Flood Risk Management in Cities

Daisuke Murakami and Yoshiki Yamagata

Abstract While bayside areas, which enjoy coastal natural environment, amenity, scenic landscapes, and so on, are typically attractive residential areas, they are very often vulnerable to flooding too. Unfortunately, flood risk is gradually increasing in Asian cities. In particular, the Tokyo metropolitan area is known as a high-risk metropolis. Building flood risk resilience while keeping the attractiveness of the bayside area is a critical issue in Tokyo. The objective of this study is to analyze the trade-off between benefits from the ocean and flood risk as a first step to increase urban resilience. To quantify the trade-off, this study uses the hedonic approach. We first review related hedonic studies and discuss which hedonic model is suitable to apply in our analysis. Subsequently, we perform a hedonic analysis of condominium prices and quantify the benefits from ocean-related variables, including ocean view and proximity to the ocean, and the negative effects from the flood risk. Here, a spatial additive multilevel model is used. The analysis results reveal that the flood risk is highly underestimated while the benefits from the ocean are appropriately evaluated in the target area.

Keywords Flood risk · Trade-off · Hedonic analysis · Normalcy bias · Yokohama

1 Introduction

A gradual increase of natural disaster risks is projected on the global scale (Pachauri et al. 2014). Dettinger (2011) and Kundzewicz et al. (2014) projected that storms are more and more frequent and severe in East Asia, North, Central, and Caribbean America, while Hirabayashi et al. (2013) and Kundzewicz et al. (2014) projected an increase of flood risks in Asia and some other areas. These regions include

D. Murakami (✉) · Y. Yamagata
Center for Global Environmental Research, National Institute
for Environmental Studies, 16-2, Onogawa, Tsukuba 305-8506, Japan
e-mail: murakami.daisuke@nies.go.jp

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megacities like Tokyo and New York and many growing cities, which are typically in developing countries, and are vulnerable to disaster risks (OECD 2012). Building resilience is increasingly important especially in these cities (Hammond et al. 2015).

Unfortunately, cities are not always resilient against disaster risks. Cities are typically located in bayside/riverside areas where storm and flood risks are high, because these areas are convenient for trading, agriculture, and so on. Furthermore, inside these cities, people usually prefer living nearby the ocean (or rivers) that enjoys coastal natural environment, amenity, and landscapes. Numerous studies have empirically verified the significant attractiveness of bayside areas (e.g., Pompe and Rinehart 1994; Jim and Chen 2009; Hamilton and Morgan 2010; Landry and Hindsley 2011; Yamagata et al. 2015a, 2016).

It is important to increase the resilience of bayside cities while keeping their attractiveness. However, policy making for that purpose is not necessarily straightforward because of the trade-off between risks and other factors (e.g., Rascoff and Revesz 2002). For example, a land-use regulation to a high-risk area might stop some economic activities, while an embankment construction, which decreases flood risks, might destruct natural environment and obscure scenic ocean views. Even compact city policy (see, Chapter "Urban Economics Model for Land-Use Planning"), which is a popular policy toward sustainable development, does not specifically consider disaster risks (OECD 2012). A city compaction can lower the flood risk resilience if the policy concentrates people in a bayside area.

Unfortunately, urban structures are not necessarily adaptive to disaster risks. For example, Fig. 1 shows the spatial distributions of population density (source: Census 2010) and anticipated inundation depth (source: National Land Numerical Information download service; URL: http://nlftp.mlit.go.jp/ksj-e/index.html) in the central area of Tokyo. This figure suggests that the eastern area with large population density is also a high-risk area (note that this area also is known as a high-risk area of liquefaction and earthquakes). Although the Tokyo Metropolitan

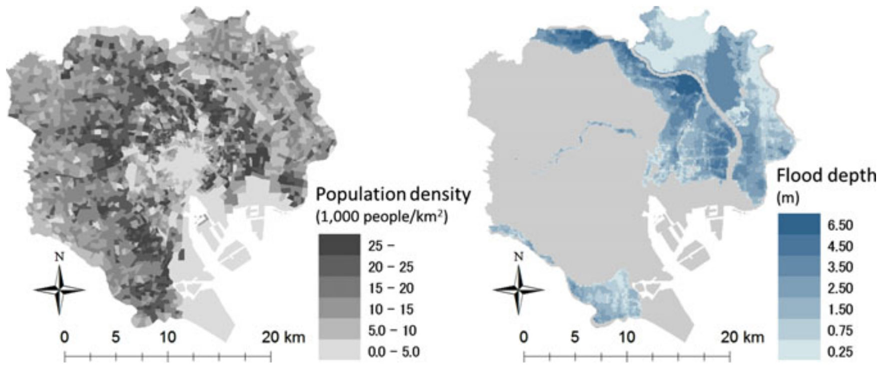

Fig. 1 Population density (*left*) and anticipated flood depth (*right*) in the 23 wards of Tokyo

Government has published hazard maps to disseminate disaster risks, the population in this vulnerable area is still growing.

