Received: 11 June 2023 | Revised: 12 July 2024 | Accepted: 15 August 2024

DOI: 10.1111/jfr3.13035

ORIGINAL ARTICLE

CIWEM Chartered Institution of Water and Environmental Management | Journal of Flood Risk Management | WILEY

Agent-based intra-regional relocation model considering spatial local amenity for urban planning-based flood risk management: Assessing the impact of urban development on flood exposure

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Funding information
Japan Society for the Promotion of Science, Grant/Award Number: JP21K18747; Japan Science and Technology, Grant/Award Number: JPMJSC2312

Abstract

Integrated flood risk management based on urban policies remains challenging compared with infrastructure due to the unclear risk-reduction effects over time. To consider heterogeneity in social responses to urban planning measures, a previous study developed an agent-based household relocation model under flood risk (AHR-FLOOD) by combining flood-inundation and agent-based relocation models. However, accurate modelling of relocation incentives remains challenging. This study aimed to improve AHR-FLOOD by introducing spatial amenities based on transportation convenience and reflecting their impact on the decision-making processes of agents to analyze the development of different flood risk areas. AHR-FLOOD considering access to public transportation reproduced the spatial characteristics of the actual population and housing prices. The development of low-risk areas reduced flood exposure and resulting flood damage. However, this effect was less clear for low-income individuals, but the development of low-amenity areas had the potential to induce low-income population to move to safe areas. Chain migration was observed as a long-term effect of the spatial amenity policy. This study presents insights into the effect of transportation policies on flood safety for long-term spatial distance management in an agent-based approach with the rigorous modelling and validation of local amenity impact on household relocation choices.

KEYWORDS

agent-based model, flood risk management, household relocation, spatial distance management

1 | INTRODUCTION

Floods cause serious damage to people and property worldwide and are expected to intensify further because of climate change and urbanization. Therefore, integrated flood risk management, including urban policies (development of low-risk areas and restrictions), construction restrictions, and flood insurance, is highly desired.

However, these countermeasures are less prioritized than structural measures in practice, possibly owing to their unclear effects (or long-term adverse impacts) on flood risk reduction.

The impacts of land use policies on local scale land use and population changes have been analyzed using several approaches, such as statistical regressions (Bin & Landry, 2013), computational general equilibrium models (Carrera et al., 2015; Chalise & Naranpanawa, 2016; Teramoto et al., 2010), and agent-based models (ABMs) (Mustafa et al., 2018; Nabinejad & Schüttrumpf, 2016; Tsai et al., 2015; Zhang et al., 2022). Among these, ABMs are used to analyze household scale impacts and spatial heterogeneity as microscale interactions between humans and the environment. Zhang et al. (2022) investigated the impacts of land use restrictions on cropland abandonment based on the decision-making processes of agents. Mustafa et al. (2018) developed an ABM and analyzed the impacts of developmental restrictions on land use and the resulting flood risk changes in Wallonia, Belgium. These studies focused on land use regulations and predicted the associated urban land use changes through the reactions of residents.

In Japan, land use regulation is difficult because of strong land ownership (Sorensen, 2002). Therefore, discussions on amenity policies, especially compact city policies, that will incentivize people to settle in target (low flood risk) areas as part of urban development (Iizuka et al., 2020; Ito & Kawazoe, 2023; Soga et al., 2014) are being conducted. Nagai and Kurahashi (2019) developed an ABM for household relocation based on living and commuting costs and evaluated the impact of a compact city, particularly on the daily transportation choices of residents, in Kanazawa, Japan. Tanaka et al. (2022) developed an agent-based household relocation model under flood risk (AHR-FLOOD) by combining two-dimensional flood inundation and agent-based household relocation models to compare the long-term impacts of river improvement and low-risk area development in Kyoto, Japan. Furthermore, they compared the reduced annual flood damage quantitatively among different types of countermeasures. Because social responses to policies, such as household relocation, are strongly dependent on the economic environment (including the real estate market), modelling the decision-making process on both the supply and demand sides using bottom-up approaches, such as ABMs (Carro et al., 2023; Geanakoplos et al., 2012; Magliocca et al., 2011) is crucial.

Owing to their high flexibility, ABMs generally require careful parameter settings and quantitative validation. However, because of the difficulty experienced in rigorous validation of ABMs, much effort is not applied to go beyond a "proof of concept" in most cases (Janssen & Ostrom, 2006). Although some studies addressed ABM development using various types of validation, such as empirical (Windrum et al., 2007) and process validations (Zhuo & Han, 2020), their validation targets (e.g., land use simulations for ABMs) are still limited to binary information (urban areas or others). Despite the discussion of proof of concept raised by Janssen & Ostrom, 2006, a holistic review by Zhuo and Han (2020) still pointed out the challenges of rigorous validation of ABMs. Tanaka et al. (2022), an aforementioned example of ABM application to flood risk analysis, were also at the model development and behavioural analysis stage; thus, their model validation was limited to the growth rate of the entire local economy and did not include other fine spatial scale indicators, such as population and economic asset distributions. For a rigorous impact assessment of urban development policies to study flood risk changes, it is important to improve the quantitative representation of spatial heterogeneity in a population by better describing individual relocation behaviours.

The convenience of public transportation in accessing work, learning, shopping, and recreational places is a key factor for relocation decision-making (Lieske et al., 2021; Rashidi & Ghasri, 2019); thus, its inclusion is a primary step for improving AHR-FLOOD. In addition to compact city planning, some policies are substantially related to the provision of a transportation system. For example, collective housing relocation of a community after a disaster, which is intended for moving people from a flood-prone area to a safer area, can deteriorate their accessibility to places where they went in their daily lives (Matsumaru et al., 2012). Furthermore, urban development policies in low flood risk areas often face a tradeoff; they drive people away from the riverside, whose landscape can contribute to a better quality of life (Fachrudin & Lubis, 2016).

To enable discussions on household relocation measures for flood risk management, this study proposes to (1) improve the reliability of AHR-FLOOD by introducing spatial amenities based on transportation convenience and reflecting their impact on the decision-making processes of agents and (2) conduct a quantitative assessment of transportation developmental scenarios based on the validated model. The research framework is summarized in Figure 1. Section 2 briefly explains the structure of AHR-FLOOD proposed by Tanaka et al. (2022) and its minor updates for a more robust modelling. Section 3 presents the study area, basic model input data and propose an index for public transportation convenience as a major factor of local amenities and its application to AHR-FLOOD, which is the primary improvement applied in this study. Section 4 describes model validation against the observed spatial distribution of housing prices and population. Based on the validated model, Section 5 simulates flood exposure changes in several local amenity developmental scenarios (represented by the improvements in transportation convenience) and

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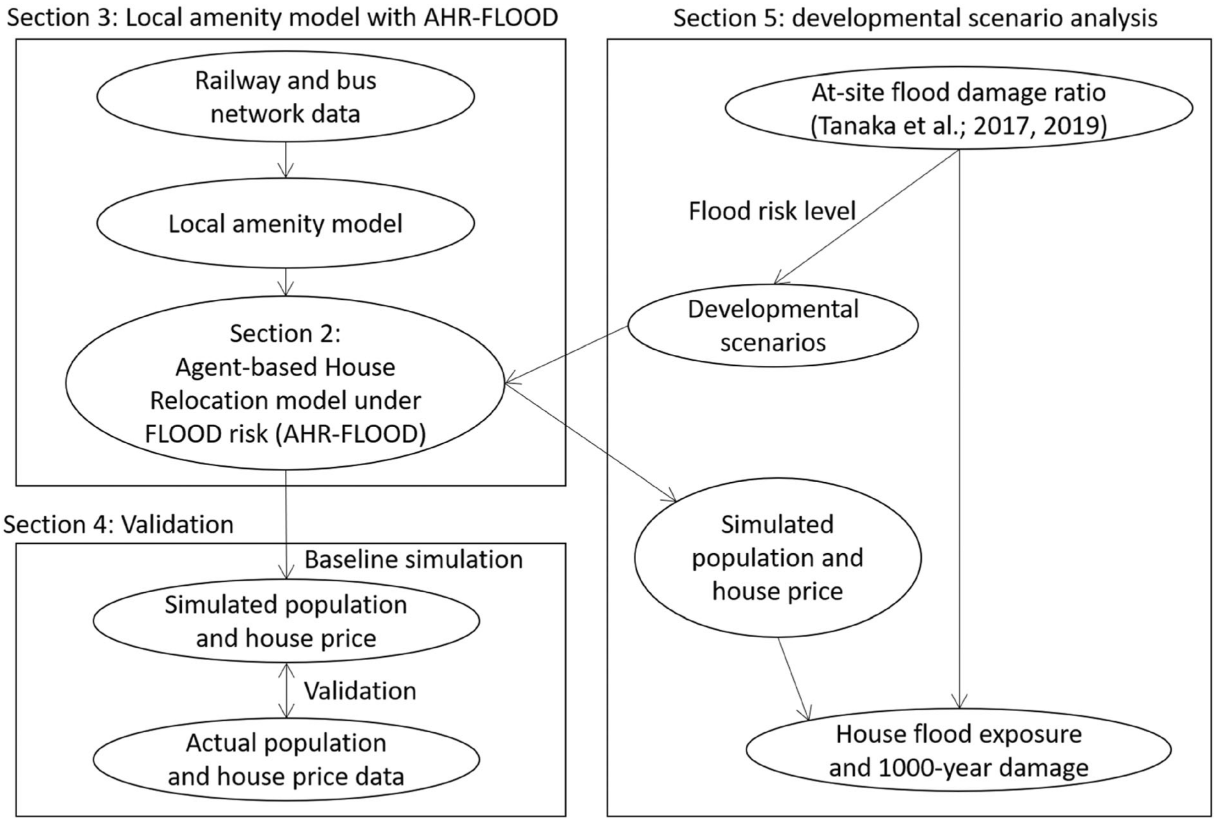

FIGURE 1 The methodological framework of this research with the corresponding section number.

examines the differences among these scenarios considering the impact of development on long-term flood risk. Section 6 describes the results and conclusions.

