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Estimating Household Preferences for Coastal Flood Risk Mitigation Policies Under Ambiguity

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Key Points:

- We couple flood simulation with a stated preference experiment to investigate residents' preference to mitigate flood risk under ambiguity
- Economic values of coastal flood risk mitigation measures are estimated by reduction of expected loss, risk premium and ambiguity premium
- Ignoring ambiguity premium might cause an undervaluation of coastal flood risk mitigation

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Risk mitigation policies (like dike rising) are essential to address increasing coastal flood risks due to global warming. Furthermore, the optimal level of risk mitigation policy should be determined by public preferences for risk reduction. However, it is difficult to reveal public preferences for coastal flood risk reduction because projections of coastal flood risks inevitably involve uncertainty. This study aims to estimate household preference for coastal flood reduction under ambiguity and multiple projections of coastal flood risks. By coupling storm surge inundation simulations and stated preference experiments with decision models, we estimate the expected loss reduction, risk premium, and ambiguity premium for coastal flood risk mitigation policies. The study shows that ignoring the ambiguity premium causes significant undervaluation of coastal flood risk mitigation.

Plain Language Summary Climate change has contributed to more frequent and severe storm tide in coastal areas and enhanced flood risk. Thus, risk mitigation policies are essential to address increasing coastal flood risks from global warming. The policymakers must integrate multiple projections of coastal flood risk to make policy decisions. These decisions should reflect stakeholders' preferences on risk and ambiguity. Risk is uncertainty with a clear probability distribution, and ambiguity is uncertainty without a clear probability distribution. Currently, this key requirement has not yet been met. To fill this gap, this study investigates residents' preference to mitigate flood risk under ambiguity by coupling flood simulation and surveying residents on their willingness to pay for insurance to mitigate risk under average and worst-case scenarios. The ambiguity premium is an additional payment for an individual to reduce flood risk with an unknown probability distribution in comparison to flood risk specified with a well-known probability distribution. We found that ignoring ambiguity premium causes undervaluing coastal flood risk mitigation.

1. Introduction

Climate change has contributed to more frequent and severe storm tide in coastal areas and enhanced flood risk (Emanuel, 2005; Feng & Chao, 2020; Feng et al., 2018; Goldenberg et al., 2001; Hansen et al., 2005; Hinkel et al., 2014; IPCC, 2021; Little et al., 2015; Marsooli et al., 2019; Mori & Takemi, 2016; Mori et al., 2021; Muis et al., 2016; Nicholls et al., 1999; Smith & Katz, 2013). In response, policymakers are seeking risk mitigation policies to defend coastal communities against flooding, such as dike rising, building code restrictions, land use restrictions, and public flood insurance based on scientific projections of coastal flood risks. A key requirement for these projections is that they need to involve uncertainty due to the stochastic nature of extreme events and insufficient knowledge of the mechanisms of tropical cyclones (Grinsted et al., 2013; Henderson-Sellers et al., 1998; Knutson et al., 2010; Little et al., 2015; Wong & Keller, 2017). Such uncertainty poses challenges for policymakers to design and implement risk mitigation policies.

Uncertainty can be classified as "aleatory uncertainty" and "epistemic (or deep) uncertainty" (Hoffman & Hammonds, 1994; Merz & Thieken, 2009). The former refers to the natural randomness of a relevant event. The latter refers to a situation where there is too little information to specify a single probability density function (PDF). Concerning coastal flooding, the latter might be due to a lack of sufficient knowledge on typhoon systems such as cyclogenesis factors, developmental processes, and their movements. In economic terminology, aleatory uncertainty is classified as "risk" and epistemic uncertainty corresponds to "ambiguity" (Camerer & Weber, 1992; Etner et al., 2012). While risk is represented by a single well-defined PDF, ambiguity is often

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represented with multiple PDFs derived from different models with various parameter settings (Kunreuther et al., 2013; Merz & Thieken, 2009).

Policymakers face ambiguity, or multiple projected PDFs, regarding coastal flood risk when making risk mitigation policies (Oppenheimer et al., 2016; Sriver et al., 2018). The most common approach is to use the average projection of multiple predictions (Boettle et al., 2016; Knutti, 2010; Knutti et al., 2010; Oddo et al., 2020; Stephenson et al., 2012; Watkiss et al., 2015). While the average projection is straightforward and reasonable, it might lead to ignoring the possibility of the worst case. That being said, worst-case projection is often considered in flood risk management such as in probable maximum flooding (Schwerdt et al., 1979) and plausible worst-case estimates (Buchanan et al., 2016; Ranger et al., 2013). Although a risk mitigation policy designed for worst-case projection can prevent almost all inundation risks, it requires large costs to implement the policy (Hinkel et al., 2014; Vousdoukas et al., 2018). Thus, policymakers face the problem of which and how multiple projections should be used to make risk mitigation policies.

This problem is particularly important when designing structural flood mitigation measures such as dikes or sea walls. These structural measures can only prevent flood damage from storm surges with predefined design levels (e.g., 100-year storm surge), thus, their effect might be quite different between average and worst projections (Kunreuther et al., 2013). For example, suppose that areas A and B face 1 and 2 m storm surges in average projection and 2 and 4 m storm surges in the worst projections, respectively. Dikes with a height of 3 m can protect both areas in average projection but cannot protect area B in the worst projection. This example emphasizes the importance of worst projections as well as average projection for designing structural flood mitigation measures.

Accordingly, policymakers are required to integrate multiple projections of coastal flood risk to make policy decisions; to what extent they allocate resources to safety margins in structural measures against the worst projection (Downton et al., 2005; Shrader-Frechette, 1991). One of important aspects for socially better choice is economic value of structural measures. In economics, the net benefit (i.e., benefit minus cost) of structural measures should be maximized. The main goal of this paper is to provide benefit information on structural measures for mitigating flood risk under ambiguity.

Benefit of structural measures for an individual is measured with his/her willingness to pay (WTP) for them. If economic loss due to storm surge was predicted with certainty, his/her WTP would be equivalent to the amount of the loss. Generally, the prediction of economic loss due to storm surge involves risk and ambiguity. People often prefer a fixed loss to a stochastic loss when both expected values of loss are same. It implies that they are willing to pay extra money for avoiding the stochastic loss compared to avoiding the fixed loss. This extra payment is "risk premium." It is zero if the economic loss has no random variability (or fixed amount as expected loss). Similarly, People often prefer a fixed loss to a stochastic loss with its well-known probability distribution to one with its unknown probability distribution when both expected values of loss are same. They are willing to pay extra money for avoiding the latter compared to the former. This extra payment is "ambiguity premium." It is zero if a unique projection of coastal flood risks is specified. Thus, benefit of structural measures under risk and ambiguity should involve risk premium and ambiguity premium in addition to reduction of expected loss. This is particularly important for residential sectors because many studies revealed that decisions affecting civilians are often affected by risk and ambiguity (Camerer & Weber, 1992; Etner et al., 2012).