Such an underestimation of the disaster risk is attributable to the normalcy bias (e.g., Omer and Alon 1994), which refers to a mental state that people tend to be too optimistic about unusual and inconvenient events such as disasters. This bias allows people to reside in high-risk areas without specifically considering disaster risks.

To cope with the normalcy bias and to increase the resilience against flooding, it is necessary to quantify the trade-off between flood risks and other factors. The objective of this chapter is to discuss how to quantify such a trade-off, and to empirically analyze whether or not the disaster risk is underestimated. The subsequent sections are organized as follows. The next section introduces the hedonic approach which we will use, and discuss which hedonic model is suited for our analysis. Then, the risk trade-off is analyzed using that model. Finally, we conclude our discussion.

2 Hedonic Approach

2.1 Hedonic Analysis of Flood Risk

The hedonic approach (Rosen 1974) is a representative approach to quantify economic values of non-market goods, such as accessibility, environment, and disaster risks. This approach evaluates their economic values by regressing them on property values. Existing hedonic studies have revealed the positive premium of natural resources, including greens, parks, and the ocean (see, Waltert and Schläpfer 2010; Brander and Koetse 2011). Thus, the results of hedonic analyses regarding natural environment are intuitively consistent in many cases.

By contrast, the results of hedonic analyses regarding flood risk are controversial. Daniel et al. (2009) showed in their meta-analysis of 19 relevant studies that the premium of flood risk varies between −52 and +58 %. For example, Bin and Kruse (2006) and Atreya and Czajkowski (2014) suggested a statistically significant positive economic value of flood risk that is counterintuitive, Cavailhès et al. (2009) showed an insignificant value, and Bin et al. (2008) and Samarasinghe and Sharp (2010) showed a statistically significant negative premium.

A consensus is that flood risk has a significant negative impact after a catastrophic flood (see, Zhai et al. 2003; Bin and Polasky 2004; McKenzie and Levendis 2010; Atreya et al. 2013). However, Bin and Landry (2013) showed that the negative influence disappeared in about five or six years after the flood. Atreya et al. (2013) also suggested the disappearance of negative impacts in four to nine years. These results imply that people forget flood events quickly, and the underestimation of the risk appears just like before the threat (see, McKenzie and Levendis 2010).

Based on the literature review, it is likely that the inundation risk is underestimated in the Tokyo bayside area where catastrophic flooding may occur within decades. Voss (2006) estimated that the Tokyo metropolitan area is the most vulnerable metropolis in the world because of the high risk of storms, floods, and other disasters. Furthermore, a great earthquake called the Nankai-Trough earthquake is projected to hit the Tokyo area within 30 years. The increase of disaster risk resilience is among the most crucial issues in Tokyo.

As a first step of building resilience in Tokyo, the rest of this chapter analyzes whether flood risks are underestimated in Yokohama city, which is a bayside city nearby Tokyo.

2.2 Hedonic Models

As discussed, the hedonic analysis regresses risk variables and other variables on property prices. In case of using condominium price, Eq. (1) is one of the most basic models:

$$\ln(y_{i-j}) = \sum_{p=1}^{P} x_{i-j,p}\beta_p + \varepsilon_{i-j}, \quad \varepsilon_{i-j} \sim N\left(0, \sigma_\varepsilon^2\right), \tag{1}$$

where i and j are indexes of condominium units and buildings, respectively; y_{i-j} is the price of ith unit in jth building; $x_{i-j,p}$ is pth explanatory variable whose influence on $\ln(y_{i-j})$ is assumed to be linear; β_p is the regression coefficient; and ε_{i-j} is the unit-level disturbance with variance of σ_ε^2.

Although Eq. (1) has been widely used in hedonic analyses, it has some serious limitations. Firstly, it does not consider the multilevel structure of condominiums (units-buildings), whose ignorance can introduce a serious bias in parameter standard errors (Hox 1998). Secondly, it does not consider the possible non-linear influences from explanatory variables (e.g., flood risk might have a non-linear impact such that the influence becomes significant only when the risk exceeds a threshold). Thirdly, Eq. (1) tends to suffer from 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 omitted 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 dependent patterns, we can mitigate their influences by applying a model considering spatial dependence (see, e.g., Schabenberger and Gotway 2004; LeSage and Pace 2009).

