High-resolution national land use scenarios under a shrinking population in Japan

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Abstract
In sharp contrast with the global trend in population growth, certain developed countries are expected to experience rapid national population declines. Considering future land use scenarios that include depopulation is necessary to evaluate changes in ecosystem services that affect human well-being and to facilitate comprehensive strategies for balancing rural and urban development. In this study, we applied a population-projection-assimilated predictive land use modeling (PPAP-LM) approach, in which a spatially explicit population projection was incorporated as a predictor in a land use model. To analyze the effects of future population distributions on land use, we developed models for five land use types and generated projections for two scenarios (centralization and decentralization) under a shrinking population in Japan during 2015–2050. Our results suggested that population centralization promotes the compaction of built-up areas and the expansion of forest and wastelands, while population decentralization contributes to the maintenance of a mixture of forest and cultivated land.

1 INTRODUCTION
Throughout human history, human activity has greatly affected global land cover. In particular, the expansion of agricultural areas to support an increasing global population has caused major ecosystem changes over the last...
few centuries, and this trend is expected to continue (Pereira, Navarro, & Martins, 2012). In sharp contrast to the global trend in population growth, certain developed countries are expected to experience rapid population declines at the national level (United Nations, Department of Economic and Social Affairs, Population Division, 2015). Such historic changes in human population dynamics may affect land use patterns in both rural and urban areas, resulting in changes in the functioning of the ecosystem, which is the source of many goods and services that contribute to the economy and human welfare (Foley et al., 2005; Lambin & Geist, 2010).

In the last few decades, rural areas have suffered from severe population declines combined with rural-to-urban migration. These patterns were stimulated by an economic shift from agriculture to industry, increasing job opportunities in the cities. Additionally, the recent expansion of large-scale modern agriculture has caused a concentration of agricultural activities in areas with favorable conditions and the abandonment of unfavorable sites (Aide & Grau, 2004; Mottet, Latet, Coque, & Gibon, 2006). Land abandonment is coupled with population declines in marginal agricultural landscapes, especially in mountain areas (Aide & Grau, 2004; Ray Benayas, Martins, Nicolau, & Schulz, 2007). Land abandonment may have both negative and positive consequences. It may decrease landscape heterogeneity, increase fire frequency, and result in soil erosion, a loss of biodiversity, and a loss of cultural and aesthetic value (MacDonald et al., 2000; Ray Benayas et al., 2007). However, abandoned land can provide a new opportunity to restore self-sustaining ecosystems, providing various kinds of ecosystem services, if appropriate management for rewinding is conducted (Navarro & Pereira, 2012).

In urban areas, population decline can lead to the hollowing of urban landscapes. Vacant landscapes may embody the unfavorable legacies of past uses and threaten the health, safety and quality of life of residents (Nassauer & Raskin, 2014). Unmanaged vacant lands in urban and peri-urban landscapes are a source of increasing mobility costs, energy expenditure, and emissions of CO₂ and air pollutants. These areas may potentially be reclaimed as green spaces, which supply ecosystem services. For example, green spaces in urban and peri-urban landscapes can reduce disaster risks (Liu, Chen, & Peng, 2014) and mitigate the heat island effect (Davis, Jung, Pijanowski, & Minor, 2016; Norton et al., 2015; Stone, Hess, & Frumkin, 2010). In other words, population decline may create opportunities for a transition toward more sustainable urban forms. There are two dominant and contradictory theories about sustainable urban forms: the “compact city” and the “dispersed city” (Geschke, James, Bennet, & Nimmo, 2018; Holden & Norland, 2005). The “compact city” is an urban planning concept that promotes high residential density and lowers the energy requirements for housing and daily travel (Ariga & Matsuhashi, 2012, 2013; Holden & Norland, 2005; OECD, 2012). However, such high-density development may have an inverse relationship with livability (Neuman, 2005). In contrast, a “dispersed city” suggests a relatively open urban structure, where buildings, fields, and other green areas form a mosaic-like pattern. In both cases, the restructuring of urban forms may affect human well-being and sustainability under future population declines by enhancing different ecosystem services. For example, in compact cities, large green spaces can be set aside, without human disturbance, thereby promoting the sequestration of carbon in the soil and contributing to the mitigation of global climate change (Collas, Green, Ross, Wastell, & Balmford, 2017). Dispersed cities may enhance the recreational use of urban green spaces (Soga et al., 2015), contributing to human health (Shanahan et al., 2016).