2 | AHR-FLOOD

AHR-FLOOD considers the decision-making of relocation by each household under flood risk and the associated decision-making of house pricing by developers by combining agent-based house-relocation and flood inundation models (Tanaka et al., 2022). This section summarizes the key structure of the scheme proposed by Tanaka et al. (2022). A household decides on a new residence based on the (1) composite commodity for consumption, (2) stock, (3) size of the new house and garden, and (4) local amenities (as the attractiveness) of an area of interest. The utility function is defined in the Cobb–Douglas form as follows.

$$
\begin{aligned}
&U\left(C_{iqjt}, W_{iqjt}^{E}, h_{qjt}, l_{qjt}, a_{jt}, \varepsilon_{it}\right) \\
&= C_{iqjt}^{\alpha_{\mathrm{C},\omega_1}} \cdot W^{E\,\alpha_{\mathrm{W},\omega_1}}_{iqjt} \cdot h_{qjt}^{\alpha_{\mathrm{h},\omega_1}} \cdot l_{qjt}^{\alpha_{\mathrm{l},\omega_1}} \cdot a_{jt}^{\alpha_{\mathrm{a},\omega_1}} \cdot (1+\beta\varepsilon_{it})
\end{aligned} \tag{1}
$$

where C is the composite commodity for consumption; W^E is the stock; h and l are the house and garden areas, respectively; a is the local amenity (attractiveness); ε_{it} is a random variable following the uniform distribution $[-1{:}1]$; and β is a parameter. i, q, j, and t indicate the indices of the agent, house, region (mesh), and time, respectively, implying that each variable depends on an attribution. ω is the type of household (1: single and 2: family). α_X is the parameter (weight) of X. The composite commodities for consumption C and stock W^E are determined as follows.

$$
C_{iqjt} = \alpha_{\mathrm{C}\omega_1} B_{iqjt}(T_0), W_{iqjt}^{E} = \alpha_{\mathrm{W},\omega_1} B_{iqjt}(T_0) \tag{2}
$$

where $\alpha_{\mathrm{c},\omega_1} (0 \le \alpha_{\mathrm{c},\omega_1} \le 1)$ and $\alpha_{w,\omega_1} = 1 - \alpha_{\mathrm{c},\omega_1}$ represents a preference for consumption and stock, respectively. The decision-making process of a household comprises a total of four parameters α_X.

Equation (2) was obtained using the following utility maximization equation for consumption and stocks:

$$
\begin{cases}
\max\limits_{C_{iqjt}, W_{iqjt}^{E}} & U\left(C_{iqjt}, W_{iqjt}, h_{qjt}, l_{qjt}, a_{jt}, \varepsilon_{it}\right) \\
\text{s. t.} & B_{iqjt}(T_0) = C_{iqjt} + W_{iqjt}
\end{cases} \tag{3}
$$

where

$$B_{iqjt}(T_0) = Y(t) + w(t) + \delta_M\left\{\Lambda_{\tilde{q}\tilde{j}}(t) - \Omega_{qj}(t) - \Upsilon\right\} - \rho_0\Omega_{qj}(t)T_0 - \zeta_{qj}\Omega_{qj}(t)T_0 - \xi_{\omega_{1i}}T_0 \quad (4)$$

is the total budget of the expected living period T_0. The first, second, and third terms are the total expected salary, stock at time t, and balance for migration, respectively ($\Lambda_{\tilde{q}\tilde{j}}(t)$ and $\Omega_{qj}(t)$ are the housing prices of the current and new houses, respectively, and Υ is the moving cost). ρ_0 is the maintenance cost relative to the housing price, ζ_{qj} is the flood insurance ratio for the house, and ξ_{ω_1} is the annual commute cost. Subsequent to decision-making (move or stay), stock $w(t)$ is updated based on the annual consumption.

The housing price $\Omega_{qj}(t)$ is determined by developers to maximize the expected profit $E\left[\Omega_{qj}(t)\right]$ as follows.

$$E\left[\Omega_{qj}(t)\right] = P\left(\Omega_{qj}\right)\Omega_{qj} + \left\{1 - P\left(\Omega_{qj}\right)\right\}(1-\rho)E\left(\kappa\Omega_{qj}\right) \quad (5)$$

where ρ is the social discount ratio, and κ is the declining ratio of housing prices in the next period because of degradation. Based on Ettema (2011) and Tanaka et al. (2022), we formulated the subjective probability that a house is sold at price $\Omega_{qj}(t)$ (estimated by developers) as follows.

$$P\left(\Omega_{qj}\right) = \frac{1}{1 + \exp\left\{\lambda_1 + \left[1 - s_{qj}(t-1)\right]^{-\lambda_2} \cdot \left[\Omega_{qj} - (1+\nu_y)\overline{\Omega}_{qj}(t-1)\right]\right\}}$$
$$\overline{\Omega}_{qj}(t-1) = \frac{1}{M}\sum_{m=1}^{M}\Omega_{qm}(t-1) \quad (6)$$

where ν_y is the social growth ratio, $s_{qj}(t-1)$ is the house vacancy rate during period $t-1$, and $\overline{\Omega}_{qj}(t-1)$ is the average housing price in surrounding $M=9$ meshes during period $t-1$. The above pricing processes estimated by developers has two parameters: λ_1 and λ_2. The developer's model was updated by Tanaka et al. (2022) as follows: (1) the term of vacant house ratio was powered by parameter λ_2 to control the impact of vacancy on selling probability estimation (if $\lambda_2 = 0$, the vacancy has no impact) and (2) the reference housing price was changed to the local average price $\overline{\Omega}_{qj}(t-1)$ to avoid house pricing only from the targe mesh j.

3 | STUDY AREA AND LOCAL AMENITY MODELLING

3.1 | Study area and model configuration

This study targeted the Kyoto Basin, including Kyoto City and other surrounding municipalities (Figure 2). Kyoto City has a population of approximately 1.5 million people, and most cities are designated as densely habited district (DID). Similar to most urbanized areas in Japan, the population density is particularly high around major railway stations, which are also targeted as central development areas in the Master Plan of Kyoto City (https://www.city.kyoto.lg.jp/digitalbook/book_cmsfiles/1468/book.html). In addition, this city is famous for its densely deployed bus networks. These two measures are the major public transportation measures in Kyoto. The study area is located at the confluence of the Katsura, Uji, and Kizu Rivers and exposed to fluvial flood risk historically. This study analyzes the flood risk reduction by spatial amenity policies for this fluvial flood risk.

The agents (households) for each family type ω_1 were obtained from the 2015 Population Census by the Ministry of Internal Affairs and Communications, and their basic salary data were obtained from Esri Japan's income data (https://downloads.esri.com/esri_content_doc/dbl/int/Esri_Japan_2020_Data_Update_Whats_New.pdf). The vacancy distribution was determined using the 2018 Housing and Land Survey of Japan (https://www.stat.go.jp/english/data/jyutaku/index.html). The model parameters were calibrated according to Tanaka et al. (2022) to reproduce the actual regional growth ratio. This study recalibrated the parameters to reproduce the spatial distribution of housing prices and population after introducing local amenities.

The local amenity, that is, the attractiveness of the area, was set to be uniform in Tanaka et al. (2022) on the primary assumption that actual local amenity heterogeneity is not crucial for assessing the impact of virtual amenity policies, and amenity allocations were set based on the flood risk level. However, this simplification can cause a serious issue in quantitative policy analysis, which is to be demonstrated in Section 4. To enable AHR-FLOOD to assess the amenity policy (railway development was considered as an example), this study introduced amenity levels into the model.

3.2 | Formulation of local amenities using public transportation

The relationship between various types of local amenities (such as access to public transportation, supermarkets, schools, parks, natural environments, safety, and natural disaster risk) and decision- making processes for household relocation (moving) has been extensively investigated by numerous studies. Hedonic approaches (Rosen, 1974) are preferred when relating local amenities to housing prices. Several studies have suggested that public transportation is a dominant factor in determining the housing prices in Japan. However, its formulation

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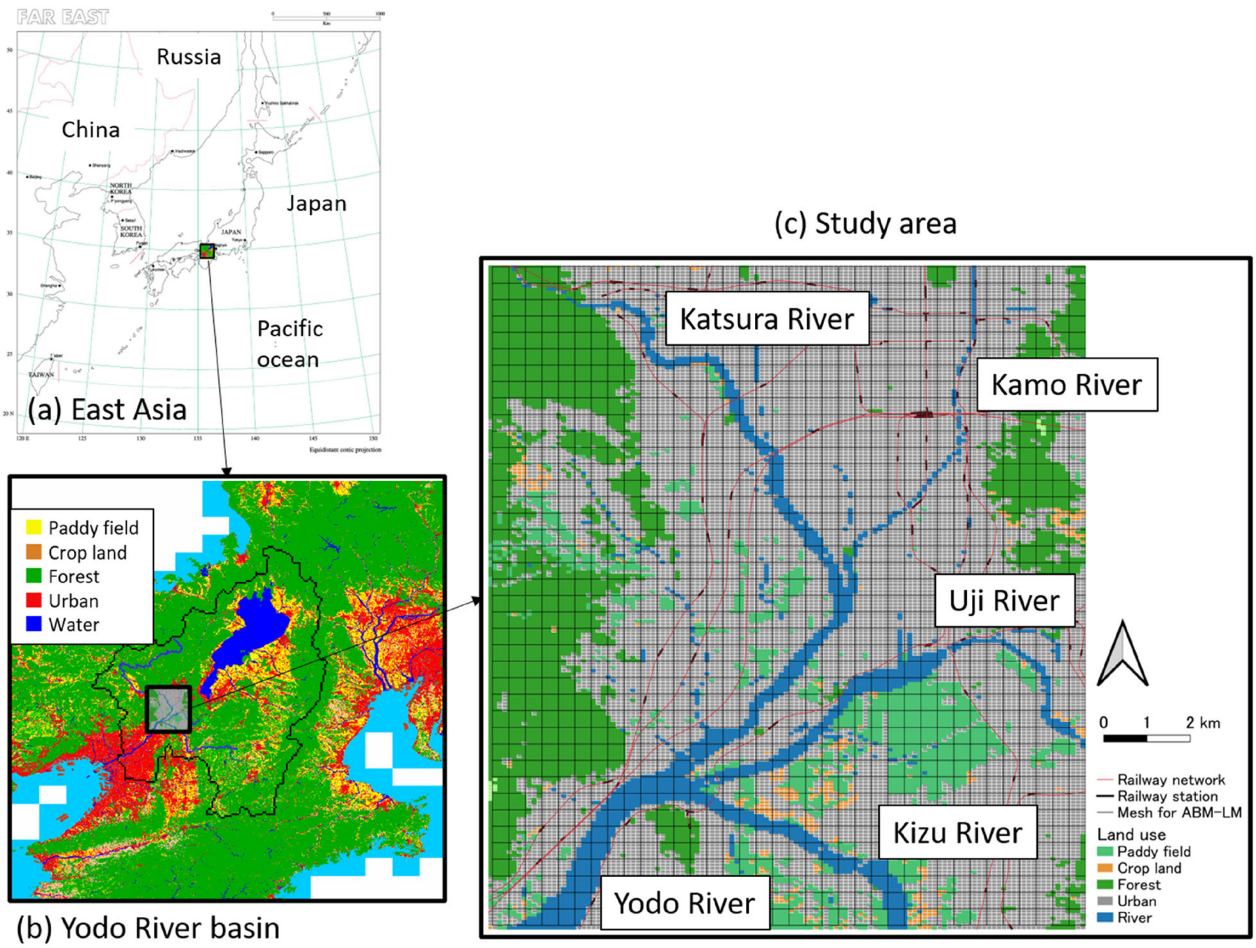

FIGURE 2 Study area location in (a) East Asia, (b) Yodo River basin. In (c) the study area map, the colour represents the land use map (light-green is paddy field; orange is cropland; green is forest; grey is urban and blue is river); the black boxes indicate 500 m meshes; and the black bars and red lines represent railway stations and networks, respectively.

varies from one study to another. Consequently, its impact on ABMs remains unclear.