Based on the above, this study applies the spatial multilevel additive regression (SMAR) model, which is formulated as follows.

$$\ln(y_{i-j}) = \sum_{p=1}^{P} x_{i-j,p}\beta_p + \sum_{q=1}^{Q} f_q(z_{i-j,q}) + s(lon_j, lat_j) + u_j + \varepsilon_{i-j},$$
$$u_j \sim N\left(0, \sigma_u^2\right) \quad \varepsilon_{i-j} \sim N\left(0, \sigma_\varepsilon^2\right) \tag{2}$$

where $z_{i-j,q}$ is explanatory variables whose impacts are allowed to be non-linear (SMAR is a model considering both linear and non-linear influence). The non-linear influence from $z_{i-j,q}$ is modeled by 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 jth building. Here, we use the Tensor product smoothing operator for $s(\cdot)$ (Wood et al. 2013). Thus, non-linearity is modeled by $f_q(\cdot)$ while the omitted variables bias is mitigated by introducing $s(\cdot)$.[1] Equation (2) considers the multilevel structure using u_j, which is the building-level disturbance (variance: σ_u^2), and the building-level disturbance ε_{i-j} (variance: σ_ε^2). In this way, all three shortcomings of Eq. (1) have been avoided.

3 Empirical Analysis

3.1 Yokohama City

Our study area is the seven central wards of Yokohama city (Naka, Nishi, Minami, Isogo, Hodogawa, Konan, and Tostuka wards; see, Fig. 2). Yokohama is situated

Fig. 2 The 7 wards in Yokohama city

[1]Although the spline function does not explicitly consider spatial dependence, the introduction of variables describing the map pattern of y_{i-j}, like the spline function, effectively captures the underlying spatial dependence and mitigates the omitted variables bias (spatial filtering; see, e.g., Getis and Griffith 2002; Murakami and Griffith 2015).

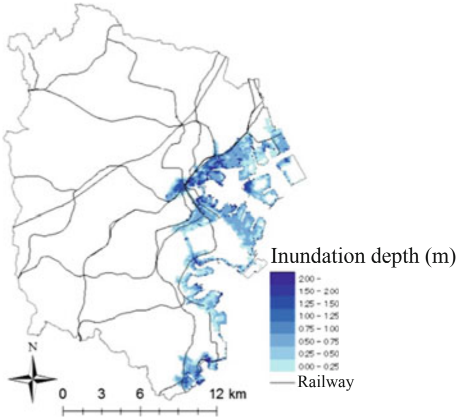

Fig. 3 Inundation area anticipated after the Nankai Trough earthquake

about 20 km south from the Tokyo central business district (CBD), and its population was 3.71 million in 2015. The seven wards include the city center around Yokohama station, a redevelopment area called Minato Mirai 21, and the biggest China town in Japan. They are all near the ocean. Also, many parks and historical buildings are found in the bayside area. Owning to them, the bayside area is a popular residential area.

On the other hand, as shown in Fig. 3, which displays the expected inundation area after the anticipated Nankai Trough earthquake, the bayside area is predicted to suffer from a flood due to the tsunami after the earthquake.

3.2 Condominium 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 average condominium prices in each building are plotted in Fig. 4. In our sample, the numbers of buildings and rooms are 694 and 27,446, respectively.

3.3 Explanatory Variables

Our hedonic analysis regresses flood risk variables, variables explaining positive influences from the ocean, and other variables.

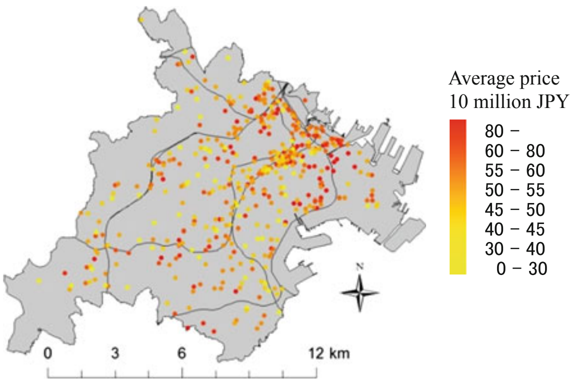

Fig. 4 Condominium prices in the target area

We estimated the flood risk around the *j*th condominium building based on the flowing flood risk function proposed by Koshimura et al. (2009):

$$Flood_j = \Phi\left[\frac{F_j - \mu}{\omega}\right] = \int_{-\infty}^{F} \frac{1}{\sqrt{2\pi\omega^2}} \exp\left(-\frac{(F_j - \mu)^2}{2\omega^2}\right) df \tag{3}$$

where F_j is the anticipated flood depth given by the flood map (Fig. 3), $\mu = 3.92$, and $\omega = 1.15$. Equation (3) describes the risk of being a victim. It is near zero if the flood depth is below 2 m, which means almost all people survive, whereas it is near one if it exceeds 6 m, which implies that almost all people are sacrificed. Note that Eq. (3) was used to estimate flood damage in Yokohama city. In addition to the building-wise indicator, we also introduced a dummy variable indicating 1 if the unit is a 1st floor unit in a flood-prone area, and 0 otherwise. This variable is needed to capture the greater risk in 1st floor units.