Numerous previous studies explore the ambiguity of flood risk (Hallegatte et al., 2011; Oddo et al., 2020; Resio et al., 2013; Wong & Keller, 2017) and propose decision support methods under ambiguity (Buchanan et al., 2016; Hunter, 2012; Rohmer et al., 2019; Sriver et al., 2018). Several studies estimate residents' preferences to mitigate flood risk without considering ambiguity (Botzen & van den Bergh, 2012; Botzen et al., 2009; Withey et al., 2019). To our knowledge, no research has investigated residents' preference to mitigate flood risk under ambiguity.

To fill this gap, we estimated homeowners' preferences for coastal flood risk mitigation under ambiguity in the Osaka bay area, Japan. Accordingly, we obtained multiple PDFs of flood risk by conducting typhoon and storm surge inundation simulations. Then, by using the multiple PDFs, a web survey was implemented to estimate homeowners' preferences for protecting their houses from coastal flooding under ambiguity. In addition, we estimated risk premium and ambiguity premium. Finally, we explored the geographical distribution of risk and ambiguity premiums. This information might be useful for policymakers to design risk mitigation policies tailor-made to each area.

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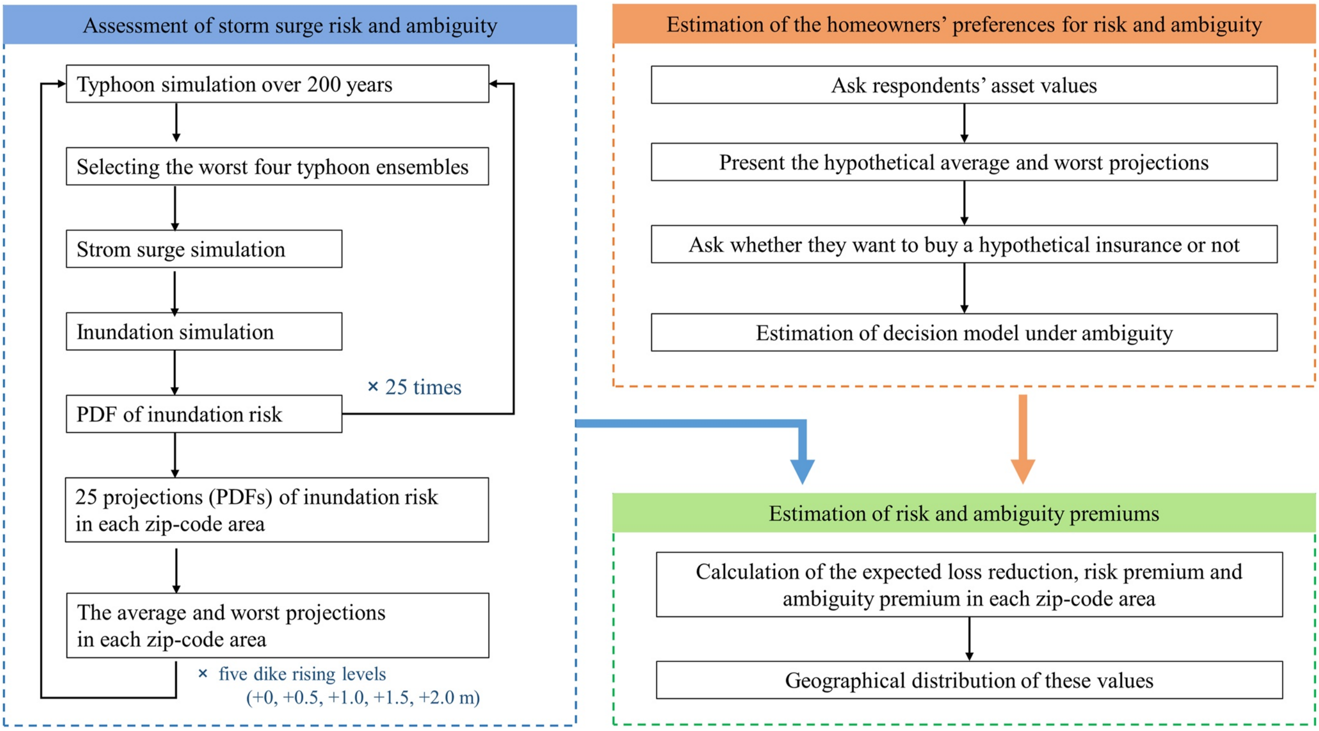

Figure 1. Study flow of methodological framework.

The remainder of this study has been organized as follows. Section 2 describes coastal flood risks in the research target area, Osaka bay. Section 3 explains methods of obtaining multiple projections of coastal flood risk as ambiguity, estimating homeowners' preferences for mitigating coastal flood risk under ambiguity, and calculating risk and ambiguity premiums. Section 4 outlines a web survey for homeowners in the target area. Section 5 shows the estimated results of these premiums and displays their geographical distribution. Section 6 discusses the results and their policy implications and Section 7 concludes.

2. Methods

To assess inundation risks and ambiguity in coastal areas, we proposed a framework as shown in Figure 1 (a) conduct a simulation of typhoon generations for 200 years using a global stochastic tropical cyclone model; (b) the total number of typhoons in this study generated over half a million in the Western Pacific Ocean, to understand the uncertainty of typhoon storm surge inundation, also to avoid unnecessary inundation simulations, the significant four typhoon ensembles (each ensemble including 25 typhoon cases) are selected (after fulfilling the conditions), and the storm surges of Osaka Bay are simulated by a full-coupled surge-wave-tide coupled model (SuWAT); (c) predict the inundation depth due to storm surges using the inundation simulation model; (d) repeat step (a) to (c), get 25 projections of the inundation risk for each dike level: current level and rising by 0.5, 1.0, 1.5, and 2.0 m (25×5); (e) the average and worst projections of the inundation risks are specified by each zip-code in the web-based survey; (f) estimate households' preferences by asking them to choose whether to buy hypothetical insurance to cover all losses from coastal flooding by presenting the average and worst scenarios of the inundation risks to their houses; (g) by using the choice experiment data, a decision model is applied for estimating risk premiums and ambiguity premiums; (h) analyze the geographical distribution of risk premiums and ambiguity premiums by geographic information system (GIS).