This study used three types of public transportation access indices for local amenity modelling in AHR-FLOOD:

1. The inverse of distance to the nearest railway station within the walking distance (AM1)
2. The number of railway stations within the walking distance and their frequency (AM2)
3. The number of railway and bus stations within the walking distance and their frequencies (AM3)

AM1 is the simplest index and is often used as an explanatory variable of housing prices in hedonic price modelling (Lieske et al., 2021). It is expressed as follows.

$$a_j = \begin{cases} d_{k_0 j}^{-1} & (d_{k_0 j} \le d_{\max}) \\ a_{\min} & (d_{k_0 j} > d_{\max}) \end{cases} \tag{7}$$

where $d_{k_0 j}$ is the distance from mesh j to its nearest station k_0; $d_{\max}$ is the maximum walking distance; and $a_{\min}$ is the minimum amenity outside the walking distance of any railway station. To avoid the amenity from being zero in the Cobb–Douglas utility function (Equation 1), it was set to $a_{\min} = 10^{-5}$. Based on the standard walking speed of 80 m/min used in the real estate sector and the typical acceptable time of 15 min to the nearest railway station, $d_{\max}$ was set to 1.2 km. AM2 is a complicated index that focuses on the density of railway stations and their importance rather than the physical distance and is formulated as follows.

$$a_j = \begin{cases} \sum_{k=1}^{K} (1 - T_{kj}) N_k & (K \ge 1) \\ (1 - T_{k_0 j}) N_{k_0} & (K = 0) \end{cases} \tag{8}$$

Walking distances for AM2 and AM3 were the same as that for AM1. K is the number of railway stations within the walking distance, T_{kj} is the walking time from

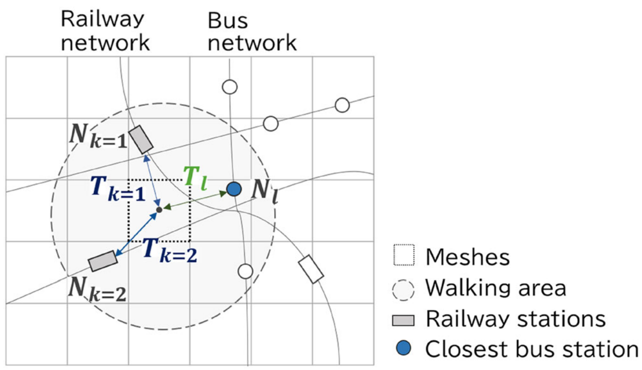

FIGURE 3 Schematic diagram of spatial amenities based on access to public transportation from home (the black circle). The grey boxes show available railway stations within the walking distance of 1.2 km (the dashed circle); the white circles show bus stations in which the blue one is the nearest station.

mesh j to station k; and N_k is the number of trains per hour during off-peak times. Off-peak times represented the overall importance of the station rather than the rush hour based on a nationwide survey by Nagao et al. (2010). We assumed that people accessed the nearest railway station using other vehicles, such as bicycles, cars, and buses, in areas where no train was available within walking distance $K=0$. AM3 is an integrated index that considers the number and frequency of bus operations because Kyoto is famous for its dense networks and frequent city bus operations. We assumed that not all buses within the walking distance were used daily. This index is formulated as follows.

$$a_j = \begin{cases} \sum_{k=1}^{K}\left[\left(1-T_{kj}\right)N_k\right]\cdot \max\limits_{l}\left\{\left(1-T_{lj}\right)N_l\right\}^{\alpha_{\mathrm{tb}}} & (K \geq 1) \\ \left(1-T_{k_0 j}\right)N_{k_0}\cdot \max\limits_{l}\left\{\left(1-T_{lj}\right)N_l\right\}^{\alpha_{\mathrm{tb}}} & (K=0) \end{cases} \tag{9}$$

where l is the nearest bus station within the walking distance, T_{lj} is the walking time from mesh j to bus station l; and α_{tb} is a weighting parameter between railway and bus stations (Figure 3).

Each index of the study area was calculated using public data (Table 1). The relationship between each index and housing prices per unit area (HPUA) is shown in Figure 4. The spatial distribution of the HPUA was derived by interpolating the actual real estate trade records obtained from the At Home dataset (At Home Co., Ltd, 2020). After trial and error, the α_{tb} parameter of index AM3 was set to 0.3 to best represent the HPUA. AM1 exhibited a high value near railway stations, but the priority of each station or the accessibility to the stations outside the maximum walking distance was not

TABLE 1 Data sources of different public transportation system.

Data	Sources (URL)	Year
Railway network	Geospatial Information Authority of Japan (GIAJ) (Railway Data) (https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-N02-v2_3.html)	2020
Number of trains	Yahoo! Japan train timetable (https://transit.yahoo.co.jp/)	2022
Bus route network	GIAJ (Bus Route Data) (https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-N07.html)	2011
Number of buses	GIAJ (Bus Stop Data) (https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-P11.html)	2010

expressed and thus considered simple. AM2 demonstrated the highest convenience to Kyoto Station, which is the central station in this area, and the contrast in the number of trains among different stations. Compared with AM2, AM3 showed a wider area as high transportation convenience in the northeast part of the study area, which is the central business district connected to Kyoto Station with a dense bus route network. The correlation coefficients between the HPUA and AM1, AM2, and AM3 were 0.264, 0.664, and 0.696, respectively. In summary, AM2 was a good representative convenience index. Among the three indices, AM3 explained the HPUA best, which was assumed to be unique for the study area. Thus, the following analyses uses AM3 as the local amenity index.

4 | VALIDATION OF AHR-FLOOD

We examined the performance of AHR-FLOOD using the local amenities derived above. The validation in this study targeted the mean spatial distribution of the population and HPUA from 2015 to 2019 because (1) the temporal changes in the housing prices during these 5 years were unclear, (2) data before 2014 were not available to public, and (3) Japan had a small economic growth ratio value from 2015 to 2019 (0.76% on average). Instead, we tested the first-order approximation of local amenities with respect to public transportation accessibility using AHR-FLOOD.

Considering constant economic conditions (economic growth ratio $\rho=0.0$), we ran the model for 20 years, after which the population and housing prices became constant. The initial population and housing prices were set to those of 2015. Without local amenity modelling, agents simply followed economic rationality and moved to

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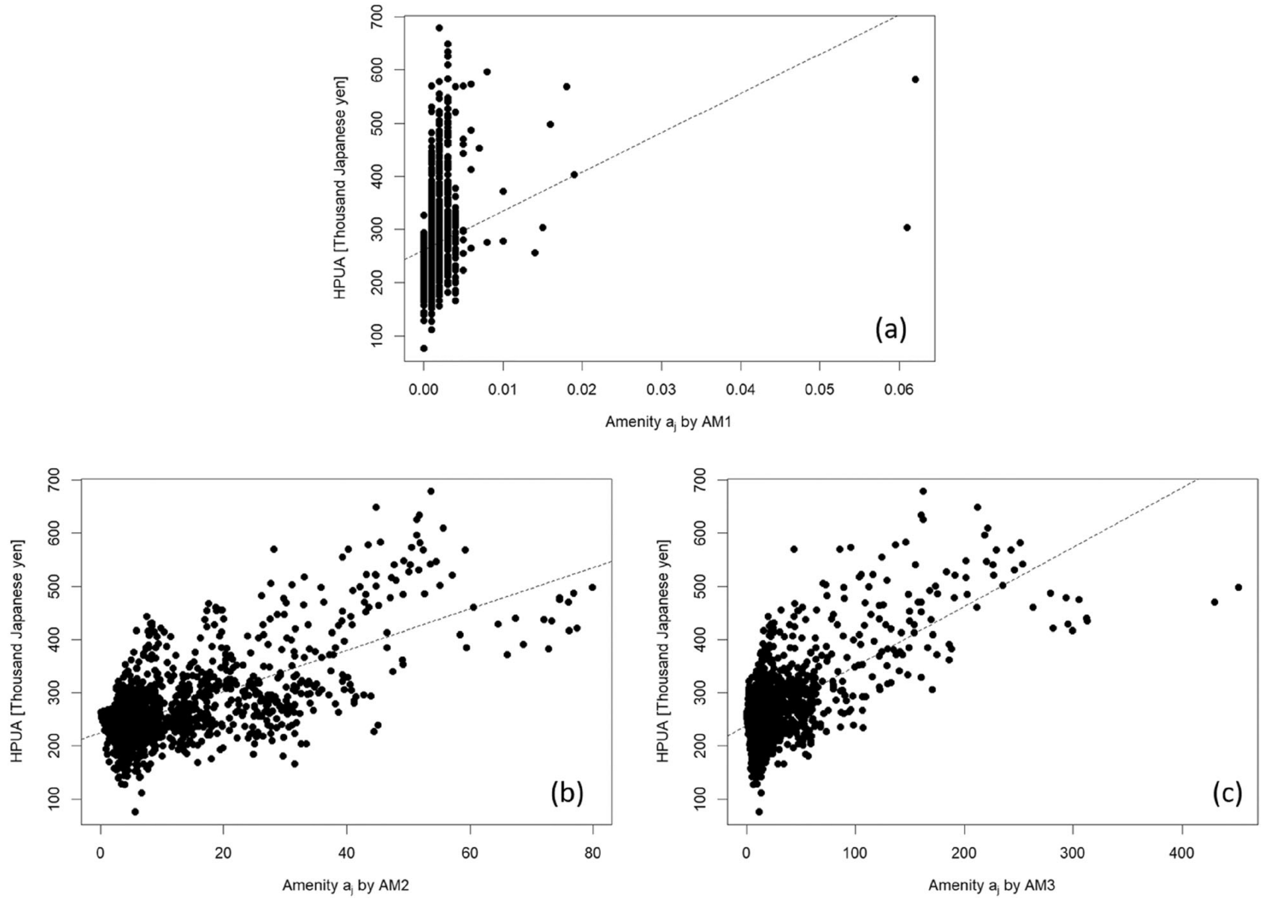

FIGURE 4 Scatter plots of local amenity by (a) AM1, (b) AM2, and (c) AM3 versus house price per unit area (Thousand Japanese yen) at all meshes. A solid line represents the regression line.

places with low housing prices (originally unpopular areas, such as rural and inconvenient regions), which is different from the reality. Therefore, this stationary (baseline) simulation examined whether the initial (actual) population and HPUA were sustained using local amenity modelling and their impact on the decision-making of agents.