On the other hand, this study considers "Ocean dist.," which refers to the Euclidean distance to the ocean (log-scale), and "Ocean view," which is the visible ocean area (log-scale), as variables explaining the positive aspects of the ocean. Ocean view was calculated using a digital surface model (DSM: Fig. 5), which had been acquired from a LiDAR (Light Detection and Ranging) observation. Our DSM is a collection of 0.5 m by 0.5 m cells recording heights of the ground and objects on it such as buildings and trees. In a word, DSM describes 3D urban structure. Ocean view was calculated by counting visible ocean cells from each condominium unit within 500 m, which is assumed as the maximum visible range following Yasumoto et al. (2012). Note that we also calculated "Open view," by counting visible cells within 500 m, and "Green view," by counting visible tree cells. For further details about 3D visibility calculation, see, Yamagata et al. (2015a, 2016).

This study analyzes the trade-offs not only within ocean-related variables, but also other variables. To be specific, we evaluated the trade-offs between flood risk and landscape, natural environment, and accessibility. Table 1 summarizes the explanatory variables to evaluate flood risk. Based on a preliminary analysis,

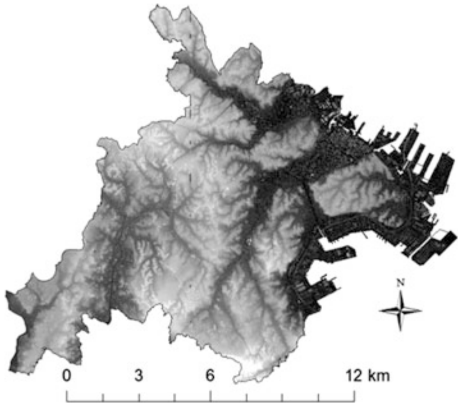

Fig. 5 Digital surface model (DSM)

non-linear impacts were allowed for unit attributes (Area, Floor), Flood, landscape variables (Open view, Green view, Ocean view), and a time variable (Time).

3.4 Results

Table 2 and Fig. 6 summarize the linear and non-linear influences respectively, from explanatory variables ($x_{i-j,p}$ and $z_{i-j,q}$), estimated by the SMAR model. As discussed, this model considers (i) the multilevel structure, (ii) spatial dependence (to mitigate the omitted variables bias), and (iii) non-linearity. The Akaike Information Criteria (AIC) of the SMAR model was −79,053, whereas that of Eq. (1) ignoring (i), (ii) and (iii) was −36,557, the AIC of the multilevel model considering (i) was only −76,336, and the AIC of the spatial multilevel model considering (i) and (ii) was −76,407.[2] Thus, (i), (ii), and (iii) must be considered to quantify and infer the impact of each explanatory variable appropriately.

Table 2 displays statistically significant negative influences of "Semi Ind," and significant positive influences of "Green" and "Major dev." In other words, (semi-) industrial districts have negative economic values probably due to factors such as gas emissions and noise from firms, and poor landscapes; whereas green areas have positive economic values; and, condominiums developed by major developers are preferable. These results are intuitively reasonable.

Figure 6, which summarizes the non-linear estimates, suggests significant influences from "Area." "Floor," "Open view," "Green view," and "Ocean view." Estimates of "Area" and "Flood" simply demonstrate that larger and upper floor units are preferable.

[2]If AIC is small, the model is accurate. Roughly speaking, two models have a significant difference in their accuracy when the gap of their AICs is more than 2.

Table 1 Explanatory variables, including risk, landscape, natural environment and accessibility variable (color table online)

