicted to suffer a serious flood damage after great earthquakes. The objective of this study is to analyze the trade-off between benefits and risks from the ocean, and provide some insights toward hazard adaptive/resilient urban design. We first perform a hedonic analysis of condominium prices, and quantify values of ocean-related attributes, including ocean view and proximity to the ocean, and the (negative) value of the flood hazard risk. Here, a multilevel spatial hedonic model is used. Then, desirable bayside urban form under the trade-off is discussed based on these analyses results.

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## 1. Introduction

A goal of urban planning is maximizing the value of urban space considering key factors, such as convenience, natural environment, hazard risks, and so on. Hedonic approach (Rosen, 1974) is a representative approach to quantify economic values of non-market goods (convenience, environment, risks, and so on) by regressing them on property prices. So far, numerous hedonic studies reveal significant influences of environment-related variables, such as abundance of green and view to the ocean, and risk-related variables as well. Hedonic studies about natural environment are nicely summarized in Waltert and Schläpfer (2010) and Brander and Koeste (2011), and those about risks (flood) are in Merz et al. (2010), respectively.

Among natural environmental factors, ocean has a considerable impact on human well-being. Especially, strong influence of ocean view has often been demonstrated. For example, Yu et al. (2007) suggest that ocean view has positive economic value, and the value changes depending on the quality, while Jim and Chen (2009) show the strong impact of ocean view over other views, including mountain and street views. Of course, proximity to the ocean, which increases the chance to enjoy many benefits from the ocean, is also an important factor, and many previous studies show the significance (e.g., Paterson and Boyle, 2009).

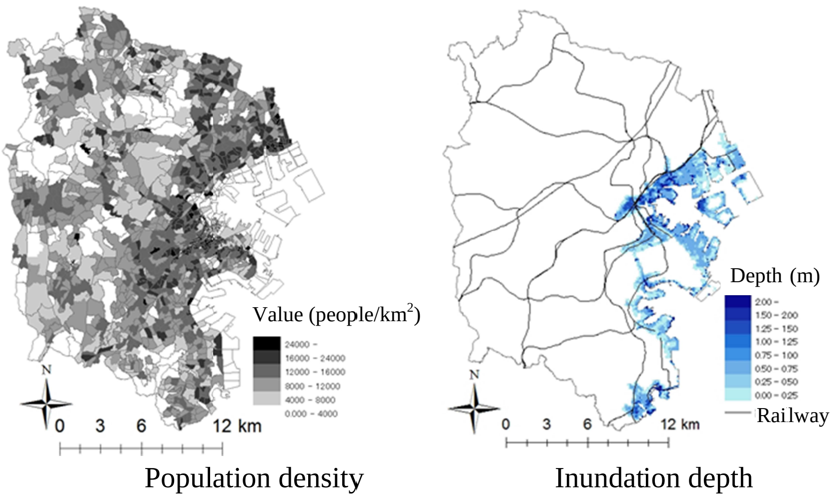


**Fig. 1.** Spatial distribution of climate monitoring stations in Tokyo. District level census population density (2005) (left) and the depth Tsunami inundation, will suffer, after the Nankai Trough earthquake (right). The inundation depths are calculated by digitizing the inundation depth map provided by Yokohama city.

On the other hand, many bayside areas are also flood prone areas. For example, Figure 1 shows the population density in Yokohama city, and a prediction of Tsunami inundation depth followed by the Nankai Trough earthquake, which is a great earthquake to come within a couple of decades. Figure 1 shows that many residents are in the flood prone area; many of them must get serious damages after the Tsunami. Noteworthy, the dangerous situation is introduced despite Yokohama city provides flood risk information in multiple ways, including a web-GIS system and hazard maps.

The high population density in flood prone areas might be due to the underestimation of flood risks. Actually, Michael (2007) demonstrated existence of such underestimation of flood risk in a hedonic analysis. In behavioristic psychology, the underestimation is well known as the normalcy bias (e.g., Omer and Alon, 1994). This bias suggests that people tends to think that a disaster will never occur because it has never occurred. Namely, peoples are apt to be too optimistic about suffering from disasters. Further, the bias also states that person is too optimistic even after disaster strikes. This bias can result in inadequate prepare for disasters, including population concentration in flood prone areas. Thus, to mitigate flood risks, we need to address the normalcy bias, not only providing risk information on public. Some enforceable policy, such as landuse regulation, might be effective to cope with the normalcy bias.

To increase human well-being in bayside cities, flood risk reduction and increase of natural environment, convenience, and so on must be conducted simultaneously. However, risks and benefits from the ocean can have a trade-off relationship. For example, Hamilton (2006) shows that, while dike protects coastal areas from flood risks, it decrease landscapes, and property values as well.