The HPUA map in 2015 and that of the stationary simulation without and with local amenities are shown in Figure 5a–c. The simulation without local amenities failed to represent the spatial characteristics of housing prices; instead, mountainous areas with poor public transportation were more popular in this simulation, which is different from the reality (Figure 5b). By contrast, the simulation with local amenities motivated agents to move to high-amenity areas (Figure 5c). As a result, the spatial characteristics were represented much better with local amenity (Figure 5e) than without it (Figure 5d). The correlation coefficients between the simulated housing prices with and without local amenities and the actual prices were 0.515 and −0.149, respectively. For low-priced houses, where more residents are expected to use cars together with public transportation, the proposed local amenities performed limitedly. Further improvements should be incorporated in future studies.

The same comparisons for the population are shown in Figure 6a–c. Compared with the housing prices estimation (Figure 5c), the simulation without amenity modelling fairly performed in population estimation (Figure 6c) because it did not consider the scraps and builds by developers; thereby, the magnitude of the population was bounded by the actual number of vacant houses. However, the population in the simulation without local amenities (Figure 6b) was distributed in patches because of the unclear housing price pattern. As a result, there found several hot spots with large gap between the simulated and actual populations (Figure 6d), whereas that with local amenities exhibited a more similar trend to the actual population (Figure 6e). As a result, the correlation coefficients between the simulated population with and without local amenities and the actual populations were 0.958 and 0.931, respectively. Furthermore, this result may be affected by the initial setting of the

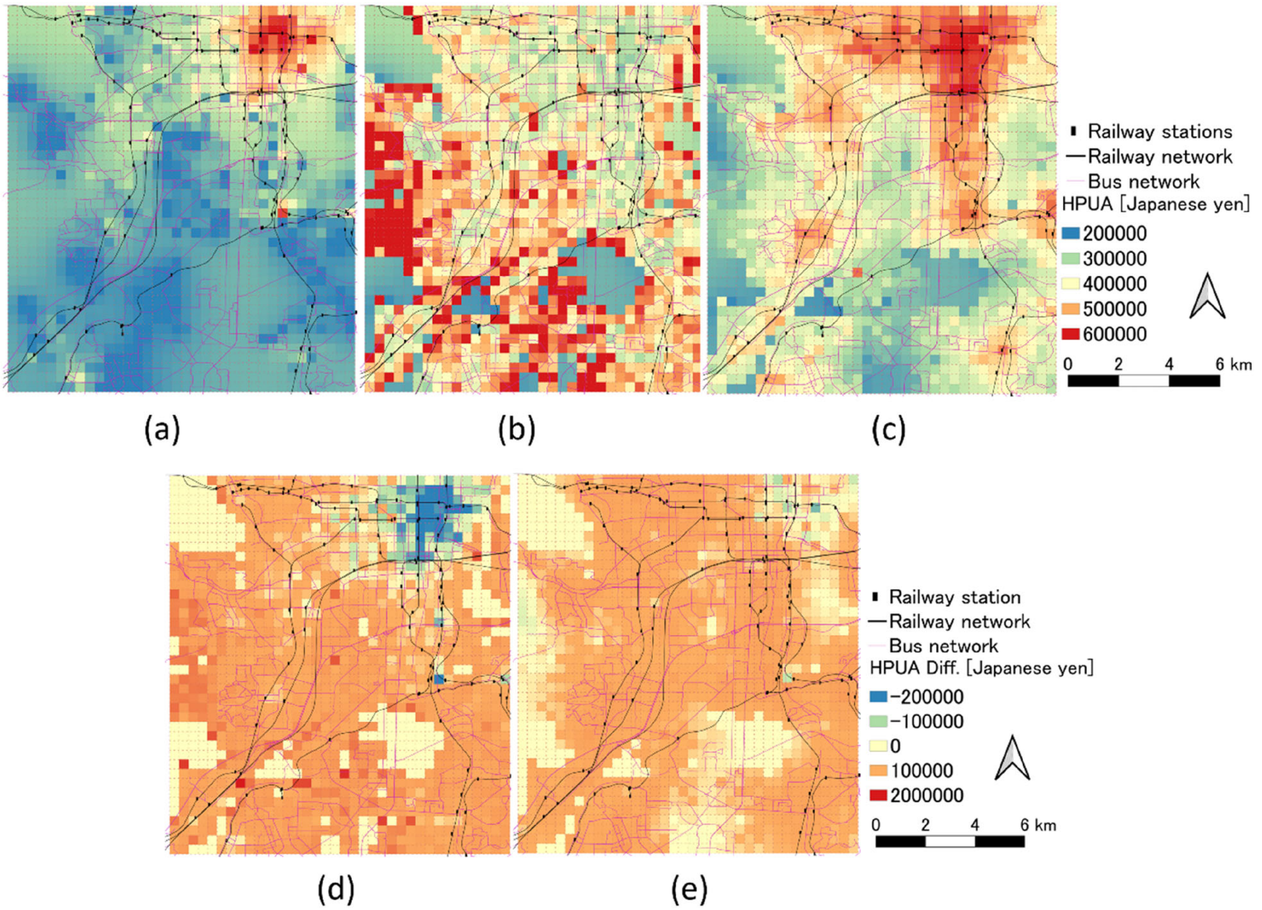

FIGURE 5 Map of House price per unit area simulated using (a) the At Home dataset, (b) without local amenities, and (c) with local amenities via AM3, (d) difference between (b) and (a) and (e) difference between (c) and (a).

HPUA. The initial conditions of the spatially uniform HPUA were tested as a supplementary simulation (Figure S1), which indicated that amenity modelling substantially contributed to the performance of AHR-FLOOD in the HPUA and population estimations. From these results, we concluded that the proposed local amenity modelling represented the overall behaviour of agents for household relocation and the real estate market with respect to public transportation amenities and was used for the analysis of following scenarios.

5 | DEVELOPMENTAL SCENARIOS

5.1 | Flood risk assessment

Tanaka et al. (2019) quantified the flood risk of the study area at a 90 m resolution. The frequency of extreme floods was estimated by a rainfall-based flood frequency model (RFFM) (Tanaka et al., 2017). The RFFM separately models the frequency of basin-averaged total rainfall (BATR) and its spatiotemporal distribution. The probability distribution of BATR was derived by fitting the generalized Pareto distribution to the observed BATR data. The spatiotemporal rainfall patterns were prepared from historical storm profiles. The dependence of BATR on rainfall duration and spatial rainfall concentration of rainfall patterns was considered by connecting the three random variables with a copula function. The storm events composed of BATR and a rainfall pattern, whose occurrence probability was analyzed above, were input to a distributed rainfall-runoff model 1 K-DHM (Tanaka and Tachikawa, 2015). The simulated discharge was then provided as the boundary condition of a flood-inundation model IMCR (Tanaka and Tachikawa, 2015) constructed at a 90 m resolution on the study area. The IMCR model employed the local inertial equations (Bates et al., 2010) to 1-dimensional (1-D) river and 2-D floodplain simulations. All the above processes were validated in the study area by Tanaka et al. (2017). The simulated flood depths at each 90 m mesh were further translated into the damage ratio of houses by flooding using fragility curves developed by the Ministry of Land, Infrastructure, Transport and Tourism (2020). The flood damage ratio in the

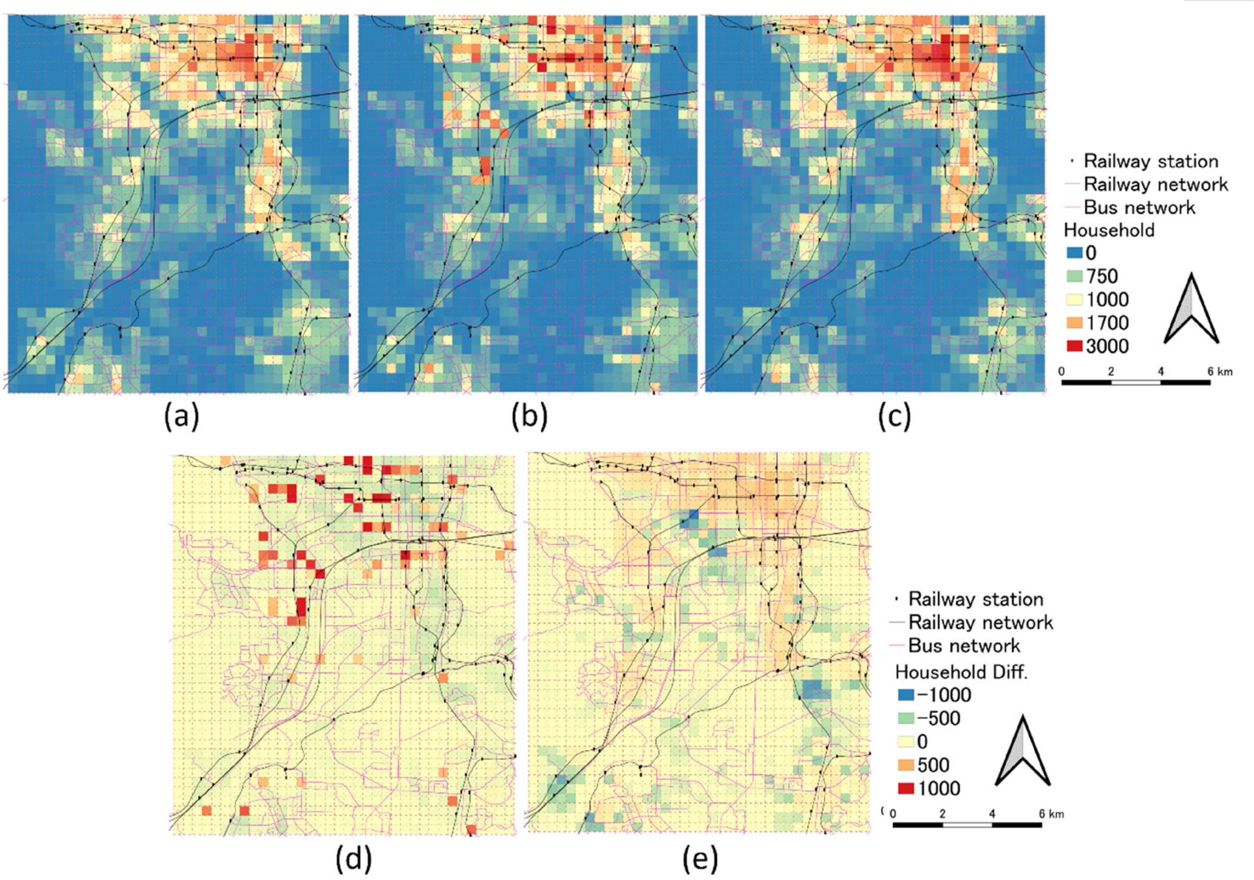

FIGURE 6 Population map simulated using (a) the 2015 Population Census, (b) without local amenity, and (c) with local amenity via AM3, (d) difference between (b) and (a) and (e) difference between (c) and (a).