Future scenarios of land use change coinciding with depopulation are quite valuable to develop strategies to mitigate the negative effects of land abandonment and to exploit the emerging opportunity for land use restructuring to improve human well-being in both rural and urban areas. Spatially explicit population projection has played an important role in studies of the environment and sustainability (Bengtsson, Shen, & Oki, 2006), and land use scenarios under a shrinking population should be consistent with a high-resolution population projection. A population-projection-assimilated predictive land use modeling (PPAP-LM) approach, in which a spatially explicit population projection is incorporated as a predictor in land use models, can offer a powerful framework to draw future land use scenarios in the context of changing populations. However, previous studies have focused on a regional scale (Manson, 2006; Thorn et al., 2017), and no studies, to our knowledge, have developed and compared national-scale future land use scenarios associated with population projections (but see Alig, Kline, & Lichtenstein, 2004, which simulated change in U.S. urban land).
Diverse land use change models have been developed to analyze interactions between driving factors and land use changes and to predict future land use changes at various scales (Dietzel & Clarke, 2007; Lin, Chu, Wu, & Verburg, 2011; Verburg & Overmars, 2009; Verburg, Ritsema van Eck, de Nijs, Dijst, & Schot, 2004). Most existing land use models use process-based approaches (Dietzel & Clarke, 2007; Verburg et al., 2004) and have been developed for countries with population growth expressed by a simple Markov process (Dietzel & Clarke, 2007; Verburg et al., 2004). Some have explicitly incorporated the relationship between land use and demographic dynamics, especially in countries with population growth (Li et al., 2015; Luo, Xing, Wu, Zhang, & Chen, 2018). However, population "shrinking" involves more complex processes and is not always explained by a simple mechanism (but see Verburg & Overmars, 2009). A machine-learning approach (Castella, Kam, Quang, Verburg, & Hoanh, 2007; Faleiro, Machado, & Loyola, 2013; Li & Yeh, 2002; Verburg et al., 2002) is a powerful alternative tool that can be used to develop a national-scale predictive land use model under depopulation. This approach can accommodate complex and spatially heterogeneous relationships between population distributions and land use patterns, and models can be selected with high predictive ability (Lin et al., 2011; Verburg et al., 2002). Moreover, this approach can be used to identify complex processes from spatial patterns in land use changes under a "shrinking" population that cannot be expressed by simple mechanisms.

In the 21st century, Japan has become one of the most depopulating countries in the world. Even before the detection of these problems at a national scale, Japan experienced a rapid population decline and land abandonment regionally after the late 1950s to 1960s. In rural areas, traditional agricultural landscapes have been altered by land abandonment and agricultural intensification, which is a major threat to biodiversity (Fukamachi, Oku, & Nakashizuka, 2001). Urban areas in Japan have experienced both sprawl to the suburbs and the hollowing of old residential areas. To promote urban renovation to develop compact cities, the Japanese government established the Location Optimization Plan System in 2014, under the Act on Special Measures concerning Urban Reconstruction. As of May 1, 2018, 161 municipalities have announced their own location optimization plans (http://www.mlit.go.jp/toshi/city_plan/toshi_city_plan_fr_000051.html). Although a growing number of cities in Japan have set the compact city as a city planning goal under population decline, residents do not always respond positively to excessive population concentration (Tanaka, Iwamoto, & Nishina, 2014). In such a situation, social consensus about the desirable population and land use gradients in rural and urban areas is not established.

In this study, we developed land use change scenarios for 2015–2050 under a shrinking population in Japan by applying the PPAP-LM and evaluated the effect of population distribution on future land use structure. We applied the model to two feasible spatially explicit population scenarios: centralization and decentralization (Ariga & Matsuhashi, 2012). We compared the consequences of different patterns of population distribution on future land use structure. We made the projected high-resolution land use available online (https://doi.org/10.17605/OSF.IO/A9QVY). It can be used to predict the effect of land use changes on biodiversity and ecosystem services.