Selection of the hedonic model is crucial to analyze the trade of between flood risks and benefits from the ocean. Unfortunately, the multiple regression model, which is used many hedonic studies (e.g., Paterson and Boyle, 2002; Jim and Chen, 2009; Sander and Polasky, 2009) can lead misleading result because of its following limitations: (i) it cannot capture non-linear influences; (ii) it cannot capture spatial dependence; (iii) it cannot consider the multilevel structure (units-buildings), which must be considered if condominium prices are modeled. Ignorance of (i) can yield biased parameter estimates. Ignorance of (ii) and/or (iii) increase the risk of type I errors in the inferences (see, LeSage and Pace, 2009; Gelfand et al. 2007; Yamagata et al. 2013). However, to the best of the authors' knowledge, no hedonic study analyzes the trade-off considering (i), (ii), and (iii).

The objective of this study is analyzing the trade-off between benefits from the ocean and flood risks, and discussing desirable urban form based on the result. The trade-off is analyzed by a hedonic analysis of condominium prices in Yokohama city (see, Section 3.2). Reminder of this study is organized as follows. The next introduces a hedonic model considering (i) non-linearity, (ii) spatial dependence, and (iii) multilevel structure. Section 3 applies the model and some alternatives to evaluate the trade-off. Section 4 discuss how to cope with this trade-off based on the analysis result.

## 2. Hedonic model

### 2.1 Basic regression (BR) model

Our basic regression model is formulated as follows:

$$\ln(y_{i-j}) = \boldsymbol{x}'_{\boldsymbol{i\text{-}j}}\boldsymbol{\beta} + \varepsilon_{i-j}\,, \tag{1}$$

where $i$ and $j$ denote the indexes of condominium room and building, respectively; $y_{i\text{-}j}$ denotes the price of condominium; $\boldsymbol{x}_{i\text{-}j}$ $[\,P\times1\,]$ denotes the vector of regressors; $\boldsymbol{\beta}$ $[\,P\times1\,]$ denotes the regression coefficient vector; and $\varepsilon_{i\text{-}j}$ denotes the zero-mean normally distributed disturbance whose variance is given by $\sigma_\varepsilon^2$. While BR is one of the standard hedonic models, it ignores (i), (ii), and (iii).

### 2.2 Multilevel regression (MR) model

BR does not consider the multilevel structure of condominiums (units-buildings), whose ignorance can introduce a serious bias in parameter standard errors (Hox, 1998). The multilevel regression (MR) model is an extension of BR with both unit-level disturbance ($\varepsilon_{i\text{-}j}$) and unit-level disturbances, which is formulated as follows:

$$\ln(y_{i-j}) = \boldsymbol{x}'_{\boldsymbol{i\text{-}j}}\boldsymbol{\beta} + u_j + \varepsilon_{i-j}\,, \tag{2}$$

where $u_j$ is the building-wise normally distributed disturbance, whose variance is given by $\sigma_u^2$.

Although Yamagata et al. (2013) suggests that MR furnishes reasonable hedonic estimates, it still ignores (i) non-linearity, (ii) spatial dependence. To consider the possible non-linear impacts of flood risks and/or benefits from the ocean, (i) must be considered. Consideration of (ii) is required to mitigate the omitted variables bias. When we construct a statistical model, it is common that some factors, whose data are not available, are omitted from the model. Therefore it is crucially important to eliminate the effects of such confounding factors. Although the conventional way against this problem is to use instrument variables (Gibbons and Overman, 2012), the selection of good instrument variables is not an easy task. Then, if omitted factors have spatial autocorrelation patterns, we can mitigate the problem through the application of spatial autocorrelation models (e.g., LeSage and Pace, 2009; Seya et al., 2013; 2014).

The next section discusses a model considering (i), (ii), and (iii).

### 2.3 Spatial multilevel additive regression (SMAR) model

We use the spatial multilevel additive regression (SMAR) model to consider all points discussed just above. The SMAR model is defined as follows:

$$\ln(y_{i-j}) = \boldsymbol{x}'_{\boldsymbol{i\text{-}j}}\boldsymbol{\beta} + f_1(z_{1,i-j}) + \cdots f_q(z_{q,i-j}) + \cdots f_Q(z_{Q,i-j}) + s(lon_j, lat_j) + u_j + \varepsilon_{i-j}, \tag{3}$$

where $z_{q,i\text{-}j}$ ($q$=1, …, $Q$) is the regressor, whose impact on $\ln(y_{i-j})$ is possibly non-linear. The non-linear impact is modeled through the smoothing spline function, $f_q(\cdot)$. For the smoothing function, we used the conventional thin plate spline (Wood, 2003). $s(\cdot)$ is the bivariate spatial smoothing spline function, and $lon_j$ and $lat_j$ are the longitude and latitude of the $j$-th building. Here, we use the Tensor product smoothing operator for $s(\cdot)$ (Wood et al., 2013). The parameter estimation can be achieved using mixed model software such as the gamm4 package in R, which we used.