fragility curve for houses is defined as a function of the maximum flood depth and the ground slope. Based on the occurrence probability of various storm events derived above, the return period of flood damage ratio at each mesh is obtained. In each AHR-FLOOD simulation, T-year flood damage is calculated by multiplying the flood damage ratio by the simulated house price at each mesh and then summing up the mesh flood damage.

The study area contains the three major rivers (Figure 2), whose flood control plan is designed for the return period of 150 years. After ongoing river improvements, the study area is considered safe against 150-year floods; however, floods over the design level may result in devastating damages, especially in urbanized areas including the study area. Such risk is expected to escalate in a changing climate. Therefore, the Japanese government sets the 1000-year flood in the present climate as a Level 2 (L2) class and encourages local municipalities or residents to prepare for such risk by presenting the hazard map of the L2 flood (MLIT, Kyushu Regional Development Breau, 2016). On these backgrounds, this study targets a 1000-year flood depth based on the above flood risk assessment by Tanaka et al. (2019). The result when selecting the annual averaged flood damage as an alternative, more typical index is also discussed.

5.2 | Spatial amenity policy

This study analyzed the impact of spatial amenity policy (SAP), defined as transportation development, on household relocation and the resulting flood risk compared with the business-as-usual (BAU) scenario. To examine the impact of the development area, we maintained the same magnitude of 14.5 trains per hour and set it on different meshes among the scenarios. The spatial increment in amenity was subsequently calculated for all meshes using Equation (9), which expresses the impact of public transportation development on the surrounding areas. The magnitude corresponded to a typical railway station where express trains stopped and two different lines were available. Furthermore, the development area of each scenario was not necessarily on the existing railway network but was flexible, including relevant amenity policies (such as bus terminals and shopping centres). Assuming a standard-sized house and apartment room, 1000 (150 and 50) houses/apartment rooms were added to the target mesh (developed area) and its surrounding eight and further 16 meshes. In the BAU and all other developmental scenarios, the simulation started with the aforementioned validation (a 40-year stationary simulation when internal variables of AHR-FLOOD were assumed to be organized). Note that no scenario of land use regulation was treated in this study because the scenario is considered hard to implement due to the strong land ownership of Japan as mentioned in Introduction.

To discuss the impact of the SAP on flood risk distribution, we classified the target area into nine categories, three amenity levels by three flood risk levels (Figure 7), of which five were analyzed for clarity (A–E). Three meshes were selected from each class as the developmental location to account for the uncertainty associated with the local environment (amenities and flood risk) within the same category (black dots in Figure 7). The statistical properties of each mesh in the initial conditions (after the 40-year stationary simulation) are summarized in

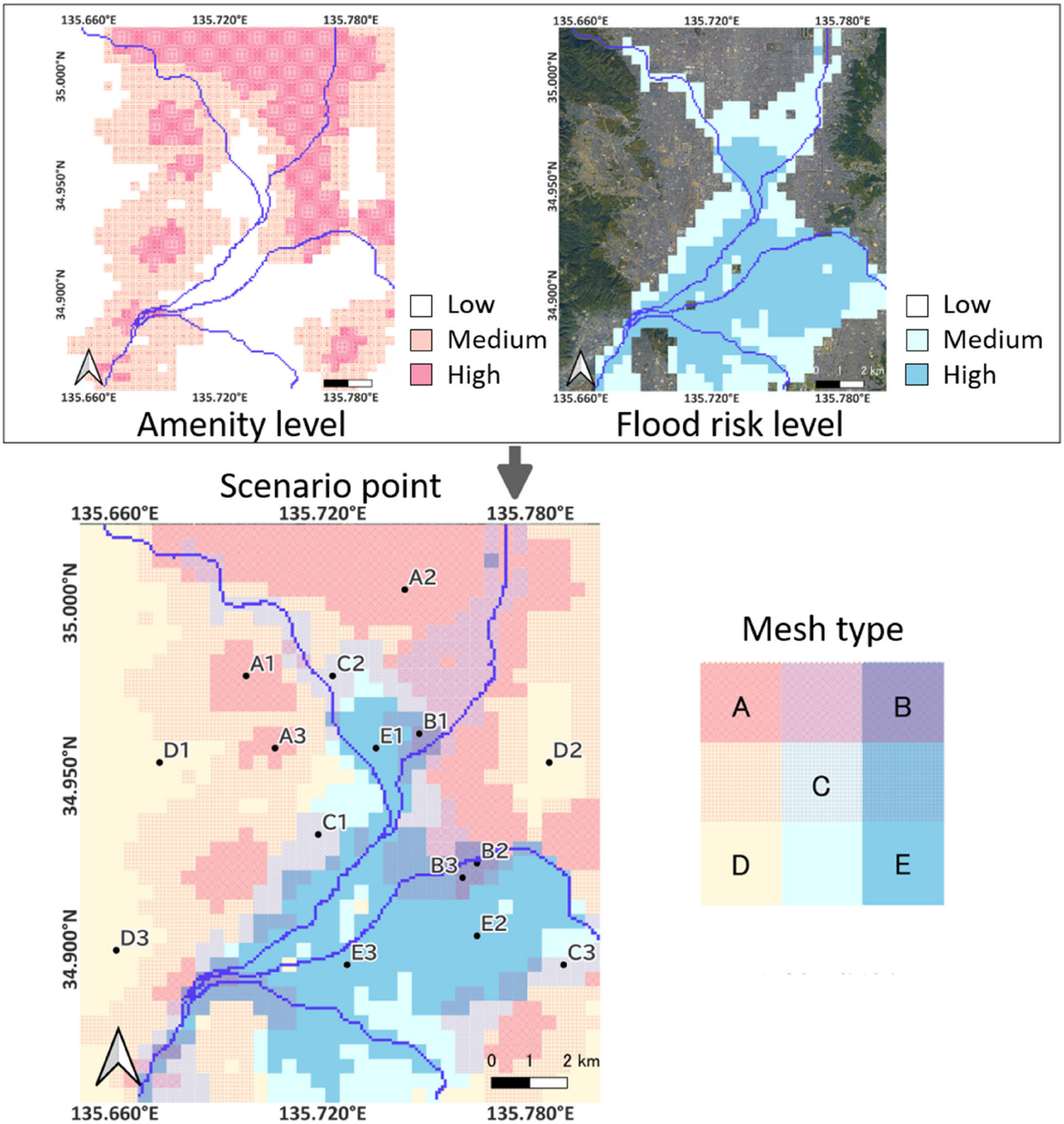

FIGURE 7 Regional classification using the three amenities (low, medium and high in white, pink and red, respectively) and flood risk (low, medium and high in white, light-blue and blue, respectively) levels and 15 target locations (A1–E3) in each developmental scenario. The lower panel merges the upper two maps. The three locations are randomly selected from each mesh type.

TABLE 2 Statistical summary of target meshes in developmental scenario locations.[a]

Location	House price per unit area[b] (1000 Japanese yen/m^2)	Amenity[c]	House vacancy rate[d] (%)	Number of households[e]	Low-income rate[e] (%)
A1	*472*	*48.9*	4.50	*925*	39.6
A2	*551*	*126*	0.100	*1674*	12.3
A3	461	27.3	6.70	666	42.1
B1	*471*	28.6	18.9	260	69.7
B2	454	*42.9*	15.5	*721*	63.4
B3	396	30.4	7.20	394	61.9
C1	403	12.2	18.8	318	74.9
C2	446	14.3	12.7	496	56.6
C3	416	14.3	15.2	443	62.0
D1	380	7.70	30.2	227	*91.5*
D2	385	6.60	*61.6*	103	36.6
D3	276	4.90	13.8	64	*79.2*
E1	382	8.50	*45.9*	140	77.5
E2	276	3.80	*69.1*	24	79.1
E3	339	3.70	20.5	109	*91.8*

[a]Grey hatches indicate the 1st–3rd highest values of each item.
[b]At Home Co., Ltd. Via IDR Dataset Service of National Institute of Informatics (https://www.nii.ac.jp/dsc/idr/athome/).
[c]Derived via Equation (9) from railway and bus network data published by Geospatial Information Authority of Japan (https://nlftp.mlit.go.jp/ksj/).
[d]Housing and Land Survey 2018 through e-Stat (https://www.stat.go.jp/english/data/jyutaku/index.html).
[e]2015 Population Census data provided by (c) ESRI Japan.

Table 2. Lower-amenity meshes D and E have higher house vacancy rate and smaller housing prices and population compared with A and B. Flood risk management in Japan is now shifting from an infrastructure-based approach into integrated risk management under the initiative of River Basin Disaster Resilience and Sustainability by All (MLIT, 2020). However, its collaboration with compact city policies is challenging because urban planning is based on a range of factors; as a result, amenity policies and flood risk management are harmonized with in some cases while conflicted in other cases. Therefore, this study targeted the locations with different combinations of amenity and flood risk levels for the sufficient coverage of possible scenarios within the Planning Area of the study area.