## METHODS

PPAP-LM is a machine-learning approach used to project a high-resolution land use change trajectory corresponding to a population change scenario. It consists of the following three phases: pre-processing of data, construction of land use models, and projection of future scenarios (Figure 1).

### 2.1 Study area

The study area was Japan, an archipelago consisting of 6,852 islands with a total land area of 377,972 km² (Statistics Bureau, Ministry of Internal Affairs and Communications, 2017). Approximately 66.3% of the land is covered by forest, 11.9% is cultivated land, and 5.1% is developed (Statistics Bureau, Ministry of Internal Affairs and Communications, 2017). The total population of Japan in 2015 was about 127.01 million. One-third of the
population resides in and around Tokyo, which is the capital and is situated on the central plain. Greater Tokyo is the most populous metropolitan area in the world. Between 2010 and 2015, the population of Japan declined by 0.96 million, the first such occurrence since the Population Census began in 1920 (Statistics Bureau, Ministry of Internal Affairs and Communications, 2017). The population is expected to drop to 86.74 million by 2060 (National Institute of Population and Social Security Research in Japan, 2012). Japan is divided into 47 prefectures and has a total of 1,741 municipalities.

2.2 | Data description

Data were based on 30” lat. × 40” long. ca. 1-km grids (Tertiary Mesh Units, TMUs: 367,705 units) covering the whole Japanese archipelago because most statistical information prepared by Japanese administrative agencies are recorded at this scale. TMUs enable analyses of different statistical surveys without being constrained by differences in survey area. A summary of explanatory variables, variable names, and data sources used for the PPAP-LM approach is provided in Table 1.

2.2.1 | Longitudinal land use data at a national scale

The “Land Utilization Tertiary Mesh Data” in the National Land Numerical Information (National Land Information Division, National Spatial Planning and Regional Policy Bureau, Ministry of Land, Infrastructure, Transport and Tourism of Japan, 2015) for 1976, 1987, 1991, 1997, 2006, 2009, and 2014 were used as longitudinal land use data. Land cover classifications were based on satellite images compiled in TMUs. Each record included areas (m²) of 12 land cover types in a TMU calculated from a 100-m resolution land use map. Since the definition of some land use categories varied among survey years, these classifications were integrated into eight common categories.
comparable among years: paddy field, forest, wasteland, built-up area, trunk transportation land (including roads and railways), waterbody (including beaches), golf courses, other agricultural land (including fields and orchards), and other artificial land. Other artificial land was defined as artificial land use, except for agricultural land and built-up areas, such as green space in urban areas, athletic fields, open space on factory sites, schools, and port areas.

To apply a PPAP-LM approach to the land use change model, a set of land use data and population data for the same time periods is required. Therefore, longitudinal land use maps with irregular intervals (1976, 1987, 1991, 1997, 2006, 2009, and 2014) were transformed to maps for the years with available population data (i.e. 1980, 1985, 1990, 1995, 2000, 2005, and 2010). Inverse time-weighted interpolation was applied to time-series data, which is analogous to inverse distance-weighted interpolation applied to spatial data (Figure 1). The calculation process was as follows. Let \( \hat{u}(t,s,v) \) be an interpolated value for land use type \( v \) at TMU cell \( s \) in year \( t \) based on observed samples, \( u(t_i,s,v) \) in year \( t_i \), \( i = 1, 2, \ldots, N \) was calculated as follows:

\[
\hat{u}(t,s,v) = \begin{cases} 
\frac{\sum_{i=1}^{N} u(t_i,s,v) w(t,s,v)}{\sum_{i=1}^{N} w(t_i)}, & \text{if } |t-t_i| \neq 0 \text{ for all } i \\
\, \ldots, & \\
\, \ldots, & \\
u(t_i,s,v), & \text{if } |t-t_i| = 0 \text{ for any } i
\end{cases}
\]  

(1)