To summarize, the model shown in Eq. (3), which we employed for the empirical analysis, has three notable advantages. (i) it can capture the non-linear effects of flood risks and benefits from the ocean as well as the other variables; (ii) it explicitly considers the multilevel structure of condominiums by introducing both building-wise disturbance ($u_j$) and unit-wise disturbance ($\varepsilon_{i\text{-}j}$); and (iii) it considers the spatial autocorrelation by the introduction of the term $s(lon_j, lat_j)$. To the author's knowledge, only Brunauer et al. (2013) have considered all of these aspects in the hedonic analyses, although they did not focus on benefits and risks from the ocean, which we focus.

## 3. Empirical analysis

### 3.1 Study area

Our study area was the seven central wards of Yokohama city (Naka, Nishi, Minami, Isogo, Hodogawa, Konan, and Tostuka wards), which is the second largest city in Japan with a population of over three million (Figure 2). The study area is located less than thirty minutes from south of the Tokyo central business district (CBD) by train.


**Fig. 2.** The 7 wards in Yokohama city

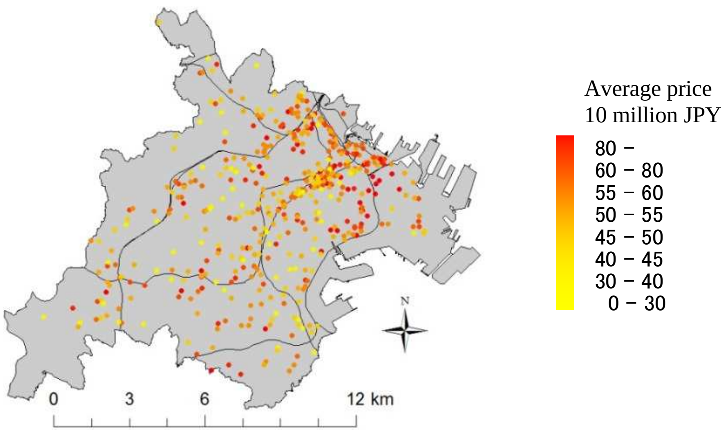


**Fig. 3.** Average condominium prices in the target area

### 3.2 Data

We used the data on condominium prices from 1993 to 2008. The data were provided by Marketing Research Center (MRC) Co. Ltd. These price data were based on registration (seller pricing) and not on transaction (actual traded price). However, with regard to residential condominium prices in Japan, discount negotiation is considerably rare, except in cases of high-grade residences. Therefore, the registered price level is representative of the market situation. The geographical distribution of the averaged prices in each building is given in Figure 3. The number of building samples and room samples is 694 and 27,446, respectively.

### 3.3 Variables

Our hedonic analysis regresses logged condominium prices on variables categorized into flood risk, benefit from the ocean, other environmental attributes, location attributes, and attribute of condominiums.

The flood risk is quantified by "**Flood risk**," which represents the inundation depth shown in Figure 1, and the benefit from the ocean is quantified by "**Ocean dist.**," which represents the logarithm of the distance to the ocean [km], and "**Ocean view**," which represents the goodness of view to the ocean, which is calculated as discussed in Appendix.1.

Other environmental attributes used as regressors are as follows: "**Open view**," which represents the openness of view, "**Green view**," which represents the goodness of view to trees; "**Green**," which represents the logarithm of the number of tree cells within 500 m (irrelevant of whether or not visible); "**Park dist.**," which represents the logarithm of the distance to the nearest urban park [km]. Detail of calculations of Open view, Green view, and Green are described in Appendix.1.

Location attributes used as regressors include following variables: "**Station**," which represents the logarithm of the travel time to the nearest train/bus station on foot [minute]; "**C1 res.**," which indicates category 1 (C1) residential districts (RD) [dummy]; "**C1 low**," which indicates C1 low-rise exclusive RD [dummy]; "**C1 high**," which indicates C1 medium-to-high exclusive RD [dummy]; "**C1 exclusive**," which indicates C1 exclusive RD [dummy]; "**C2 res.**," which indicates category 2 (C2) RD [dummy]; "**C2 high**," which indicates C2 medium-to-high exclusive RD [dummy]; "**C2 exclusive**," which indicates C2 exclusive RD [dummy]; "**Industry**," which indicates industrial districts [dummy]; "**Semi Ind.**," which indicates semi-industrial districts [dummy]; "**Commerce**," which indicates commercial districts [dummy]; "**Neigh. Com.**," which indicates neighborhood commercial districts [dummy].

Condominium attributes considered are as follows: "**Area**," which represents the logarithm of room area [$m^2$]; "**Floor**," which represents the logarithm of floor of the room; "**Num. dev**.," which represents the numbers of related developers; logarithm of view variables ("**Open view**," "**Green view**,"); "**Major dev**.," which represents the ratio of major developers called MAJOR 8 (Sumitomo Realty & Development Co., Ltd, Tokyu Land Corporation, Mitsubishi Estate Co., Ltd., Towa Real Estate Development Co., Ltd., Daikyo Inc., Nomura Real Estate Development Co., Ldt., Mitsui Fudosan Residential Co., Ltd. and Tokyo Tatemono Co., Ltd.) to the other developers; "**SRC**," which represents the steel reinforced concrete structure [dummy]; "**WRC**," which represents the steel wall concrete structure [dummy]. Besides, to capture the time trend we also introduce "**Time**," which represents the elapsed months from January 1993 [Year].