Table 3 presents the criteria for flood risk and amenity level assessments. The amenity criterion of 10 (30) corresponded to an environment where 6 (12) trains per hour and 8 (30) buses per hour were available within 5 min walking distance. Furthermore, we extracted the 1000-year flood depth at a 500 m resolution (adjusted to AHR-FLOOD using upscaling) as the largest flood class, overlayed it with the simulated population and HPUA using AHR-FLOOD, and subsequently calculated the 1000-year flood damage to houses as a flood risk index. A specific return period of 1000 years

TABLE 3 Criteria of flood risk and amenity levels.

Level	Flood risk (1000-year depth) (m)	Amenity
Low	<0.5	<10
Medium	0.5–3.0	10–30
High	>3.0	>30

was selected because it is the largest flood level in Japan for which nonstructural countermeasures, such as urban management are recommended (Koide et al., 2022).

6 | RESULTS AND DISCUSSIONS

6.1 | Regional metrics

We run AHR-FLOOD under 15 development scenarios, that is, amenity increase at A1 to E3. Hereinafter, each scenario also refers to the developed mesh such as A1 or B1. The simulated changes in the (a) population and (b) HPUA from the initial state compared with BAU are illustrated in Figure 8. The "change" in the following results was derived as the different of the change from the initial state and that from BAU. As expected, the population and housing prices increased in the target mesh

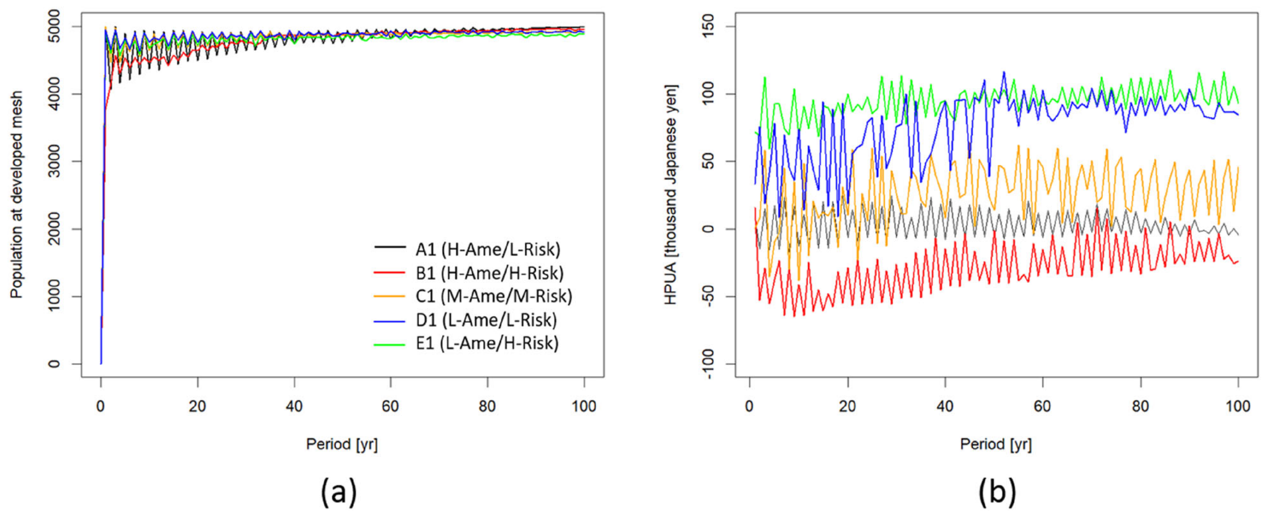

FIGURE 8 Time series of (a) population and (b) house price per unit area compared with the business-as-usual scenario at a developed mesh for A1 (black), B1 (red), C1 (orange), D1 (blue), and E1 (green) scenarios.

in all cases. The population increased by 5000 (all new houses) in the first few years, possibly because of a high demand for a developed area with increased amenities. In the developmental scenarios considering the high-amenity areas (A1 and B1), the rate of increase was slow because only medium- to high-income households could afford to move. Consequently, the increment of HPUA from BAU were smaller for A1 and B1. In particular, B1 became negative initially because of a relatively high initial vacancy ratio (Table 2).

The time series of household exposure at different flood risk levels ([a] low, [b] medium, and [c] high) and house damage caused by the 1000-year flood for the entire study area are shown in Figures 9 and 10, respectively. In summary, the maximum increase was observed in the population under the flood risk level of the developed area (types A and D were low; C was medium; and B and E were high) in each scenario because of a direct impact of the SAP. Accordingly, housing damage differences from BAU corresponded to the development of each flood risk level. At the maximum, B3 induced a flood damage increase of 150 billion Japanese yen (5% of the 1000-year flood damage in BAU), whereas D2 decreased 90 billion Japanese yen by developing a low-risk area. Although this study analyses the 1000-year flood damage, the same as Figure 9 but for the annual expected flood damage as alternative statistics is shown in Figure S2, indicating the overall similar trend as Figure 9, while the contrast of flood damage among different risk levels at the developed location (high for B and E, middle for C and low for A and D) is less clear.

The time series of population change compared with BAU in low-risk areas for low-income households is illustrated in Figure 11a. Although the household increase corresponded to the developed area in each scenario, its tendency remained unclear compared with Figure 8. For household relocation, the decision-making process of low-income population was more affected by an increase in housing price than by amenity enhancement owing to budget constraints. For clarity, the time series of households in the low-risk areas were extracted for A1–A3 and D1–D3. Although the result varied among different target meshes in the low-risk areas, the medium- and high-income households (Figure 11c) steadily increased over time, whereas the low-income households (Figure 11b) decreased during some years, indicating the sluggish response of low-income households to the SAP because of budget constraints. However, the development of D, a low-amenity mesh, exhibited a higher increase in the households in low-risk areas than A. As shown in Table 3, mesh type D has a low amenity and thus low housing prices; therefore, developing D attracted more low-income population than medium- and high-income populations.

6.2 | Spatial analysis

The spatial distribution of population changes (by developing A1 and D1) after 5, 20, and 60 years are illustrated in Figure 12. Clearly, the population increased in developed and surrounding areas over time, a large portion of which came from neighboring areas. After 20 years, the population changes were more contrasting than after 5 years. Finally, after 60 years, the households in high-risk areas (meshes in the blue frame) moved to medium flood risk areas (those in the black frame). These medium-risk areas exhibited a decreasing population after 20 years. The households first left the developed areas, and subsequently, those in the high-risk areas moved to the medium-risk areas, indicating chain

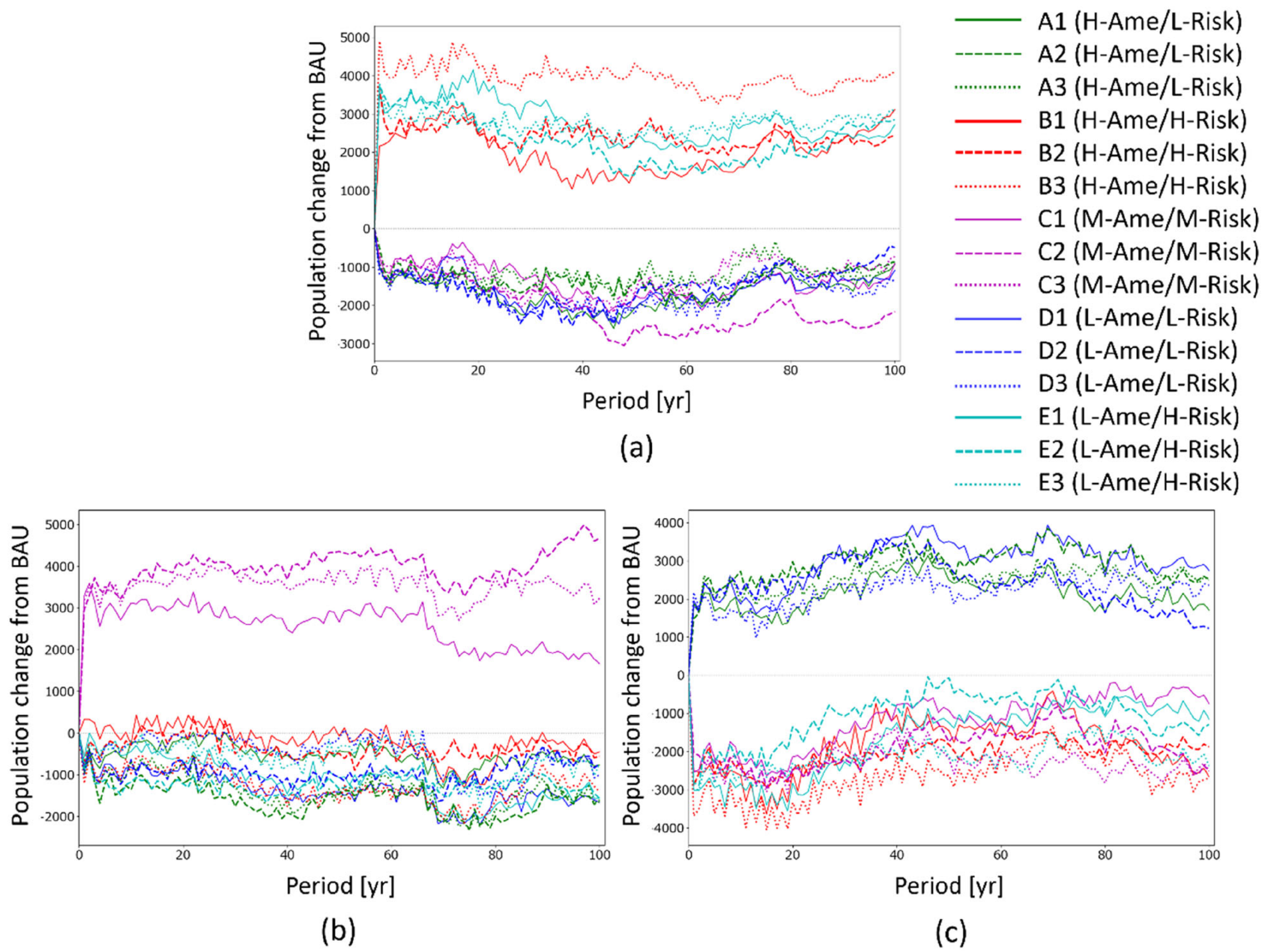

FIGURE 9 Time series of population difference compared with the business-as-usual scenario in (a) low-, (b) medium- and (c) high-risk areas in all 15 scenarios (A [green], B [red], C [pink], D [blue], and E [light-blue]). The three locational scenarios in each mesh type are indicated using different line types.