2.1. Study Area

Increased mean and extreme sea levels, alongside ocean warming and acidification, are projected to exacerbate risks for human communities in low-lying coastal areas (IPCC, 2019). In addition, Japan experiences huge typhoons, causing serious flood damage. Osaka Bay is one of the most vulnerable areas in terms of coastal inundation in Japan and is ranked fifth among the world's 120 cities in terms of expected annual losses due to coastal flooding in 2050 (Abadie et al., 2017). In 2018, Typhoon Jebi caused 14 deaths and 1,014 injuries and destroyed 686 houses in Osaka Bay. Figure 2 shows our study area which ranges between 22.23 km long by 19.32 km wide, along with the coastal areas of Osaka Bay extending between Osaka prefecture and Hyogo prefecture, and including Osaka city, the third-largest city in Japan. According to the Census Mesh Data (the Statistics Bureau of Japan, 2015), it has 1.63 million households with 3.30 million people, of which our target respondents represent 25% of the households.

2.2. Typhoon Simulation

An extreme storm surge occurs due to the combination of an intense typhoon, dangerous tracks, and fast-moving speeds. A combination does not occur often, and extreme surges rarely occur. Therefore, numerous simulated typhoons are required to predict storm surges in a particular region. Thus, we used the global circulation model (GCM) as one of the choices. However, the typhoons in the GCMs have a large bias, and the length of the simulation period is insufficient for analyzing extreme storm surge events. A stochastic tropical cyclone model (STCM) is often used to increase the number of simulated typhoons with different parameter values such as track/direction, minimum sea-level pressure, and translation speed based on Monte Carlo simulations. Among several approaches of STCMs, one of GSTCM takes the translation model giving increments of translation speed and direction by random variables using PDFs of their rates of change estimated from historical data (Rumpf et al., 2007; Vickery et al., 2000). The other GSTCM regards TCs as a group of points, and advection is calculated by the environmental field with the bata-effect (e.g., Emanuel et al., 2006). Unlike other STCMs developed for specific ocean basins, GSTCM was expanded to implement an annual global simulation of tropical cyclones, which is necessary for assessing climate change factors. To project coastal flood risk in Osaka Bay, we conducted synthetic typhoon simulations using GSTCM (Nakajo et al., 2014). And, we calibrated the parameters of the GSTCM using data from the International Best Track Archive for Climate Stewardship provided by the National Oceanic and Atmospheric Administration.

2.3. Inundation Simulation of Storm Surges

This study conducts typhoon simulations over 200 years by using GSTCM under the current climate conditions and selects the four worst typhoon ensembles among simulated typhoons satisfying the following three conditions: (a) the minimum distance to Osaka Bay is less than 200 km; (b) the minimum central pressure is less than 950 hPa; (c) the velocity of the typhoon at landfall is higher than 20 km/hr. Then, by adding inputs like the simulated properties (track, speed, and central pressure) of the four selected typhoon ensembles, storm surges in Osaka Bay are simulated using the SuWAT (Kim et al., 2008; Mori et al., 2019). The model simulates storm surge heights and maximum wind wave heights using the nonlinear shallow water equation and spectral wave model SWAN (Simulating Waves Nearshore), respectively. Entering the simulated storm surge properties, we predict the inundation depth of each 30 m mesh area in Osaka Bay using an inundation simulation model based on the 2D shallow water equation (Ha et al., 2021; Liang, 2010).

2.4. Elicitation of Households' Preferences: The Stated Preference Method

We estimated households' preferences for full protection from coastal flood risk under ambiguity using the stated preference method, which asks the respondents to make hypothetical choices in controlled experiments (Johnston et al., 2017; Louviere et al., 2000). The current study attempts to estimate households' preferences under ambiguity by coupling GSTCM and a stated preference experiment. Our stated preference survey included a choice experiment. The respondents were asked whether they would buy hypothetical insurance that covers all household losses from coastal flooding under multiple projections of the inundation risk as ambiguity. Using the choice experiment data, we estimate a decision model to calculate the risk and ambiguity premiums.

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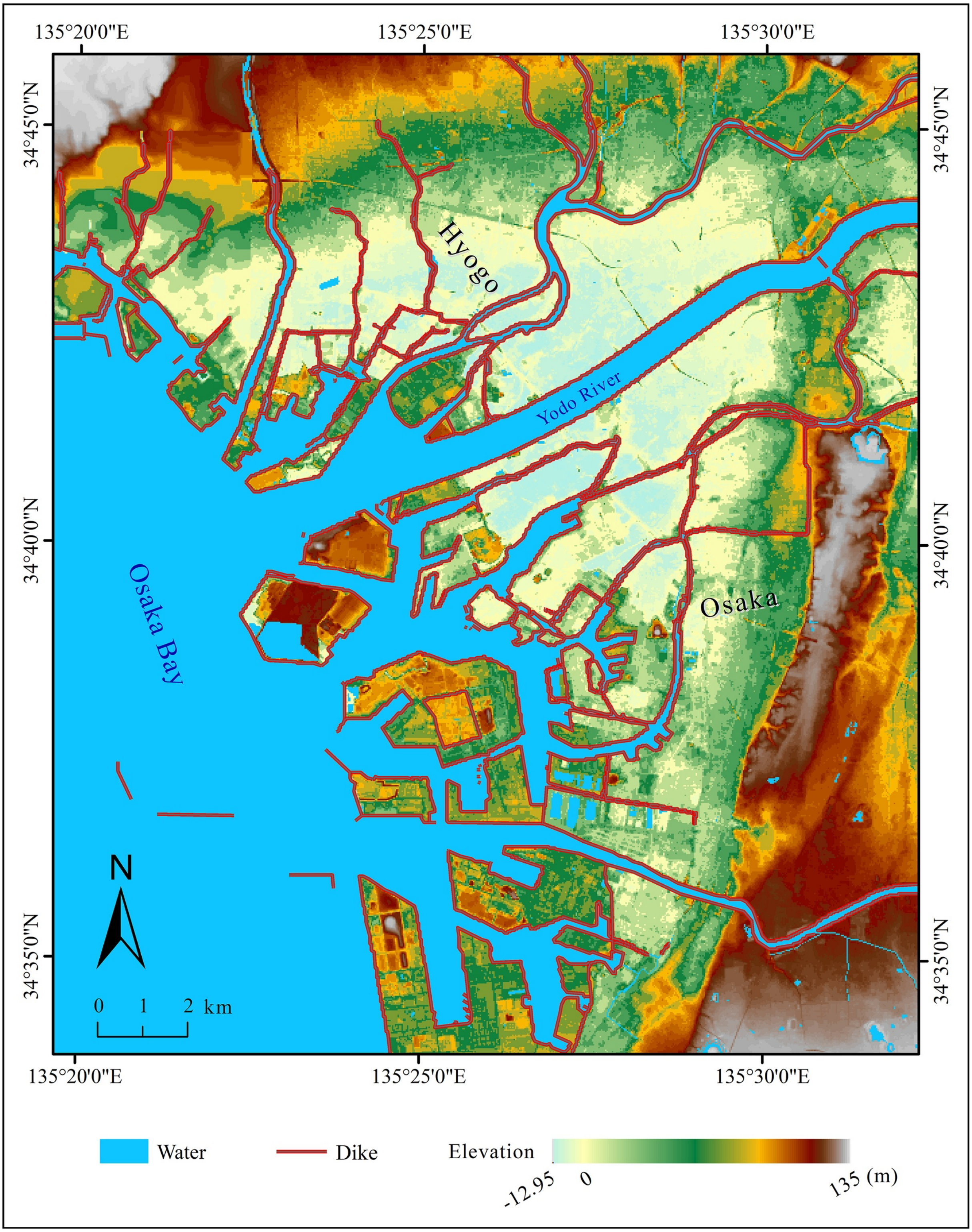

Figure 2. Study area in Osaka Bay, Japan.