TABLE 1  Summary of explanatory variables, variable names, and data sources used for the PPAP-LM approach

| Type               | Variable name(s) | Description                                                                 | Data source                                                                                     |
|--------------------|------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
| Population         | Pop1             | Population within focal TMU                                                | Grid-based national population census data for 1980–2010 (Statistics Bureau, Ministry of Internal Affairs and Communications, 1980, 1985, 1990, 1995, 2000, 2005; National Land Information Division, National Spatial Planning and Regional Policy Bureau, Ministry of Land, Infrastructure, Transport and Tourism of Japan, 2017) |
|                    | Pop1_p           | Population within focal TMU in previous time step                          |                                                                                                |
|                    | Pop5             | Population within 5-km radius                                               |                                                                                                |
|                    | Pop5_p           | Population within 5-km radius in previous time step                         |                                                                                                |
|                    | Pop10            | Population within 10-km radius                                               |                                                                                                |
|                    | Pop10_p          | Population within 10-km radius in previous time step                        |                                                                                                |
| Topographical      | Elv              | Average elevation (m)                                                       | Japan Engineering Geomorphologic Classification Map (Wakamatsu et al., 2005)                     |
|                    | Slp              | Average slope increment (tangent \( \theta \))                             |                                                                                                |
|                    | Rlf              | Relative relief (m)                                                         |                                                                                                |
|                    | Gm               | Geomorphologic class                                                        |                                                                                                |
| Spatial            | Lon              | Longitude                                                                   |                                                                                                |
|                    | Lat              | Latitude                                                                    |                                                                                                |
| Legacy effect      | pEx              | Proportion of excessively artificialized land use in the previous time step | “Land Utilization Tertiary Mesh Data” in National Land Numerical Information for 1976, 1987, 1991, 1997, 2006, 2009, and 2014 (National Land Information Division, National Spatial Planning and Regional Policy Bureau, Ministry of Land, Infrastructure, Transport and Tourism of Japan, 2015) |
where

\[ w_i(t) = \frac{1}{|t - t_i|^p} \] (2)

as defined by Shepard (1968). A value of \( p = 2 \) was used as the power parameter to avoid overweighting the nearest sample and to generate a smooth curve of \( \hat{u}(t, s, v) \) around \( t_i \). Through this interpolation procedure, the weighted average of the areas of the eight land use categories for each grid and each year was obtained.

### 2.2.2 | Population data at a national scale

Grid-based national population census data for 1980–2010 were used (Statistics Bureau, Ministry of Internal Affairs and Communications, 1985, 1990, 1995, 2000, 2005; National Land Information Division, National Spatial Planning and Regional Policy Bureau, Ministry of Land, Infrastructure, Transport and Tourism of Japan, 2017). The census was conducted every 5 years, and the number of residents was aggregated in the TMUs. Additionally, population data were aggregated at three distance scales, 1 (original data), 5 and 10 km, and used as explanatory variables. Although the total population in Japan increased during this period, at a local scale many rural and urban areas had already experienced a population decline. A mixture of both population trends in the training data captures the characteristics of land use changes under both a shrinking and a growing population. Moreover, population changes can have a lagged effect on land use (Veldkamp & Fresco, 1996). Therefore, populations at three distance scales in a previous time step were used as explanatory variables.

### 2.2.3 | Topographical factors

The land surface of Japan is covered by mountains, and landforms are steep and rugged. Plains cover only 29% of the land surface and are located along the seacoast. The population is heavily concentrated in these limited flat areas. Therefore, topographical factors are important determinants of the spatial distribution of land use patterns. Information from the Japan Engineering Geomorphologic Classification Map (Wakamatsu, Kubo, Matsuoka, Hasegawa, & Sugiura, 2005) was used to determine geographic and topographical features of each tertiary mesh: average elevation (m), average slope increment (tangent \( \theta \)), relative relief (m), and geomorphological class. The original 20 geomorphological classes were reclassified into four categories: lowland, diluvial upland, mountain, and volcano.

### 2.2.4 | Spatial factors

Unmeasured variables, such as climatic factors or historical events, can result in spatial autocorrelation in the prediction error (Legendre, 1993). Therefore, spatial variables were included in the models to reveal geographical trends in land use to mitigate spatial autocorrelation (Márquez, Real, Olivero, & Estrada, 2011; Nakao et al., 2014). The longitude and latitude of each tertiary mesh were included as spatial variables in the models.