Category	Variables	Description	Assumed influence
Unit attributes	Area	Logarithm of unit area [m^2]	Non-linear
	Floor	Logarithm of floor of the unit	
Building attributes	SRC	Steel reinforced concrete structure [dummy]	Linear
	WRC	Steel wall concrete structure [dummy]	
	Num.dev	Number of related developers	
	Major dev	Ratio of major developers called MAJOR 8[a]	
Risk	Flood	Death ratio estimates projected after the Nankai Trough earthquake	Non-linear
	Flood_1F	Dummy of 1st floor units in the flooded area	Linear
Land-scape	Open view	Logarithm of the visible area [km^2]	Non-linear
	Green view	Logarithm of the visible tree area [km^2]	
	Ocean view	Logarithm of the visible ocean area [km^2]	
Natural Environ.	Green	Logarithm of the number of tree cells within 500 m (irrelevant of whether or not visible)	Linear
	Park	Logarithm of the distance to the nearest urban park [km]	
	Ocean	Logarithm of the distance to the ocean [km]	
Access	Station	Logarithm of the travel time to the nearest train/bus station on foot [minute]	Linear
Location	C1 res.	Dummy of category 1 (C1) residential districts (RD)	Linear
	C1 low	Dummy of C1 low-rise exclusive RD	
	C1 high	Dummy of C1 medium-to-high exclusive RD	
	C1 exclusive	Dummy of C1 exclusive RD	
	C2 res.	Dummy of C2 low-rise exclusive RD	
	C2 high	Dummy of C2 medium-to-high exclusive RD	
	C2 exclusive	Dummy of C2 exclusive RD	
	Industry	Dummy of industrial districts	
	Semi Ind.	Dummy of semi-industrial districts	
	Commerce	Dummy of commercial districts	
	Neigh. Com.	Dummy of neighborhood commercial districts	
Time	Time	Elapsed months from January 1993 [Year]	Non-linear

[a]MAJOR 8 comprises 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., Ltd., Mitsui Fudosan Residential Co., Ltd. and Tokyo Tatemono Co., Ltd

Significant non-linear influences are found from landscape variables. The positive impact from "Open view" increases rapidly once the value exceeds a certain threshold (around 10, see Fig. 6). It suggests that while very nice view (in terms of the amount of visibility) may be capitalized into condominium prices, poor to moderate views might not. The estimates of "Ocean view" also suggest that ocean view has a positive impact only if the quality is prominent. The effect of "Green view" has also been found to be non-linear. That is, Green view has a statistically significant negative influence when it has a value of less than 6 or more than 10. It

Table 2 Estimated linear influences from $x_{i-j,p}$

Category	Explanatory variables	SMAR	
		Coef.	*t*-value
Intercept	Intercept	7.784	38.46***
Building attributes	SRC	−0.018	−1.20
	WRC	0.007	0.17
	Num.dev	0.007	0.62
	Major dev.	0.054	4.47***
Risk	Flood_1F	0.094	2.01**
Environment	Green	0.038	4.47***
	Park dist.	−0.007	−1.54
	Ocean dist.	−0.003	−0.25
Access	Station dist.	−0.001	−0.19
Location	C1 res.	−0.027	−1.41
	C1 low	−0.020	−0.95
	C1 high	−0.002	−0.11
	C1 exclusive	0.003	0.11
	C2 res.	−0.003	−0.09
	C2 high	−0.007	−0.22
	C2 exclusive	0.005	0.18
	Industry	0.028	0.68
	Semi Ind.	−0.073	−3.38***
	Commerce	−0.009	−0.41
	Neigh. Com.	0.005	0.26
See Fig. 5 for estimated non-linear influences from $z_{i-j,q}$			
AIC		−79,053	
Room level variance		0.0028	
Building level variance		0.0138	

Significant levels: ***0.1 %; **1 %; and *5 %

implies that a moderate amount of “Green view “is preferable, but scarce and too much “Green view” is not.

The signs of the economic values of natural environmental variables (Green: +; Park dist: −; Ocean dist: −) are also intuitively reasonable although only “Park” and “Ocean dist.” are statistically significant. The negative sign of “Station dist” is also reasonable. In summary, values of landscape, natural environment, and accessibility are reflected appropriately in this area.

On the other hand, if Flood risk is appropriately recognized, Floor and Flood_1F must have negative signs. However, Floor is statistically insignificant with positive sign, and Flood_1F is positively significant statistically at the 5 % level. Thus, the flood risk might not be reflected appropriately as a negative factor. The result is consistent with a suggestion from the literature review in Sect. 2.1 that a clear negative premium of flood risk appears only if the area suffered from a major flood within the past several years (see, also Daniel et al. 2009).