The GIS data on Park and Ocean were provided by the Yokohama city government. View variables are calculated as explained in Appendix.1. The other variables are acquired from the condominium price dataset of MRC Co. Ltd.

This study allows non-linear influences for continuous variables except for distance variables (Ocean dist., Park dist., and Station dist). We assume linear influence for the distance variables because non-linear impacts of distance variables can produce distance-increasing effects, which is difficult to interpret (e.g., influence of a railway station inflates according to the distance from the station increases).

### 3.4 Parameter estimates

Table 1 summarizes the parameter estimation results of BR, MR, and SMAR, and Figure 4 shows non-linear influences estimated by SMAR. The large gap of Akaike Information Criteria (AIC) between BR and MR show that the model accuracy is drastically improved by considering the multilevel structure of condominiums. Actually, the building-wise variance, which is ignored in BR, is much greater than the room-wise variance (0.0193 vs 0.0033, in the MR model case). As a result, due to the type I error, *t*-values of BR are highly overestimated compared to MR and SMAR. This result suggests that consideration of the multilevel structure is crucially important in hedonic analysis of condominium prices.
Significant levels: ***:0.1%; **:1%; *:5%, and . :10%

Estimates of linear influences in MR and SMAR are similar: both models indicate significant negative influences of "C1 res." and "Semi Ind," and "Park dist," and significant positive influences of "Major dev." Still, some notable differences are found between estimates, in which non-linear influences are allowed. While "Area" and "Floor" are significant at the 1% level in both models, they indicate substantial non-linear influences in SMAR that these impacts inflate as their value increase.

Some differences between MR and SMAR are also in environment-related regressors. Firstly, while the MR model suggests the negative significant influence of "Open view ," which is difficult to interpret, the effect of "Open view" estimated by SMAR model becomes positive and it increases rapidly with the increase of the value of "Open view". It means that very nice view (in terms of amount of visibility) may be capitalized into condominium prices, but slightly nice view may not have any positive impacts. The effect of "Green view" has also been found to be non-linear. That is, before around 10, the effect of *f*(Green view) is constant at approximately 0.02 (positive), but after around 10, it decreases rapidly with the increase of the value of "Green view". It means that a *moderate amount* of "Green view "may raise condominium prices, but *too much* "Green view" may decrease condominium prices. Such information could be useful for condominium developers and/or urban designers.

Let's move to the view describing benefits from the ocean ("Ocean dist." and "Ocean view"). "Ocean dist." in the MR model is negatively significant at the 1% level, whereas it is not significant in the SMAR model. Because ignorance of spatial dependence can lead biased *t*-values (see Anselin, 1988), the MR model might have overestimated the premium of "Ocean dist." With regard to "Ocean view," the MR model estimates that it is positively significant at the 1% level irrespective of the quality of ocean view. On the other hand, the SMAR model suggests that only scenic ocean view has statistically significant influence. The influence from Ocean view increases as the quality increases. Consideration of such non-linearity would be required to evaluate benefit from the ocean appropriately.