### 2.2.5 | Legacy effect of excessively artificialized land use

Excessively artificialized land use may leave legacies on future land uses, such as infrastructure and contaminants, when areas become vacant (Nassauer & Raskin, 2014). Therefore, to express the legacy effect of excessively artificialized land use, the sum of the built-up area and other artificial land in the previous time step was included as an explanatory variable.

### 2.3 | Construction of predictive land use models

Classification and Regression Trees [CART] (Breiman, Friedman, Olshen, & Stone, 1984) were used to construct predictive land use models for five major land use types: paddy field, forest and wasteland, built-up area, other agricultural land, and other artificial land (Figure 1). This method has been applied in various fields, such as medical
diagnosis, meteorology, plant physiology, soil sciences, and wildlife management, and has recently been used to successfully model land use change (Du, Shin, Yuan, & Managi, 2018). CART models have various advantages: they are relatively immune to multicollinearity, robust to non-normal distributions of variables, and capable of determining complex interactions among explanatory variables, without specifying them a priori (Breiman et al., 1984). Additionally, these analyses are easy to interpret because they provide a hierarchical view of relationships among variables, allowing the identification of close correlations (Dea’th & Fabricius, 2000).

The CART model uses binary recursive partitioning, and the resulting models can be represented as binary trees. The tree is built by first including all observations together in the root node. Then, each explanatory variable is assessed in turn to determine the optimal split that divides observations into left and right descendant nodes. The fundamental idea is to select each split in a subset so that the data in each of the descendant subsets are "purer" than the data in the parent subset. Purity was calculated based on the Gini index. Optimality is defined as the split that results in the maximum reduction in the average impurity of the two (left and right) nodes. Tree construction continues until the number of cases assigned to each leaf is small or the leaf is sufficiently homogenous. However, a maximally grown tree is usually over-fitted to training data (Therneau & Atkinson, 2018). Therefore, a computational step to constrain the tree to its best size is required to avoid the problem of over-fitting. A common approach in tree-based techniques is to freely allow the maximum growth process and then prune the overgrown branches of the tree.

In this study, 90% of the whole dataset was sampled as the training dataset to construct the model, and 10% was retained as test data to evaluate the model. Then, the initial tree was built using the training dataset, allowed to attain the maximum size, and pruned by 10-fold cross-validation. In the cross-validation process, the training dataset was further divided into 10 parts; each subset was removed in turn and used as a test sample for predictions based on the remaining 90% of the training dataset. The average error rate based on 10 repeated calculations was plotted against the tree size to obtain the complexity parameter, and the optimal complexity parameter for the tree was chosen as the smallest tree with an error rate within one standard error (SE) of the minimum. By using this complexity parameter, the tree with optimal complexity was obtained (Venables & Ripley, 2002).

The final model with optimal complexity was applied to the test data. The following four frequently used measures of model accuracy were evaluated: Pearson’s r, mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). Further, to evaluate the effect of “error propagation” by using the prediction result of the previous time step as the input for the current time step, a simulation was conducted for 1985–2010 using the predicted value for the previous time step as the input for the current time step, and the predictions were compared with real data.

2.4 | Projection to future scenarios

Two future population distribution scenarios were considered: a “centralization” scenario and a “decentralization” scenario (Ariga & Matsuhashi, 2012; Matsuhashi & Ariga, 2016). These population scenarios correspond to the centralization and decentralization of a population within a municipal unit. The total population size in each municipal unit was consistent with previous municipal population projections based on the data from the Population Census of Japan and Vital Statistics of Japan (National Institute of Population and Social Security Research in Japan, 2008). Projections of population size are provided in each TMU every 5 years from 2015 to 2050. The scenario was constructed by applying the following procedures recursively for every 5-year period: (1) the population size in each TMU was projected using the cohort change ratio method; and (2) the population size was corrected with reference to a previous municipal-level population projection. For each scenario, different sets of cohort change rates over multiple initial population size classes were applied to ensure the concentration and dispersion of the population distribution. The cohort change rates were determined with reference to observed values between 2000 and 2005 in centralized and decentralized municipal units (i.e. municipal units with increasing and decreasing intra-municipal population size heterogeneity, respectively). Population size corrections were
performed by multiplying a factor by the population size projected in each TMU using the cohort change ratio method to maintain consistency with previous municipal-level population projections from the Population Census of Japan and Vital Statistics of Japan (National Institute of Population and Social Security Research in Japan, 2008). Technical details of constructing population scenarios were presented in Ariga and Matsuhashi (2012). The datasets are available in the Kankyō Tenbōdai section of the National Institute for Environmental Studies website (http://tenbou.nies.go.jp/). Our land use–population model was projected using these two population scenarios, and the projections were compared among land use models.