2.4.1. Experimental Design of Web Survey

We conducted the choice experiments on households' preferences for purchasing hypothetical insurance through a web survey. The steps were as follows:

1. Explain the impact of disasters on daily life and past damages due to coastal flooding (abstracted from the leaflet by the Japanese government).
2. Ask respondents about the estimated values of their house and furniture. These data were used in the latter part of the survey.
3. Explain that the projections of inundation risk inevitably include ambiguity and that 25 PDFs of coastal flooding risk were projected as ambiguity.
4. Explain that the damage to the house from coastal flooding is classified into four categories according to the inundation depth: "no flooding," "flooding under the floor," "flooding on the floor," and "house submerged" when the inundation depth is less than 0.01 m, from 0.01 to 0.5 m, from 0.5 to 2.0 m and over 2.0 m, respectively.
5. Two projections of coastal flood risk were randomly chosen from a set of five inundation projections that are typical in the target area (Figure S1 in Supporting Information S1). The more serious one was the worst projection, while the other was the average projection. Then these projections were presented to the respondents.
6. When "flooding under the floor," "flooding on the floor," and "house submerged" occur due to coastal floods, we assumed that 1%, 50%, and 100% loss of the households' assets (house and furniture) value as responded to in step (2). The economic loss due to inundation was automatically calculated on the web system and presented to the respondents.
7. To evaluate the economic value that eliminates the risk of damage due to coastal floods, respondents were asked whether or not they would buy hypothetical insurance that fully compensates them for the inundation damages (Figure 3). It also shows an example of scenarios for the choice experiment and the key parts of the questionnaire. The question was as follows: "Suppose that the government sells a new type of insurance, that covers all losses from coastal flooding with full compensation for house restoration costs and households' assets, and that the insurance will be contracted once a year, would you buy this new insurance policy with the annual fee of XXX JPY?" The economic loss of AAA, BBB, and CCC were calculated at 1%, 50%, and 100% of the respondent's asset value. XXX was randomly chosen for the respondents based on their given asset value: estimated households' asset value ×0.001%, 0.005%, 0.01%, 0.05%, 0.1%, 0.5%, and 1%. The amounts of AAA, BBB, CCC, and XXX were automatically calculated in the web survey system.
8. We estimated the limited degree of confidence (LDC) model using the survey data after excluding "protest responses." The protest responses were obtained from the respondents who chose not to buy the hypothetical insurance due to the following two reasons: "I cannot understand the question" and "I cannot accept the hypothetical scenarios." The number of protest responses is 340 (34%). As a result, the effective number of observations is 660.

2.4.2. Outline of Survey Attributes

The respondents of the web surveys were recruited from 1.9 million panel members registered with Cross Marketing, a Japanese company. The web survey was conducted with 1,000 households who responded that they live at an altitude of 5 m or less among the detached houses in Osaka Bay. This survey was conducted from 16 December to 22 December in 2016. Table S1 in Supporting Information S1 shows the means and standard deviations of the socioeconomic attributes of the respondents.

2.5. Decision Model Under Ambiguity

Although some decision models under ambiguity have been developed (Gilboa & Marinacci, 2016; Lempert et al., 2006; Machina & Siniscalchi, 2014; Ryan, 2009), no model is widely accepted. We used an LDC model to address the ambiguity of coastal flood risk because this model is applied to design robust strategies for dealing with the uncertainty of climate change (Buchanan et al., 2016; Froyn, 2005; Lange, 2003; McInerney et al., 2012). The LDC model can be interpreted as a special case of a neo-additive model by Chateauneuf et al. (2007), which includes two popular decision models under ambiguity: the Choquet expected utility model (Schmeidler, 1989) and the α–maximin expected utility model (Ghirardato et al., 2004). In our context, the LDC model is given by:

$$V(P) = \alpha E_{P_A}(u) + (1-\alpha) E_{P_W}(u) \tag{1}$$

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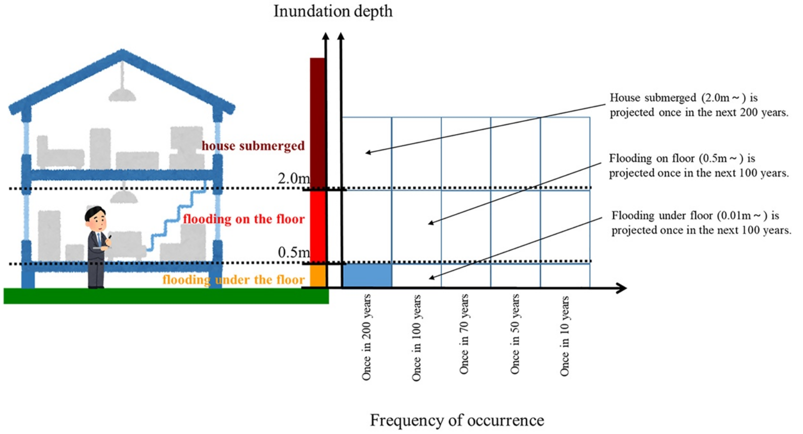
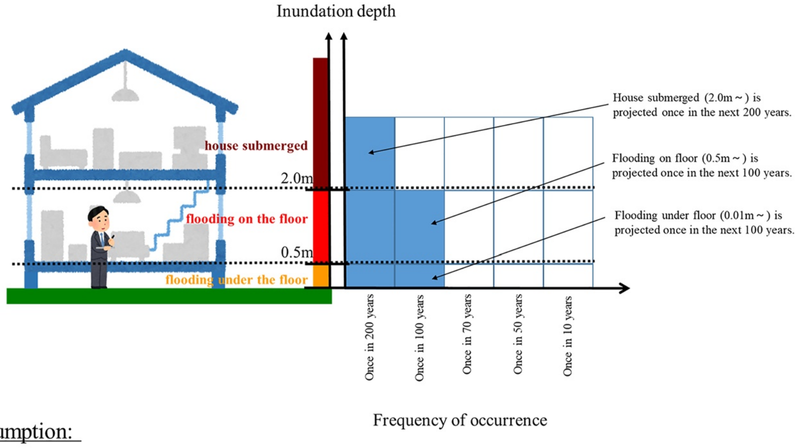
Average projection

In the **average** one among **25** projections of inundation risk from coastal flood simulation, the inundation risk of your house was projected as the following figure.