**Table 1.** Estimated parameters

| Category | Regressor | BR | | | MR | | | SMAR | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Coef. | *t*-value | | Coef. | *t*-value | | Coef. | *t*-value | |
| Intercept | Intercept | 4.317 | 88.28 | *** | 4.226 | 21.20 | *** | 8.272 | 454.37 | *** |
| Risk | Flood risk | 0.021 | 5.70 | *** | 0.034 | 1.50 | | | | |
| Environment | Ocean dist. | –0.044 | –38.10 | *** | –0.049 | –6.90 | *** | –0.002 | –0.13 | |
| | Ocean view | 0.012 | 24.18 | *** | 0.009 | 21.20 | *** | | | |
| | Open view | 0.010 | 3.82 | *** | –0.017 | –4.00 | *** | | | |
| | Green view | –0.014 | –6.13 | *** | 0.004 | 1.10 | | | | |
| | Green | 0.029 | 8.95 | *** | –0.011 | –0.70 | | | | |
| | Park dist. | –0.010 | –11.53 | *** | –0.014 | –2.60 | ** | –0.009 | –1.80 | . |
| Location | Station dist. | 0.012 | 10.95 | *** | –0.001 | –0.10 | | –0.002 | –0.26 | |
| | C1 res. | –0.049 | –13.55 | *** | –0.069 | –3.20 | ** | –0.032 | –1.71 | . |
| | C1 low | –0.013 | –3.23 | ** | –0.026 | –1.10 | | –0.007 | –0.33 | |
| | C1 high | 0.010 | 2.52 | * | –0.027 | –1.10 | | –0.004 | –0.17 | |
| | C1 exclusive | 0.045 | 9.69 | *** | 0.026 | 0.90 | | –0.001 | –0.03 | |
| | C2 res. | –0.018 | –2.65 | ** | –0.029 | –0.70 | | 0.001 | 0.03 | |
| | C2 high | –0.007 | –1.10 | | –0.037 | –1.00 | | –0.006 | –0.18 | |
| | C2 exclusive | 0.038 | 8.16 | *** | 0.028 | 0.90 | | 0.003 | 0.11 | |
| | Industry | –0.066 | –10.23 | *** | –0.017 | –0.40 | | 0.016 | 0.40 | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Semi Ind. | –0.109 | –29.08 | *** | –0.088 | –3.50 | *** | –0.057 | –2.62 | ** |
| | Commerce | 0.001 | 0.25 | | –0.032 | –1.40 | | –0.007 | –0.33 | |
| | Neigh. Com. | –0.003 | –0.92 | | 0.000 | 0.00 | | 0.000 | –0.01 | |
| Condominium | Area | 0.940 | 220.21 | *** | 1.134 | 417.30 | *** | | | |
| | Floor | 0.078 | 43.36 | *** | 0.084 | 29.80 | *** | | | |
| | Num. dev. | 0.024 | 12.89 | *** | 0.010 | 0.70 | | 0.006 | 0.53 | |
| | Major. dev. | 0.071 | 31.96 | *** | 0.069 | 4.90 | *** | 0.062 | 5.14 | *** |
| | SRC | –0.018 | –7.14 | *** | –0.010 | –0.50 | | –0.019 | –1.25 | |
| | WRC | –0.031 | –3.66 | *** | 0.024 | 0.50 | | –0.007 | –0.16 | |
| AIC | | –31405 | | | –75216 | | | –78875 | | |
| Room level variance | | 0.1365 | | | 0.0033 | | | 0.0029 | | |
| Building level variance | | 0.0000 | | | 0.0193 | | | 0.0142 | | |