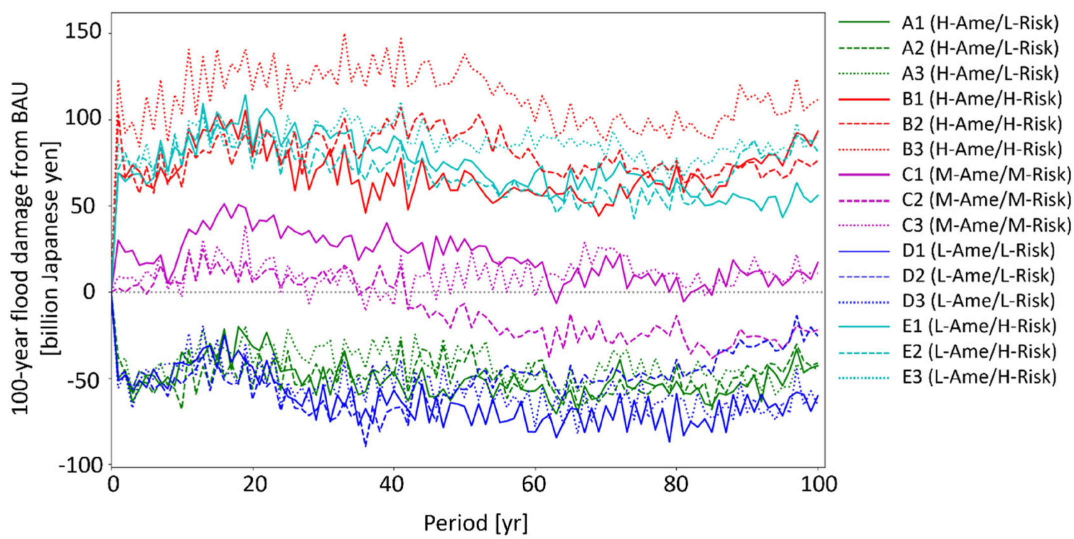

FIGURE 10 Time series of the 1000-year flood damage from the business-as-usual scenario in all 15 scenarios (A [green], B [red], C [pink], D [blue], and E [light-blue]).

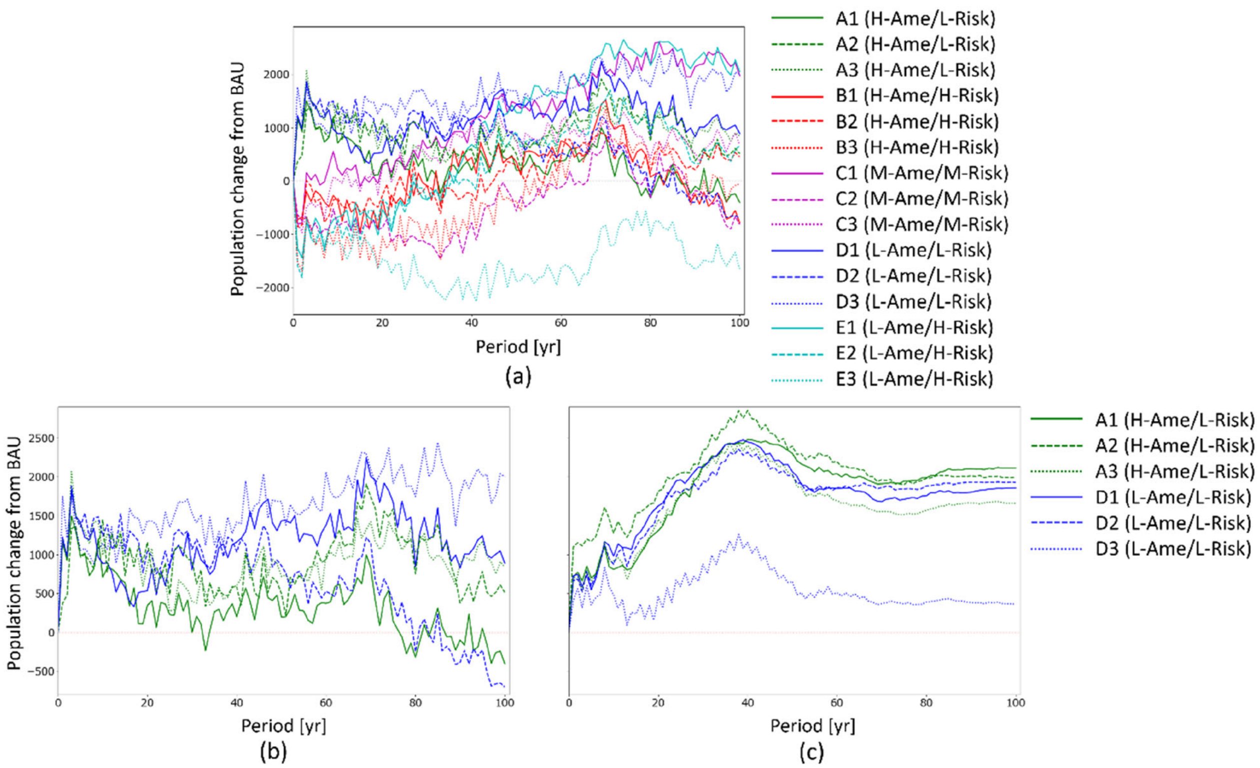

FIGURE 11 Time series of population difference compared with the business-as-usual scenario in low-risk areas only for low-income population in (a) all 15 scenarios (A [green], B [red]), C [pink], D [blue], and E [light-blue]) and (b) six scenarios (A1–A3 and D1–D3) that develop low-risk areas. For comparison, (c) six scenarios (A1–A3 and D1–D3) for middle- and high-income population are also shown. The three locational scenarios in each mesh type are indicated using in different line types.

migration processes (Dimova & Wolff, 2015; McFalls, 2003; Skop et al., 2006). As shown in Figure 7, the high-risk areas within the study area had poorer overall transportation access (i.e., lower amenities) and more low-income population living in low-price houses compared with medium- and low-risk areas. The results indicate that these households could not move to the developed areas, where the housing prices were high, but instead moved to the medium-risk areas (with high amenities) when they became available. The improved AHR-FLOOD from Tanaka et al. (2022) successfully demonstrated the indirect and long-term effects of the SAP.

7 | CONCLUSIONS

In recent years, urban development for flood risk management has been extensively discussed to avoid costly embankments for climate change adaptation. Considering the difficulty in applying land use regulations or zoning in countries, such as Japan (Sorensen, 2007), amenity improvement in safe areas, which will motivate people to settle there, is an effective policy option. However, moving away from the original location, where the flood risk is high, can be accompanied by a deterioration in transportation accessibility, especially for those people who live there for convenience. Therefore, transportation development policies that compensate for this deterioration play a crucial role in urban planning-based flood risk management.

To enable policy analysis of flood risk management through urban development, this study improved AHR-FLOOD, developed by Tanaka et al. (2022), by introducing public transportation as a local amenity into the decision-making process of households and performed a scenario analysis of the SAP, where the amenity levels were non-homogenized corresponding to the flood risk. We obtained the following findings.

1. AHR-FLOOD considering access to public transportation reproduced the spatial characteristics of the actual population and housing prices.
2. The development of low-risk areas reduced the flood exposure and resulting flood damage.
3. This effect was less clear for low-income individuals. However, the development of low-amenity areas had the potential to induce low-income population to move to safe areas.

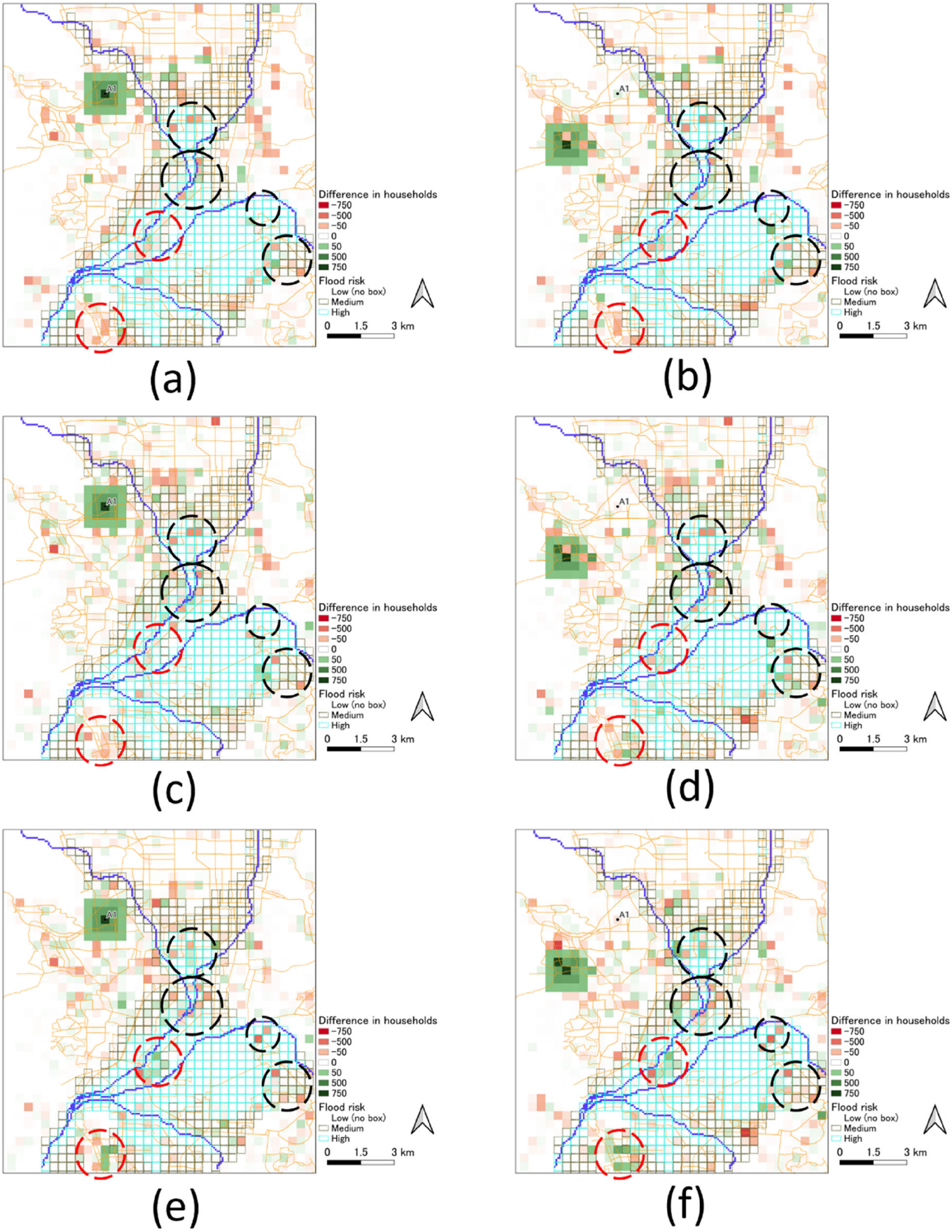

FIGURE 12 Mesh level population difference compared with the business-as-usual scenario in developing mesh type A (left) and D (right) after (a and b) 5, (c and d) 20, and (e and f) 60 years. The black and red circles indicate the areas where the population decreases and increases, respectively. The meshes bound with the blue and black boxes represent high and medium flood risk areas, respectively.