Worst projection

In the **worst** one among **25** projections of inundation risk from coastal flood simulation, the inundation risk of your house was projected as the following figure.



Scenario Assumption:

- If your house gets **flooded under floor (inundation depth is below 0.5m)** from a coastal flood, your economic loss is AAA yen (1% of your asset value).
- If your house gets **flooded on floor (inundation depth is 0.5m - 2.0m)** from a coastal flood, your economic loss is BBB yen (50% of your asset value).
- If your house gets **submerged (inundation depth is over 2.0m)** from a coastal flood, your economic loss is CCC yen (100% of your asset value).
- You do not have any insurance for compensating economic loss from a coastal flood.

Suppose that the government sells a new type of insurance, that covers all losses from coastal flooding with full compensation for house restoration costs and households' assets, and that the insurance will be contracted once a year, would you buy this new insurance policy with the annual fee of XXX JPY?

- ■ Yes, I'd like to buy the insurance with an annual fee of XXX yen.
- ■ No, I would not like to buy the insurance.

Why did you chose not to buy the insurance? Please choose one of the following options as your reason.

- ■ The insurance fee is too expensive
- ■ I cannot understand the question
- ■ I cannot accept the hypothetical scenarios
- ■ Other reasons (   )

Figure 3. The ambiguity or multiple projections of coastal flood risk (average and worst projections) were embedded into the households' preferences during the survey.

where u is the utility function to measures households' preferences for a set of goods and services, P is a set of probability distribution functions, and p_A and $p_W \in P$ are the average and worst probability distribution functions, respectively. The parameter $\alpha \in [0, 1]$ represents the degree of confidence in the expected utility based on the average projection. In our context, P is the set of multiple projections of coastal flood risk, and p_A and p_W are the average and worst projections, respectively. Accordingly, $E_{\mathrm{pA}}(u)$ and $E_{\mathrm{pW}}(u)$ are expected utilities with p_A and p_W, respectively. $V(P)$ is the expected utility with the LDC model of the homeowner facing P.

To design choice experiments in the stated preference survey, we consider the situation where a household chooses to buy insurance covering all losses from a coastal flood. Household i faces multiple projections of inundation risks in his/her house. House damage from inundation is divided into four categories; "no flooding," "flooding under the floor," "flooding on the floor," and "house submerged." The average and worst projection of coastal flood risk for household i are described as:

$$p_{iA} = (p_{iA0}, m_i;\ p_{iA1}, m_{i1};\ p_{iA2}, m_{i2};\ p_{iA3}, m_{i3}) \tag{2}$$

$$p_{iW} = (p_{iW0}, m_i;\ p_{iW1}, m_{i1};\ p_{iW2}, m_{i2};\ p_{iW3}, m_{i3}) \tag{3}$$

where $p_{iA0},\ p_{iA1},\ p_{iA2},$ and p_{iA3} are the average probabilities of "no flooding," "flooding under the floor," "flooding on the floor," and "house submerged," respectively. Similarly, $p_{iW0},\ p_{iW1},\ p_{iW2},$ and p_{iW3} are the worst-case probabilities. The house value of household i is m_i, which becomes m_{i1}, m_{i2}, and m_{i3} when it gets "flooding under the floor," "flooding on the floor," and "house submerged," respectively.

The econometric model is as follows. The LDC expected utility without insurance can be written as:

$$V_{i1} = \alpha E_{p_{iA}}(u) + (1 - \alpha) E_{p_{iW}}(u) \tag{4}$$

$$u(m) = \frac{m^{1-r}}{1 - r} \tag{5}$$

where u is the constant relative risk aversion (CRRA) utility function, m denotes house value, r is the coefficient of relative risk aversion.

The LDC expected utility with insurance at the cost of mC_i is given as:

$$V_{i2} = u(m - mC_i) \tag{6}$$

where C_i is the insurance fare rate such that mC_i is a household's payment for buying insurance. A household chooses to buy insurance if the following inequality holds:

$$V_{i1} + \varepsilon_1 < V_{i2} + \varepsilon_2 \tag{7}$$

where ε_1 and ε_2 are random components of utilities and $\epsilon = \varepsilon_1 - \varepsilon_2 \sim N(0, 1)$. The probability of buying insurance can be written as:

$$\mathrm{Prob}(V_{i1} + \varepsilon_2 < V_{i2} + \varepsilon_1) = \mathrm{Prob}(\epsilon < V_{i2} - V_{i1}) = \Phi(V_{i2} - V_{i1}) \tag{8}$$

where Φ is the standard normal distribution function. Thus, the log-likelihood is written as:

$$\ln L(\alpha, r) = \sum_{i=1}^{n} [d_i \ln \Phi(V_{i2} - V_{i1}) + (1 - d_i) \ln \{1 - \Phi(V_{i2} - V_{i1})\}] \tag{9}$$

where d_i is a dummy variable taking a value of 1 if household i chooses to buy the insurance and 0 otherwise, and n is the number of respondents. This log-likelihood is maximized with our survey data to estimate the coefficients of risk aversion r and the degree of confidence α.

2.6. Estimation of Expected Loss, Risk Premium, and Ambiguity Premium

Based on the LDC model, the willingness of household i to pay for the full protection of the insurance policy (WTP_i) is calculated as follows:

$$\mathrm{WTP}_i = m_i - u^{-1}\left(\alpha E_{p_{iA}}(u) + (1 - \alpha) E_{p_{iW}}(u)\right) \tag{10}$$

where u^{-1} is an inverse function of u. The following equations define the expected loss, risk premium, and ambiguity premium. The expected loss EL_i, is defined as the full asset value m_i, minus the expected value EV_i, with the average projection of inundation risk as:

$$\mathrm{EL}_i = m_i - \mathrm{EV}_i \tag{11}$$

where $\mathrm{EV}_i = p_{iA0}m_i + p_{iA1}m_{i1} + p_{iA2}m_{i2} + p_{iA3}m_{i3}$. The certainty equivalent to risk $\mathrm{CE}_i^{\mathrm{risk}}$ is a certain value that is equally attractive to the household's asset facing inundation risks in the average projection and can be written as follows:

$$\mathrm{CE}_i^{\mathrm{risk}} = u^{-1}\left(E_{p_{iA}}(u)\right) \tag{12}$$

The risk premium, RP_i, is defined as the expected value minus the certainty equivalent for risk.