Significant levels: ***:0.1%; **:1%; *:5%, and . :10%

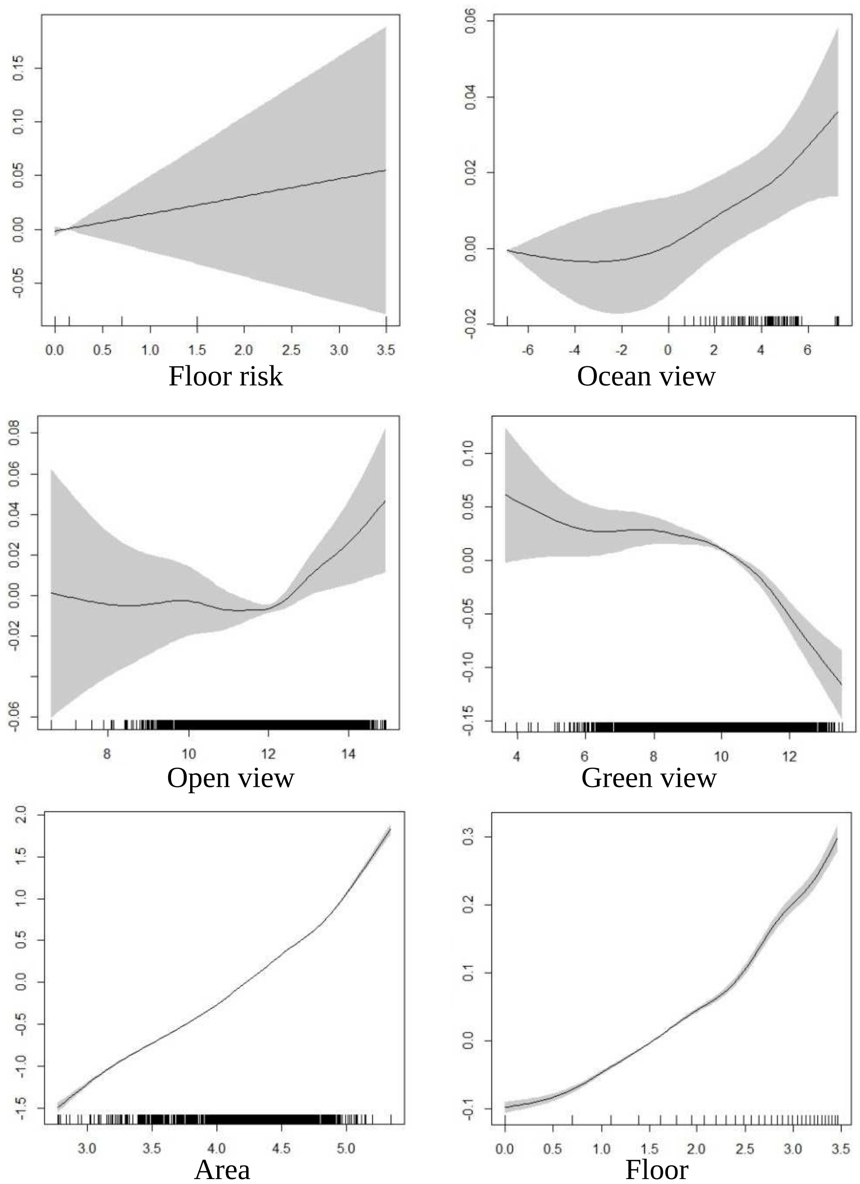


**Fig. 4.** Estimated non-linear estimates

In contrast, “Flood risk” is not significant both of these two models. It implies that, while “Ocean dist.” and “Ocean view” are appropriately reflected as significant positive benefits from the ocean, “Flood risk” is not reflected as a negative benefit from the ocean. This ignorance or underestimation of "Flood risk" can make urban form less adaptive to the flood risk. To demonstrate it, estimated influences from "Ocean dist.", "Ocean view," and "Flood risk" are summed and plotted, as well as inundation depths, in Figure 5. This figure shows that, as a result of the underestimation of the flood risk, the ocean increases economic value of flood prone areas, which are attractive in terms of "Ocean dist." and "Ocean view."

This result claims that publication of flood risk, which is conducted by Yokohama city, does not necessarily work sufficiently, and some enforceable policy that encourages appropriate action even people underestimates risks, is needed. Landuse regulation might be an effective approach. On the other hand, our hedonic approach still has some problems to be solved. For example, while we simply introduce the inundation depth in our regression model, the influence is likely to change depending on whether the depth exceeds floor height of each building. Besides, flood risk changes depending on structure of building. Consideration of these points would be an important task in the future studies.

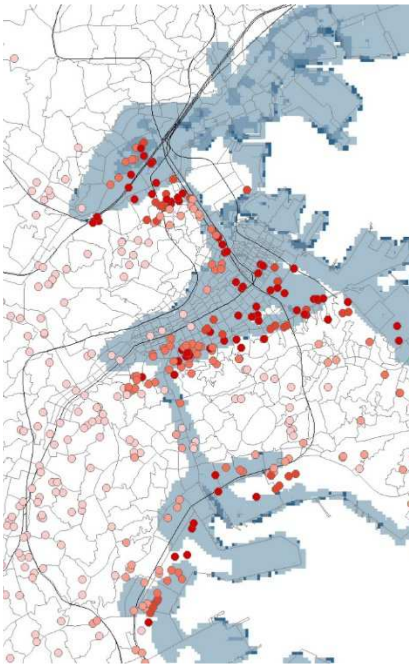

**Fig. 5.** Estimated marginal benefit from the ocean. Dots represent condominiums. Condominiums with greater marginal benefits from the ocean are colored by deep red. Blue areas denote flood prone areas.

### 3.5 An application of the analysis result for urban policy making

Flood risk adaptation policy must be discussed considering not only its influence on the risk reduction but also its secondary influences on amenity, natural environment, and so on. Fortunately, our hedonic analysis reveals economic values of these factors (e.g., the economic value of natural environment was evaluated by applying Green, Ocean dist, and Park dist for explanatory variables). Estimated economic values are useful for policy making considering not only disaster risks but also other factors.

To illustrate this, this section evaluates influences of a migration policy for multiple factors, based on the hedonic result. The procedure is summarized as follows: (a) variables describing accessibility (Station), natural environment (Green, Ocean dist, and Park dist), landscape (Open view, Ocean view, and Green view), and floor risk (Flood risk) in each minor municipal district are calculated; (b) economic values of these variables are evaluated based on the hedonic analysis result; (c) benefits that residents receive from these variables are evaluated by multiplying their evaluated economic values with populations $P_k$, where $k$ is an index of minor municipal districts.

In step (a), Open view, Ocean view, and Green view in each minor municipal district are evaluated as follows: (a-1) average floor height in each minor municipal district are estimated using ZMap-TOWN II, an individual building data provided by Zenrin Co., Ltd. (http://www.zenrin.co.jp/); (a-2) Open view, Ocean view, and Green view for each district are evaluated the by the inverse distance weighting (IDW).method. Specifically, in step (a-2), the potential of views from the geometric center of $k$-th district is evaluated by the IDW-based spatial smoothing of view variable values given in each condominium (see, Yang et al., 2007). Here, (average floor height in $k$-th district)/2 is applied for the height of the vantage point for $k$-th district.