4. Chain migration was observed as a long-term effect of the SAP especially for low-income population, even after the developed houses were filled. This is assumed to be unique to the study area, where high-amenity areas have a low flood risk.

AHR-FLOOD provided useful insights into the impact of transportation policies on long-term flood risk changes with a unified focus on spatial distance management using an ABM framework with the rigorous modelling and validation of local amenity impact on household relocation choices. Further research is required to improve AHR-FLOOD, such as providing specific convenience characteristics for individual transportation modes and classifying different destination types. For example, some cases can feature daily access to riverfront farms (Holstead et al., 2017) and coastal fishing grounds (Adelekan & Fregene, 2015), whereas others can ensure accessibility to natural landscapes without transportation facilities.

ACKNOWLEDGEMENTS

In this study, we used the "At Home Dataset" provided by At Home Co., Ltd. via IDR Dataset Service of the National Institute of Informatics. This study was supported by JSPS KAKENHI Grant Number JP21K18747 and JST SICORP Grant Number JPMJSC2312, Japan.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

Adelekan, I., & Fregene, T. (2015). Vulnerability of artisanal fishing communities to flood risks in coastal southwest Nigeria. *Climate and Development*, *7*(4), 322–338.

At Home Co., Ltd. (2020). At home dataset. https://www.nii.ac.jp/dsc/idr/athome/

Bates, P. D., Horritt, M. S., & Fewtrell, T. J. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *Journal of Hydrology*, *387*(1-2), 33–45.

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.

Carrera, L., Standardi, G., Bosello, F., & Mysiak, J. (2015). Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling. *Environmental Modelling & Software*, *63*, 109–122.

Carro, A., Hinterschweiger, M., Uluc, A., & Farmer, J. D. (2023). Heterogeneous effects and spillovers of macroprudential policy in an agent-based model of the UK housing market. *Industrial and Corporate Change*, *32*(2), 386–432.

Chalise, S., & Naranpanawa, A. (2016). Climate change adaptation in agriculture: A computable general equilibrium analysis of land use change in Nepal. *Land Use Policy*, *59*, 241–250.

Dimova, R., & Wolff, F. C. (2015). Remittances and chain migration: Longitudinal evidence from Bosnia and Herzegovina. *The Journal of Development Studies*, *51*(5), 554–568.

Ettema, D. (2011). A multi-agent model of urban processes: Modelling relocation processes and price setting in housing markets. *Computers, Environment and Urban Systems*, *35*(1), 1–11.

Fachrudin, H. T., & Lubis, M. D. (2016). Planning for riverside area as water tourism destination to improve quality of life local residents, case study: Batuan–Sikambing River, Medan, Indonesia. *Procedia-Social and Behavioral Sciences*, *234*, 434–441.

Geanakoplos, J., Axtell, R., Farmer, D. J., Howitt, P., Conlee, B., Goldstein, J., Hendrey, M., Plamer, N., & Yang, C. Y. (2012). Getting at systemic risk via an agent-based model of the housing market. *American Economic Review*, *102*(3), 53–58.

Holstead, K. L., Kenyon, W., Rouillard, J. J., Hopkins, J., & Galán-Díaz, C. (2017). Natural flood management from the farmer's perspective: Criteria that affect uptake. *Journal of Flood Risk Management*, *10*(2), 205–218.

Iizuka, S., Xuan, Y., Takatori, C., Nakaura, H., & Hashizume, A. (2020). Environmental impact assessment of introducing compact city models by downscaling simulations. *Sustainable Cities and Society*, *63*, 102424.

Ito, H., & Kawazoe, N. (2023). Promoting transportation policies in the context of compact city strategies: the case of Toyama City, Japan. *The Annals of Regional Science*, *71*(3), 775–797.

Janssen, M. A., & Ostrom, E. (2006). Empirically based, agent-based models. *Ecology and society*, *11*(2). http://www.jstor.org/stable/26265994

Koide, Y., Nishizaki, K., & Sudo, N. (2022). Flood risk perception and its impact on land prices in Japan (No. 22-E-12). Bank of Japan.

Lieske, S. N., van den Nouwelant, R., Han, J. H., & Pettit, C. (2021). A novel hedonic price modelling approach for estimating the impact of transportation infrastructure on property prices. *Urban Studies*, *58*(1), 182–202.

Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems*, *35*(3), 183–191.

Matsumaru, R., Nagami, K., & Takeya, K. (2012). Reconstruction of the Aceh region following the 2004 Indian Ocean tsunami disaster: A transportation perspective. *IATSS Research*, *36*(1), 11–19.

McFalls, J. A. J. (2003). Population: A lively introduction. *Population Bulletin*, *58*, 1–40.

Ministry of Land, Infrastructure, Transport and Tourism. (2020). River basin disaster resilience and sustainability by all Japan's new policy on water-related disaster risk reduction. https://www.mlit.go.jp/river/kokusai/pdf/pdf21.pdf

Ministry of Land, Infrastructure, Transport and Tourism, Kyushu Regional Development Breau. (2016). How to create flood hazard maps by probable maximum rainfall (title translated by the authors). https://www.qsr.mlit.go.jp/miyazaki/site_files/file/kasen/shinsui_ooyodo/shinsui_sankou01.pdf

Mustafa, A., Bruwier, M., Archambeau, P., Erpicum, S., Pirotton, M., Dewals, B., & Teller, J. (2018). Effects of spatial planning on future flood risks in urban environments. *Journal of Environmental Management*, *225*, 193–204.

Nabinejad, S., & Schüttrumpf, H. (2016). An agent based model for land use policies in coastal areas. *Coastal Engineering Proceedings*, *35*, 9.

Nagai, H., & Kurahashi, S. (2019). How to realize a Compact City: Street activeness and agent-based urban modeling. SMARTGREENS 2019: Proceedings of the 8th international conference on smart cities and green ICT systems, pp. 100–107.

Nagao, M., Nakagawa, D., Matsunaka, R., Oba, T., & Mochizuki, A. (2010). A study on the change of population around rail and tram stations in local cities focusing on their frequencies. *Infrastructure Planning Review*, *27*, 399–407.

Rashidi, T. H., & Ghasri, M. (2019). A competing survival analysis for housing relocation behaviour and risk aversion in a resilient housing market. *Environment and Planning B: Urban Analytics and City Science*, *46*(1), 122–142.

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

Skop, E., Peters, P. A., Amaral, E. F., Potter, J. E., & Fusco, W. (2006). Chain migration and residential segregation of internal migrants in the metropolitan area of São Paulo, Brazil. *Urban Geography*, *27*(5), 397–421.

Soga, M., Yamaura, Y., Koike, S., & Gaston, K. J. (2014). Land sharing vs. land sparing: Does the compact city reconcile urban development and biodiversity conservation? *Journal of Applied Ecology*, *51*(5), 1378–1386.

Sorensen, A. (2002). *The making of urban Japan: Cities and planning from Edo to the twenty-first century* (Vol. 53). Psychology Press.

Sorensen, A. (2007). Consensus, persuasion, and opposition: Organizing land readjustment in Japan. In Y.-H. Hong & B. Needham (Eds.), *Analyzing land readjustment: Economics, law, and collective action* (pp. 89–114). Lincoln Institute of Land Policy.

Tanaka, T., & Tachikawa, Y. (2015). Testing the applicability of a kinematic wave-based distributed hydrological model in two climatically contrasting catchments. *Hydrological Sciences Journal*, *60*(7-8), 1361–1373.

Tanaka, T., Tachikawa, Y., Ichikawa, Y., & Yorozu, K. (2017). Impact assessment of upstream flooding on extreme flood frequency analysis by incorporating a flood-inundation model for flood risk assessment. *Journal of Hydrology*, *554*, 370–382.

Tanaka, T., Ichikawa, Y., Yokomatsu, M., & Tachikawa, Y. (2019). Improvement of flood risk curve development by considering dependence of basin total rainfall on its spatial concentration. *Journal of Japan Society of Civil Engineers, Ser. B1 (Hydraulic Engineering)*, *75*(1), 112–121.

Tanaka, T., Yokomatsu, M., Ashino, M., & Ichikawa, Y. (2022). Novel framework for assessing long-term flood risk management pathways focusing on river channel improvement and amenity policies. *Journal of Flood Risk Management*, *15*(3), e12804.

Teramoto, M., Ichikawa, Y., Tachikawa, Y., & Shiiba, M. (2010). Study on applicability of landuse regulation strategies based on flood risk assessment. *Journal of Japan Society of Civil Engineering*, *66*(2), 130–144.

Tsai, Y., Zia, A., Koliba, C., Bucini, G., Guilbert, J., & Beckage, B. (2015). An interactive land use transition agent-based model (ILUTABM): Endogenizing human-environment interactions in the Western Missisquoi watershed. *Land Use Policy*, *49*, 161–176.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. *Journal of Artificial Societies and Social Simulation*, *10*(2), 8.

Zhang, Q., Sannigrahi, S., Bilintoh, T. M., Zhang, R., Xiong, B., Tao, S., Bilsborrow, R., & Song, C. (2022). Understanding human-environment interrelationships under constrained land use decisions with a spatially explicit agent-based model. *Anthropocene*, *38*, 100337.

Zhuo, L., & Han, D. (2020). Agent-based modelling and flood risk management: A compendious literature review. *Journal of Hydrology*, *591*, 125600.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Tanaka, T., Koga, A., & Yokomatsu, M. (2024). Agent-based intra-regional relocation model considering spatial local amenity for urban planning-based flood risk management: Assessing the impact of urban development on flood exposure. *Journal of Flood Risk Management*, *17*(4), e13035. https://doi.org/10.1111/jfr3.13035