$$\mathrm{RP}_i = \mathrm{EV}_i - \mathrm{CE}_i^{\mathrm{risk}} \tag{13}$$

There is no widely accepted definition of the ambiguity premium, while the expected loss and risk premium are clearly defined. However, we follow the definition proposed by Cubitt et al. (2018), as it can be applied to any decision model. By an analogous notion to certainty equivalent to risk, we consider the certainty equivalent to ambiguity $\mathrm{CE}_i^{\mathrm{amb}}$. It is a certain value that is equally attractive to the household's asset facing inundation risk under ambiguity and can be written as follows:

$$\mathrm{CE}_i^{\mathrm{amb}} = u^{-1}\left(\alpha E_{p_{iA}}(u) + (1-\alpha)E_{p_{iW}}(u)\right) \tag{14}$$

The ambiguity premium is defined as certainty equivalent for risk minus certainty equivalent for ambiguity.

$$\mathrm{AP}_i = \mathrm{CE}_i^{\mathrm{risk}} - \mathrm{CE}_i^{\mathrm{amb}} \tag{15}$$

Note that the following equation holds because $\mathrm{CE}_i^{\mathrm{amb}}$ is equivalent to $m_i - \mathrm{WTP}_i$.

$$\mathrm{WTP}_i = \mathrm{EL}_i + \mathrm{RP}_i + \mathrm{AP}_i \tag{16}$$

Finally, expected loss reduction, risk premium, ambiguity premium and WTP are calculated by using the LDC model.

3. Results

3.1. Coastal Flood Risk in Osaka Bay

Storm surge inundations were simulated for all selected stochastic typhoon events using the 2D flood inundation model. Due to the continuous improvement of the dike in Osaka Bay in recent years, only a few simulated storms caused inland inundation under the current sea level and climate conditions. Therefore, we selected the largest inundation areas of the four typhoon ensembles because the fifth typhoon ensemble does not cause any inundation under the current protection level of the target area. Thus, we have the four worst-case projections of inundation depth over 200 years for each mesh. Each typhoon ensemble provided a set of storm surge inundation results with probabilities. The probability distribution of such inundation results represented the variation in flooded areas caused by the uncertainty of a typhoon for a specific probability. Here, the exceedance probability of inundation was linked to the probability of the occurrence of a typhoon under ensemble forecasting. Since sometimes we only focus on the significant probabilities of occurrence, such as 1/200, 1/100, 3/200, 1/50, etc., it can be interpreted that the top four worst inundation results are projected to occur with return periods of once in 200, 100, 67, and 50 years. We consider it as a PDF of coastal flood risk. To explore the ambiguity, the process from typhoon simulation to inundation simulation was repeated 25 times to obtain 25 PDFs of inundation risk in each mesh. Finally, the simulated inundation depths of 30 m meshes were averaged over each zip-code area. Figure 4 shows the average and worst projections of coastal flood risk (based on exceedance probability) with different dike levels in each zip-code area. 1/50, 3/200, 1/100, and 1/200 denote once in 50, 67, 100, and 200 years.

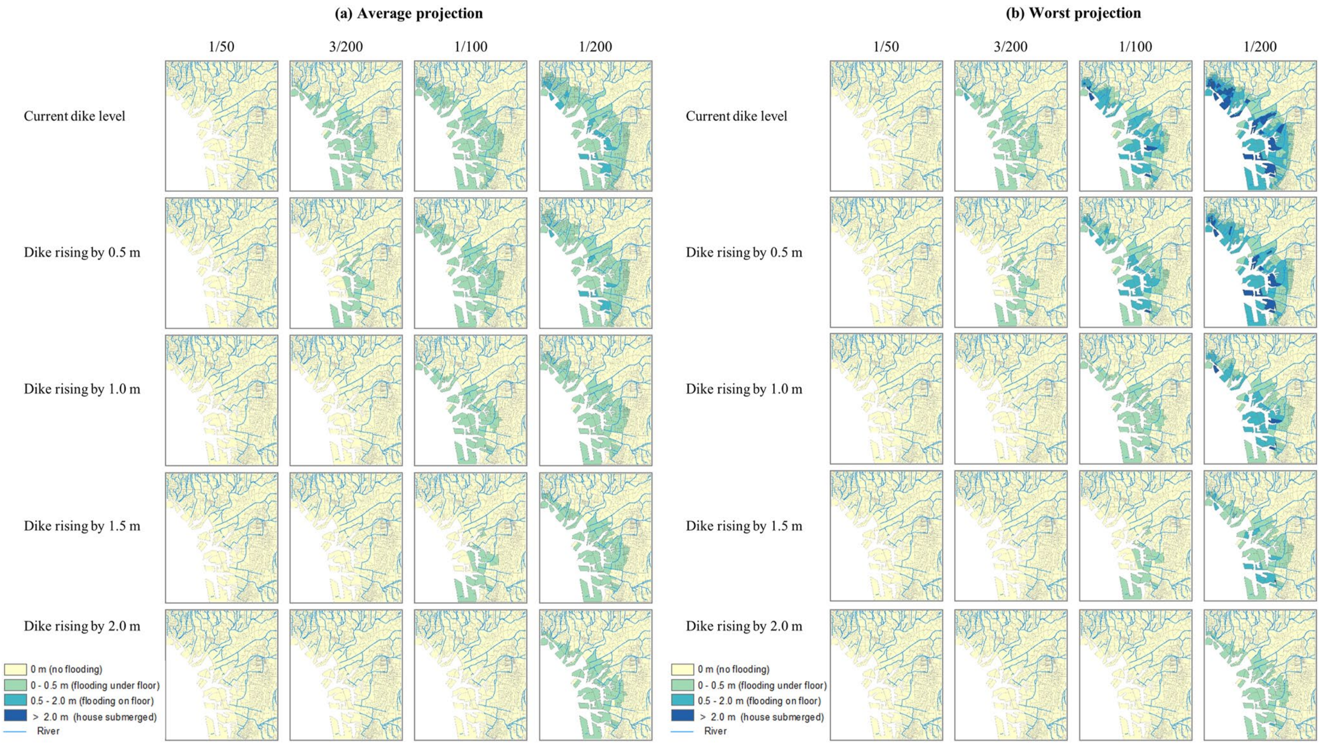


Figure 4. Projection of coastal flood risk by (a) average projection and (b) worst projection to current and different dike rising levels.

Table 1
Estimated Parameters of the LDC Model

	Model 1		Model 2	
	Coefficient	Standard error	Coefficient	Standard error
α: confidence of degree				
Constant	0.9049**	0.0385361	0.9839**	0.2625074
Age			0.0005	0.0035491
Gender			0.064	0.0729309
Family size			−0.0415	0.0331706
Education			−0.0086	0.0817453
r: risk attitude				
Constant	0.3764**	0.0123102	0.4481**	0.0774997
Age			−0.0024	0.0013095
Gender			−0.0383	0.0312893
Family size			0.0125	0.0090214
Education			0.0380	0.0275757
Sample size	660		660	
Log likelihood	−391.50034		−385.18647	
Pseudo R^2	0.134073257		0.148038376	

Note. Pseudo $R^2 = 1 - L1/L0$ where $L0$ and $L1$ represent loglikelihoods of the models with and without the constraint that all parameters are zero.
**Represent statistical significance at 1%.