In step (b), economic values of each variable, i.e., $x_{p,k}$ and $z_{q,k}$ in our hedonic model Eq.(3), are evaluated by $\exp(x_{p,k}\beta_p)$ and $\exp(f(z_{q,k}))$. $\exp(x_{p,k}\beta_p)$ and $\exp(f(z_{q,k}))$ represent marginal benefits of $x_{p,k}$ and $z_{q,k}$, respectively, which are derived from Eq.(3). Using these marginal benefits, the total marginal benefit in $k$-th district is evaluated by $P_kE_k$, where $E_k = \exp(\Sigma_p x_{p,k}\beta_p + \Sigma_q f(z_{q,k}))$ (see Eq.3) is the sum of the economic impacts from each variable. Further, the total benefit in the target area is evaluated by averaging (or summing) the district-wise benefit, $P_kE_k$.

Based on the approach of evaluating marginal benefits from each variable, we evaluates the effectiveness of three migration policies:

- BAU :Business as usual
- Adapt 1 :Migration of residents in areas where the inundation depth exceeds 0.5m. New addresses of the migrated persons are left to chance.
- Adapt 2 : Migration of residents in areas where the inundation depth exceeds 0.5m. New addresses of the migrated persons are decided based on the hedonic analysis result.

Adapt 1 distributes the migrated persons in proportion to the current populations in each minor municipal district. Adapt 2 distributes them proportional to the economic value $E_k$ in each district, to increase $P_kE_k$.

Total benefits under each of these scenarios are 1.063 (BAU), 1.060 (Adapt1), and 1.062 (Adapt2). The result demonstrates that the adaptation policies 1 and 2 decrease the total benefit because of their secondary influences to factors except for the flood risk. The result also suggests that Adapt 2 is better than Adapt 1. Actually, the decrease of the total benefit by Adapt 2 is only 0.38 times of the decrease by Adapt 1. This result demonstrates the effectiveness of utilizing the hedonic result in a migration policy.

To look Adapt 1 and 2 in more detail, marginal benefits from accessibility, natural environment, and landscape are evaluated individually in each scenario. The result suggests that Adapt 2 indicates greater scores than Adapt 1 in all of the three factors. Decreases of accessibility, natural environment, and landscape scores by Adapt 2 are 0.49 times, 0.16 times, and 0.95 times of the decreases by Adapt 1. The result shows that Adapt 2 effectively holds benefit from natural environments.

Lastly, the gap of population densities between Adapt 2 and BAU is plotted in Figure 6. This figure suggests that, considering accessibility, natural environment, and landscape, moving persons in flood prone areas to safer areas in the east part of the target area is desirable.

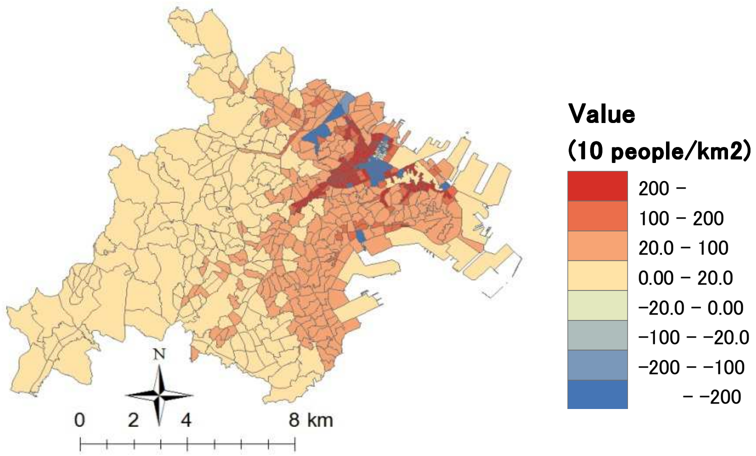


**Fig. 6.** Gap of population density (Adapt 2 minus BAU)

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## Appendix: Evaluation of Open view, Ocean view, Green view, and Green

To evaluate view variables, we perform a viewshed analysis using the digital surface model (DSM) and the digital terrain model (DTM) shown in Figure A.1 and Figure A.2, respectively. The DSM describes the height of the surface defined as the sum of the height of the ground and that of the objects on it, and the DTM describes the height of the ground surface only. They are created from airborne LiDAR data through GIS data processing. Their spatial resolution (mesh block size) is approximately 0.5 m x 0.5m. Using these data, we applied the viewshed analysis to evaluate open view, green view, and ocean view. The latter two were evaluated by counting the number of mesh blocks of green and ocean which are visible from each room. Open view was evaluated by counting the number of mesh blocks of visible DSM from each room. Details of the evaluation procedure are summarized as follows:

1. Condominium data and their shape polygons (source: Fundamental Geospatial Data of Geographical Survey Institute of Japan) were manually combined with reference to Google Maps and several condominium web pages. Then, we extracted the building polygons with information on attributes and prices.
2. Floor height of each room in each building was identified based on the room numbers.
3. Using the longitude and latitude information in step 1 as well as the height information in step 2, the 3D coordinates of each viewpoint were set for each room.
4. A viewshed analysis from each viewpoint was performed. Then we obtained the estimated values of open view. Subsequently, green view and ocean view were evaluated as follows.
5. Mesh blocks, which corresponded to tree, were identified in the following manner:
   - 5-1 The aerial photo (spatial resolution: 0.5 m x 0.5 m), which was acquired simultaneously with the LiDAR data, was classified by a maximum likelihood method, and the actual placement of trees was estimated.
   - 5-2 Based on the vertical difference between DSM and DTM, we assigned height information to the mesh blocks corresponding to trees. Here, in order to remove noise, mesh blocks in which

the estimated tree heights were less than 0.5 m were excluded (Figure A.3) from the tree meshes.