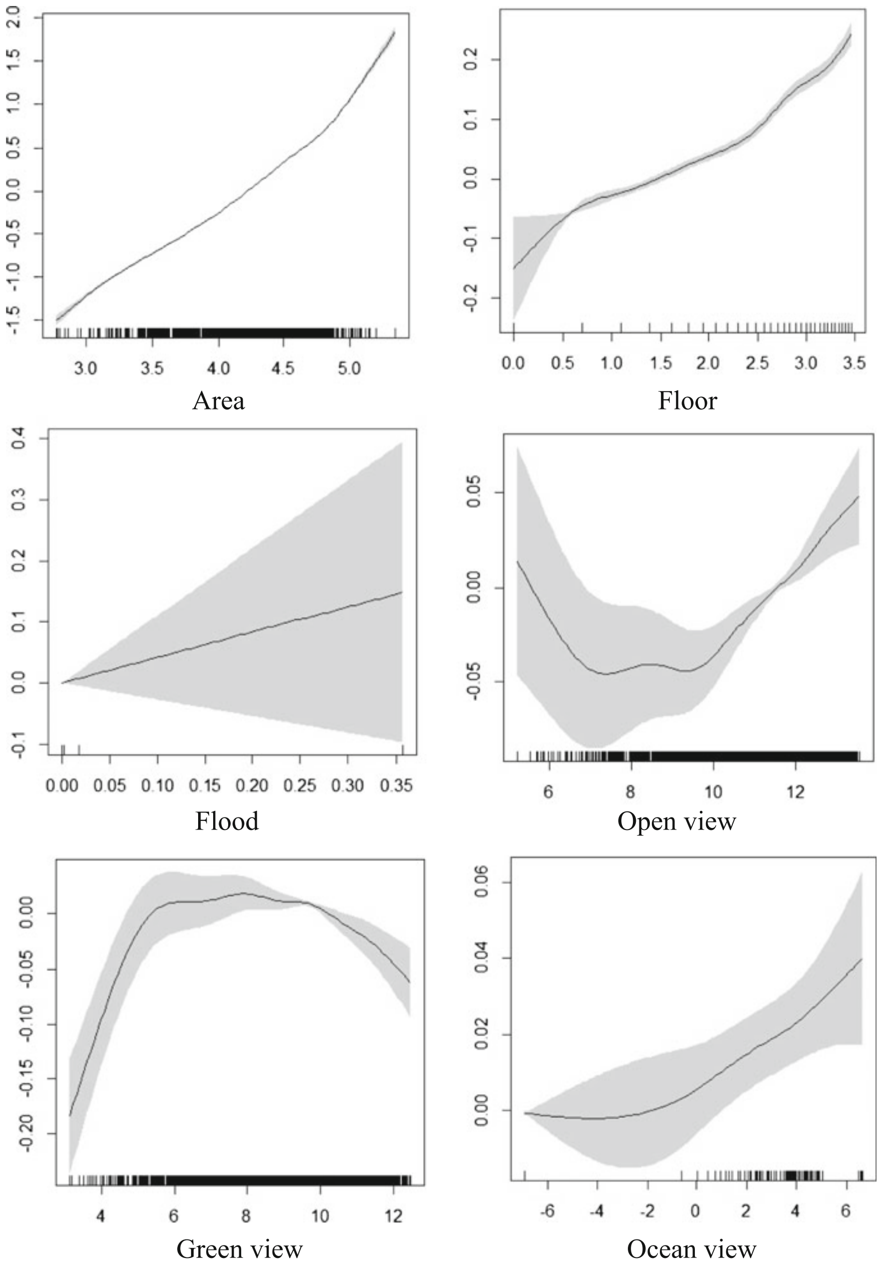

Fig. 6 Estimation results (non-linear effects). The x-axis denotes the values of regressors, $z_{q,i-j}$, the y-axis denotes the estimated non-linear influences (i.e., estimates of $f(z_{q,i-j})$), and *grey shadowed regions* represent 95 % confidence intervals

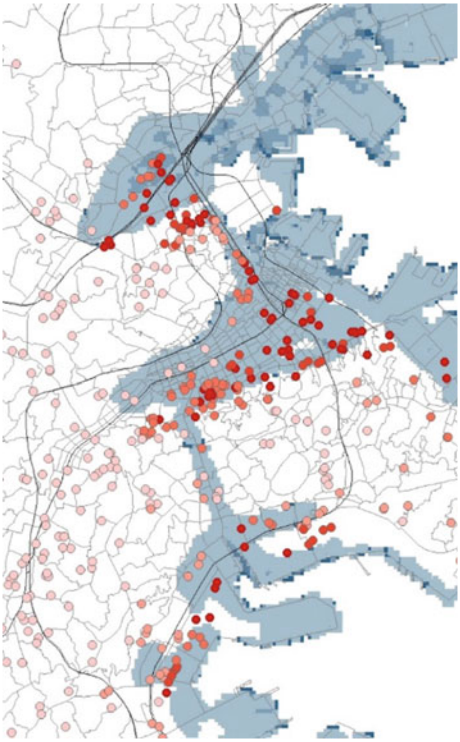

Fig. 7 Estimated marginal benefit from the ocean. *Red dots* represent condominiums. Condominiums with greater marginal benefit are colored by deep red. *Blue areas* denote anticipated flood areas (color figure online)