3.2. Estimated Parameters of the LDC Model

Table 1 reveals that the estimate of the degree of confidence in Model 1 is 0.9049 (99% confidence interval; 0.8294, 0.9804) with statistical significance at the 1% level. It indicates that the average household (sampled) decides about risk mitigation policy by weighting 90% of the average projection and 10% of the worst projection. If we assign equal weight to each of the 25 projections, the weight of the worst projection might be less than 4% (=1/25). Thus, our findings show that households tend to disproportionately pay greater attention to the worst scenario (i.e., 10% rather than 4%). The CRRA coefficient of Model 1 is 0.3764 (99% confidence interval; 0.4694, 1.4984), which is statistically significant at the 1% level. Moreover, Model 2 presents the heterogeneity of a household's socioeconomic attributes, such as age, gender, family size, and education which affects the estimated parameters of confidence of degree (α) and CRRA coefficient (r). No statistically significant estimates are found at the 5% level. Thus, we decided to use the estimated results of Model 1 to calculate risk and ambiguity premiums.

3.3. Estimation of Expected Loss, Risk Premium, and Ambiguity Premium

Using the estimated parameters of Model 1 and the sample average of household assets (34.1 million JPY), we calculate the expected loss reduction, risk premium, and ambiguity premium for full protection from the coastal flood risk. Then, each value is multiplied by the number of households in each zip-code area and aggregated for the entire target area, as presented in Table 2. The total economic value or WTP is 1,743 million JPY (about 17 million USD) for a full-protection insurance policy from coastal flood risk under ambiguity in the target area. It consists of the expected loss reduction,

Table 2
Estimated Reduction of Expected Loss, Risk Premium and Ambiguity Premium for Full Protection and Dike Rising Levels

			Value of additional dike rising			
Value (million JPY)	Benefit of full protection*	Value of 2.0 m dike rising	0–0.5 m	0.5–1.0 m	1.0–1.5 m	1.5–2.0 m
Reduction of expected loss	821	769	581	110	41	36
Risk premium	65 (0.08)	65 (0.08)	64 (0.11)	1 (0.01)	0 (0.00)	0 (0.00)
Ambiguity premium	849 (1.03)	848 (1.10)	395 (0.68)	390 (3.53)	55 (1.33)	9 (0.25)
Total economic value (WTP)	1,734 (2.11)	1,682 (2.19)	1,040 (1.79)	500 (4.54)	96 (2.33)	46 (1.26)

Note. Parentheses indicate ratios of risk premium, ambiguity premium, and total economic value (WTP) of expected loss reduction.
*Value of eliminating all damage from coastal flood with current dike level.

risk premium, and ambiguity premium, which are 821, 65, and 849 million yen, respectively. The risk premium and ambiguity premium are 8% and 103%, respectively, compared to the value of expected loss reduction for eliminating coastal flood risks in the target area. Thus, the total economic value is 211% of the expected loss reduction.

The LDC model calculates expected loss reduction and risk premium using the average prediction, while ambiguity premium is estimated with the worst prediction. The estimated LDC model indicates that a statistically representative household weighs 90% on the average projection and 10% on the worst projection, which seems to imply a small ambiguity premium compared to the value of expected loss reduction and risk premium. However, the results demonstrate that the ambiguity premium is much larger than the risk premium and almost equivalent to the expected loss reduction. This is because asset loss based on the worst projection is much larger than loss based on the average projection. As shown in Figure 4, there are many areas where houses will be submerged, or that flooding on the floor will occur in the worst projection. Simultaneously, the average prediction shows no areas of submerged houses, and a very small area of flooding on the floor will occur. Due to this relationship between geographic conditions and inundation levels, the asset loss and its dispersion in the average and worst projections are very different, as shown numerically in Table 3.

3.4. Expected Economic Value of Coastal Flood Risk Mitigation Policies

Estimating the economic value of dike rise is important for coastal flood risk mitigation policies. Our study considers four dike rising policies assuming all dikes in the target area are uniformly raised by 0.5, 1.0, 1.5, and 2.0 m, respectively. Table 2 indicates that the total economic value of the dike rising by 2.0 m is 1,682 million yen, which is close to the benefit of full protection (1,743 million yen). It implies that a dike rising by 2.0 m can prevent almost all damages from coastal floods. Further, we divided the dike rising by 2 m into four steps: "0–0.5 m," "0.5–1.0 m," "1.0–1.5 m," and "1.5–2.0 m" and calculate their values. The results demonstrate that the marginal values of dike rising decreases with higher levels of dike rising. For example, the expected loss reduction and risk premium for dike rising of "0–0.5 m" are 581 and 64 million yen, which drop sharply to 110 and 1 million yen, respectively, for dike rising of "0.5–1.0 m." The ambiguity premium is about 390 million yen for dike rising of both "0–0.5 m" and "0.5–1.0 m" and then falls largely to 55 million yen for dike rising of "1.0–1.5 m." The first dike rising by 0.5 m to the current level may mostly protect the target area from coastal flooding in the average prediction but cannot protect it in the worst prediction. However, additional dike rising by 0.5 m (or +1.0 m to the current level) can prevent coastal inundation largely, even in the worst prediction. Thus,

Table 3
Averages of Expected Values (Standard Deviations) of Economic Loss Over Zip-Code Areas

Dike rising	0 m	0.5 m	1.0 m	1.5 m	2.0 m
Average projection	0.73 (8.94)	0.21 (2.21)	0.11 (1.29)	0.08 (0.98)	0.05 (0.62)
Worst projection	6.69 (76.57)	3.62 (45.15)	0.64 (8.71)	0.16 (2.10)	0.05 (0.66)

Note. Unit: million JPY.