6. Mesh blocks, which corresponded to ocean, were estimated using the vector GIS data of ocean provided by Yokohama city.
7. Green views and ocean views were evaluated by counting the visible tree meshblocks and visible ocean meshblocks, respectively.

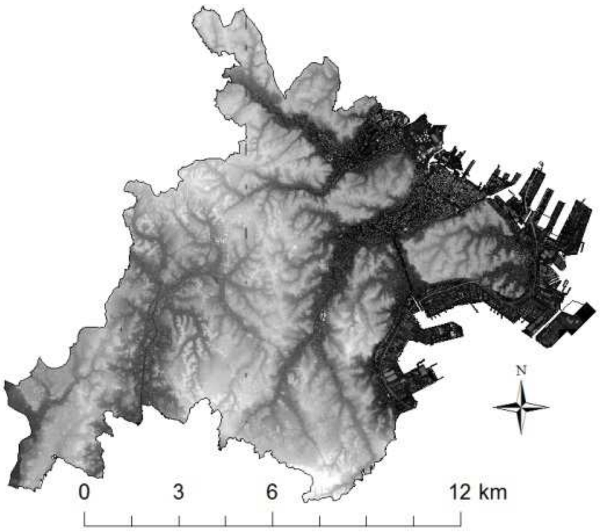


**Fig. A.1.** DSM

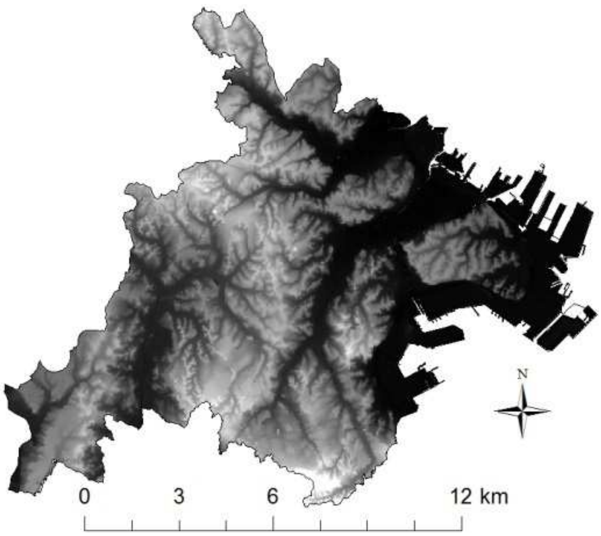


**Fig. A.2.** DTM

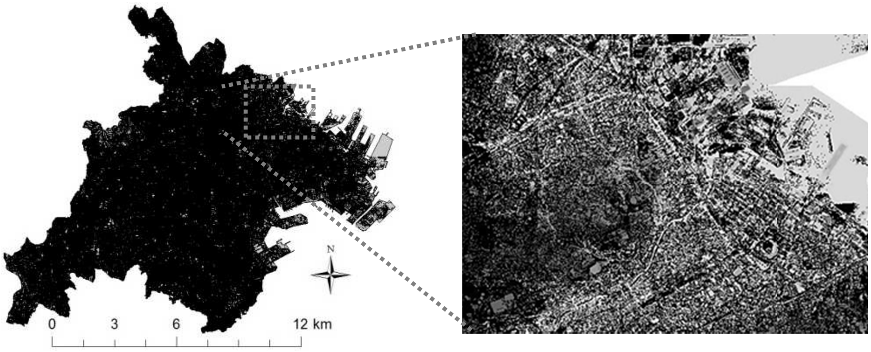


**Fig. A.3.** Tree meshes

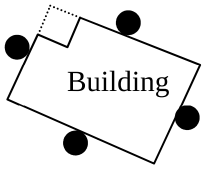


**Fig. A.4.** Four viewpoints set for each floor of each condominium

Unfortunately in step 3, we did not have any data with regard to the placement and direction of windows in each room. Hence, we needed to make an assumption on them. Here, following Yasumoto et al. (2012), (i) the height of the viewpoint was defined by [height of a floor (3 m)] × ([number of stories] – 1) + [height of human eyes (1.6 m)], and (ii) the direction of viewpoint was set at four midpoints of each side of the rectangles that approximated condominium buildings (Figure A.4). After evaluating the views of all four directions, we calculated their average. Hence, the estimated views may not change for each room on the same floor of a condominium. Besides, we set the maximum visible range to 500 m following Yu et al. (2007) and Yasumoto et al. (2012).