This ignorance or underestimation of flood risk can make urban form less adaptive to the flood risk. To examine it, estimated influences from the ocean are summed ("Ocean dist." + "Ocean view" + "Flood") and plotted in Fig. 7. This figure shows that, as a result of only "Ocean dist." and "Ocean view" being appropriately evaluated, the economic value of the anticipated flood zones is inflated. Note that Yokohama city provides flood risk information in multiple ways, including a web-GIS system and hazard maps. Our analysis result suggests that the web-GIS system or hazard map publication might not always reduce disaster risks efficiently. Considering the gradual increase of disaster risk, an urban policy that lowers disaster risks even if people underestimate risks, would be needed.

4 Concluding Remarks

This section quantifies the trade-off between flood risk and other factors, including landscape, natural environment, and accessibility. The analysis result revealed that the flood risk was highly underestimated in the study area whereas the other factors were appropriately evaluated. The underestimation of the risk would be partly due to the normalcy bias.

To increase the resilience to flood risk, an enforceable policy such as land-use regulation might be effective. Still, it is not clear how we can design such an urban policy in an efficient manner. Fortunately, since our hedonic analysis quantifies economic values of multiple factors, the results might be useful for establishing a policy preferable from multiple perspectives. Integration of the hedonic model, which can quantify economic values of micro-scale attributes (e.g., like location of trees and placement of dikes), and the spatially-explicit urban land-use model (e.g., Yamagata and Seya 2013; Yamagata et al. 2013, 2015b; see, Chapter "Urban Economics Model for Land-Use Planning"), which describes relatively global economic activities, might yield a powerful model for a sensible policy making. Furthermore, consideration of participatory censoring information might allow us real-time disaster risk management (see, Murakami et al. 2016). Extending the hedonic model and implementing it to actual policies would be an interesting research endeavor.

References

Atreya, A., & Czajkowski, J. (2014). Housing price response to the interaction of positive coastal amenities and negative flood risks. University of Pennsylvania, Working Paper (9).

Atreya, A., Ferreira, S., & Kriesel, W. (2013). Forgetting the flood? An analysis of the flood risk discount over time. *Land Economics, 89*(4), 577–596.

Bin, O., & Kruse, J. (2006). Real estate market response to coastal flood hazards. *National Hazards Reviews, 7*(4), 137–144.

Bin, O., Kruse, J. B., & Landry, C. E. (2008). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *Journal of Risk and Insurance, 75*(1), 63–82.

Bin, O., & Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management, 65*(3), 361–376.

Bin, O., & Polasky, S. (2004). Effects of flood hazards on property values: Evidence before and after Hurricane Floyd. *Land Economics, 80*(4), 490–500.

Brander, L. M., & Koetse, M. J. (2011). The value of urban open space: Meta-analysis of contingent valuation and hedonic pricing results. *Journal of Environmental Management, 92*(10), 2763–2773.

Cavailhès, J., Brossard, T., Foltête, J. C., Hilal, M., Joly, D., Tourneux, F. P., et al. (2009). GIS-based hedonic pricing of landscape. *Environmental & Resource Economics, 44*(4), 571–590.

Daniel, V. E., Florax, R. J., & Rietveld, P. (2009). Flooding risk and housing values: An economic assessment of environmental hazard. *Ecological Economics, 69*(2), 355–365.

Dettinger, M. (2011). Climate change, atmospheric rivers, and floods in California–A multimodel analysis of storm frequency and magnitude changes. *Journal of the American Water Resources Association, 47*(3), 514–523.

Getis, A., & Griffith, D. A. (2002). Comparative spatial filtering in regression analysis. *Geographical Analysis, 34*(2), 130–140.

Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science, 52*(2), 172–191.

Hamilton, S. E., & Morgan, A. (2010). Integrating lidar, GIS and hedonic price modeling to measure amenity values in urban beach residential property markets. *Computers, Environment and Urban Systems, 34*(2), 133–141.

Hammond, M. J., Chen, A. S., Djordjević, S., Butler, D., & Mark, O. (2015). Urban flood impact assessment: A state-of-the-art review. *Urban Water Journal, 12*(1), 14–29.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., et al. (2013). Global flood risk under climate change. *Nature Climate Change, 3*, 816–821.

Hox, J. (1998). Multilevel modeling: When and why. In I. Balderjahn, R. Mathar, & M. Schader (Eds.), *Classification, data analysis, and data highways* (pp. 147–154). Berlin: Springer.

Jim, C. Y., & Chen, W. Y. (2009). Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landscape and Urban Planning, 91*(4), 226–234.