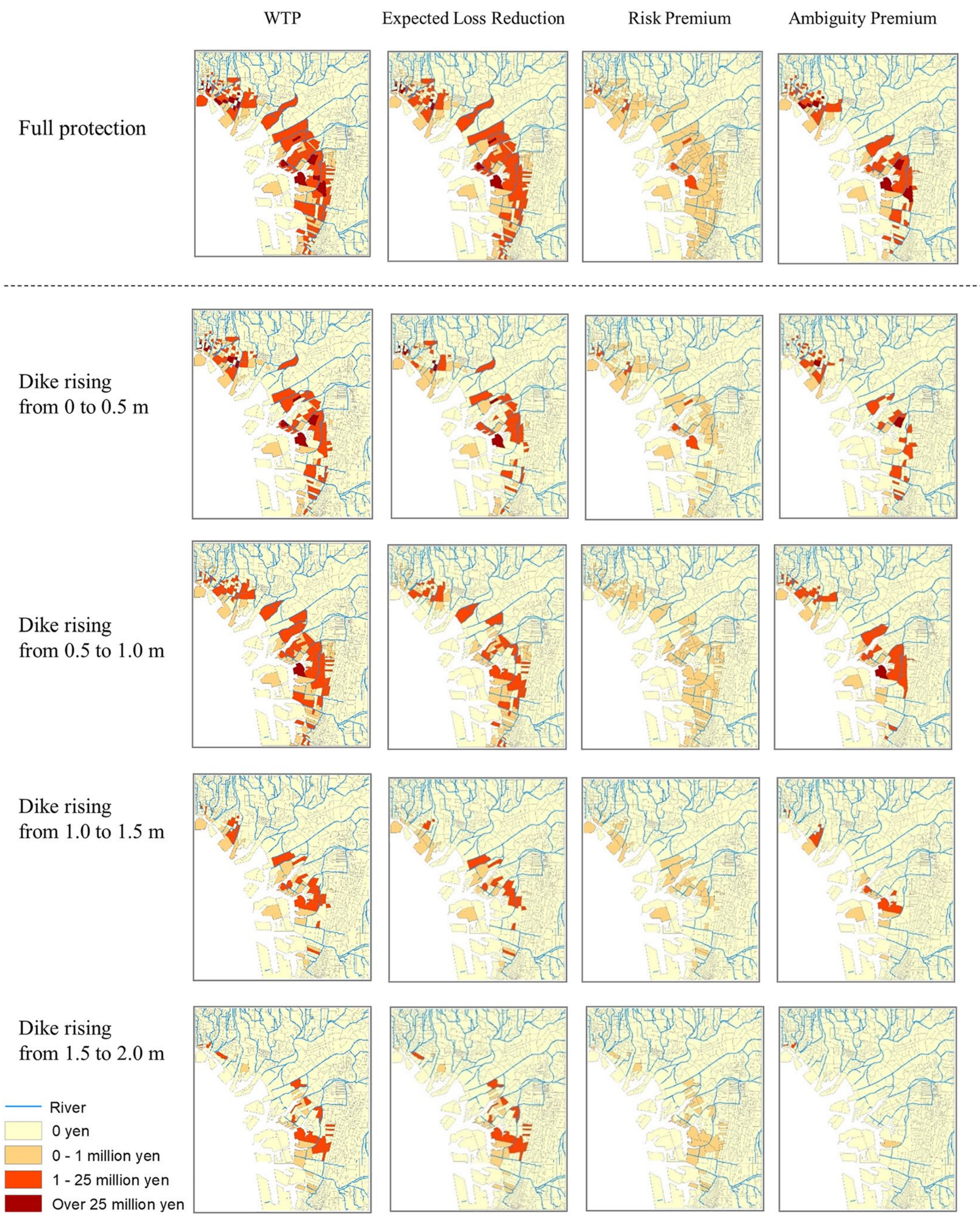


Figure 5. Geographical distributions of the expected loss reduction, risk premium, and ambiguity premium for full protection from coastal flood risk and each step of dike rising by 0.5 m from 0 to 2.0 m.

the marginal ambiguity premium decreases more slowly than the marginal value of the expected loss reduction and the marginal risk premium as the dike rises.

The geographical distributions of the expected loss reduction, risk premium, and ambiguity premium provide useful information for designing effective coastal flood risk mitigation policies. Figure 5 demonstrates that these values are disproportionately located in areas close to rivers and the sea along the Osaka Bay, the coastal areas in Amagasaki city, Osaka city, Sakai city, and the areas of Yodo riverside. Furthermore, in each step of dike rising by 0.5 m from 0 to 2.0 m, the values of the expected loss reduction, risk premium, and ambiguity premium reveal different distribution patterns, indicating that the benefited areas of dike rising also depend on the baseline level of the dike. This also stresses the need for a better understanding and robust analysis of spatial distribution patterns for designing coastal flood risk mitigation policies.

Figure 5 illustrates that ambiguity premiums are narrowly distributed compared to expected loss reduction and risk premiums. Notably, in each level of dike rising by 0.5 m (from 0 to 2.0 m), expected loss reduction occurs, and risk premiums arise in the same areas, while ambiguity premiums generally happen in different areas. These results suggest that decision on dike rising without considering ambiguity premium (or the worst projection) may cause a significant underestimation of dike rising value in some areas rather than all areas with coastal flood risk.

3.5. Policy Implication

Finally, our results provide several policy implications for mitigating coastal flood risk. Ignoring ambiguity premium causes significant undervaluation of coastal flood risk mitigation, such as dike rising. Our LDC decision model finds that a statistically representative household weighs 90% on the average projection and 10% on the worst projection. Although the weight on the worst projection is not very high, it causes a large ambiguity premium that is almost equivalent to the value of the expected loss reduction for eliminating coastal flood risk. The economic loss due to inundation under the worst projection is much larger than the loss under the average projection. Thus, the total economic value of eliminating coastal flood risk is almost half if the ambiguity premium is ignored.

4. Conclusions

This study provides a new perspective on households' preferences for coastal flood risk mitigation under ambiguity by coupling coastal flood simulations and a stated preference experiment with the LDC model and GIS. We estimated the expected loss reduction, risk premium, and ambiguity premium values for full protection from coastal flood risk, equal to the total economic value or WTP for full protection of an insurance policy. Our analysis indicates that an ambiguity premium is not negligible in economic efficiency or cost-benefit consideration of risk mitigation policies. Rather, they are distributed extremely in some areas of higher expected loss from coastal inundation. This suggests that ambiguity premiums should be measured for planning and implementing coastal flood risk mitigation policies. Although our results have extensive implications from many perspectives, there are several limitations. First, they only address the ambiguity of coastal flood risk projections rather than other sources of ambiguity such as climate change and residential population. Second, our analysis focuses on the household sector, whereas other sectors are also important, such as commercial and industrial buildings, roads and subways, and human health. Third, this paper focus on dike rising as flood risk mitigation measure. There are other important measures. For example, residents may migrate to elsewhere when risk communicated. It may affect their WTP for dike rising. Future research in these areas is required for further investigation.

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Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The typhoon data sets for this research are available at Mori et al. (2019). Inundation simulation model codes are available at: https://github.com/HEMLab/hipims. Please refer to Liang (2010) for further information on this model. The inundation simulation results and survey data of this study are available online at Dryad: https://doi.org/10.5061/dryad.47d7wm3hd.

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