Koshimura, S., Oie, T., Yanagisawa, H., & Imamura, F. (2009). Developing fragility functions for tsunami damage estimation using numerical model and post-tsunami data from Banda Aceh, Indonesia. *Coastal Engineering Journal, 51*(03), 243–273.

Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., et al. (2014). Flood risk and climate change: Global and regional perspectives. *Hydrological Sciences Journal, 59*(1), 1–28.

Landry, C. E., & Hindsley, P. (2011). Valuing beach quality with hedonic property models. *Land Economics, 87*(1), 92–108.

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton: Chapman and Hall/CRC Press.

McKenzie, R., & Levendis, J. (2010). Flood hazards and urban housing markets: The effects of Katrina on New Orleans. *The Journal of Real Estate Finance and Economics, 40*(1), 62–76.

Murakami, D., & Griffith, D. A. (2015). Random effects specifications in eigenvector spatial filtering: A simulation study. *Journal of Geographical Systems, 17*(4), 311–331.

Murakami, D., Peters, G. W., Yamagata, Y., & Matsui, T. (2016). Participatory sensing data "tweets" for micro-urban real-time resiliency monitoring and risk management. *IEEE Access, 4*, 347–372.

OECD. (2012). *Compact city policies: A comparative assessment (OECD green growth studies)*. OECD Publishing.

Omer, H., & Alon, N. (1994). The continuity principle: A unified approach to disaster and trauma. *American Journal of Community Psychology, 22*(2), 273–287.

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., et al. (2014) *Climate change 2014: Synthesis report*. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Pompe, J. J., & Rinehart, J. R. (1994). Estimating the effect of wider beaches on coastal housing prices. *Ocean and Coastal Management, 22*(2), 141–152.

Rascoff, S. J., & Revesz, R. L. (2002). The biases of risk tradeoff analysis: Towards parity in environmental and health-and-safety regulation. *The University of Chicago Law Review, 69*(4), 1763–1836.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.

Samarasinghe, O., & Sharp, B. (2010). Flood prone risk and amenity values: A spatial hedonic analysis. *Australian Journal of Agricultural and Resource Economics, 54*(4), 457–475.

Schabenberger, O., & Gotway, C. A. (2004). *Statistical methods for spatial data analysis*. Boca Raton, Florida: CRC Press.

Voss, S. (2006). A risk index for megacities. Munchener Ruck, Munich Re Group.

Waltert, F., & Schlapfer, F. (2010). Landscape amenities and local development: A review of migration, regional economic and hedonic pricing studies. *Ecological Economics, 70*(2), 141–152.

Wood, S. N. (2003). Thin plate regression splines. *Journal of the Royal Statistical Society B, 65*(1), 95–114.

Wood, S. N., Scheipl, F., & Faraway, J. J. (2013). Straightforward intermediate rank tensor product smoothing in mixed models. *Statistics and Computing, 23*(3), 341–360.

Yamagata, Y., Murakami, D., & Seya, H. (2015a). Latest high-resolution remote sensing and visibility analysis for smart environment design. In P. S. Thenkabail (Ed.), *Remote sensing handbook, Volume III: Water resources, disasters, and urban; Monitoring, modeling, and* *mapping: Advances over last 50 years and a vision for the future* (pp. 599–621). Boca Raton, Florida: Taylor and Francis Group Press.

Yamagata, Y., Murakami, D., & Seya, H. (2015b). A comparison of grid-level residential electricity demand scenarios in Japan for 2050. *Applied Energy, 158*(15), 255–262.

Yamagata, Y., Murakami, D., Yoshida, T., Seya, H., & Kuroda S. (2016) Value of urban views in a bay city: Hedonic analysis with the spatial multilevel additive regression (SMAR) model. *Landscape and Urban Planning* (accepted).

Yamagata, Y., & Seya, H. (2013). Simulating a future smart city: An integrated land use-energy model. *Applied Energy, 112*, 1466–1474.

Yamagata, Y., Seya, H., & Nakamichi, K. (2013). Creation of future urban environmental scenarios using a geographically explicit land-use model: A case study of Tokyo. *Annals of GIS, 19*(3), 153–168.

Yasumoto, S., Jones, A., Yano, K., & Nakaya, T. (2012). Virtual city models for assessing environmental equity of access to sunlight: A case study of Kyoto, Japan. *International Journal of Geographical Information Science, 26*(1), 1–13.

Zhai, G., Fukuzono, T., & Ikeda, S. (2003). Effect of flooding on megalopolitan land prices: A case study of the 2000 Tokai flood in Japan. *Journal of Natural Disaster Science, 25*(1), 23–36.