2.5 | Example for two municipalities with different socioeconomic environments

Two municipalities were selected as examples: Toyota city and Joetsu city. Although both of these municipalities are aiming to become compact cities, they differ in socioeconomic conditions. Toyota city is located in the center of Aichi Prefecture in central Honshu. While this city is known as the “Motor City” of Japan, because it is a world leader in the automotive industry, it has rich forests that account for about 70% of the city’s total area. The population of Toyota city in 2015 was 422,542. According to the latest population projection, the population in 2045 will be 399,672—a 30-year decline of 5.4%.

Joetsu city is located in the southwestern part of Niigata Prefecture in northwestern Honshu. Niigata Prefecture is famous for the Koshihikari variety of rice, and rice farming thrives in Joetsu city. However, the city is now facing a rapid population decline. The total population of Joetsu city in 2015 was 196,987 and is projected to decline to 143,032 in 2045—a 30-year decline of 27.4%.

3 | RESULTS

3.1 | Accuracy of the model

The accuracy of our model differed according to land use type. The model predicted the proportions of five land use types in test data with a high degree of accuracy (Table 2). Models for built-up areas, forests and wastelands, paddy fields, and other agricultural lands showed relatively high accuracies (Pearson’s $r > 0.80$, Table 2). However, the accuracy values for other artificial lands were relatively low (Pearson’s $r = 0.793$, Table 2). The result was robust to changes in the proportion of training data (Table S1). The simulation for 1985–2010 using predicted values from the previous time step as inputs for the current time step also showed high accuracy (Table S2), although the error was higher compared with that of the result using real data.

3.2 | Important variables for each land use type

The proportion of paddy field was most strongly determined by topographical factors. Among the topographical factors, paddy field was affected by geological features, occupying a large proportion of lowland and diluvial

| Table 2 | Pearson’s $r$, mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) for five land use models |
|---|---|---|---|---|
| Land use type | Pearson’s $r$ | MAE | MSE | RMSE |
| Paddy field | 0.899 | 0.041 | 0.007 | 0.083 |
| Forest and wasteland | 0.953 | 0.060 | 0.012 | 0.107 |
| Built-up area | 0.964 | 0.013 | 0.001 | 0.036 |
| Other agricultural land | 0.832 | 0.047 | 0.009 | 0.095 |
| Other artificial land | 0.793 | 0.011 | 0.001 | 0.035 |
upland areas (Figure S1). The importance of variables was then, in decreasing order, population, spatial factors, and legacy effects (Figure 2). The proportion of paddy field increased slightly as the population in the surrounding area increased and decreased as the proportion of excessively artificialized land use in the previous time step increased (Figure S1).

Similarly, the proportion of other agricultural land was most strongly determined by topographical factors in total. Among topographical factors, other agricultural land was affected by slope, and occupied a larger proportion of land in areas with a lower slope. Both paddy fields and other fields increased slightly as the population in the surrounding area increased and decreased as the proportion of excessively artificialized land use in the previous time steps increased (Figure S1). The proportion of other agricultural land increased slightly as the population in the surrounding area increased and decreased as the proportion of excessively artificialized land use in the previous 5 years increased (Figure S1).

Additionally, the proportion of forest was mostly determined by topographic factors, followed by population, historical, and spatial factors (Figure 2). The proportion of forest was high in mountain and volcano areas. The proportion of forest decreased as the population increased and as the proportion of excessively artificialized land use in the previous 5 years increased (Figure S1).

The proportion of wastelands was determined by both spatial and topographical factors, followed by population and historical factors (Figure S1). The proportion of wastelands was large at high latitudes, in low-lying areas, and in high-elevation areas.

**FIGURE 2** Variable importance (%) for five land use models: (a) paddy fields; (b) forest and wasteland; (c) built-up area; (d) other agricultural land; and (e) other artificial land. Lon, longitude; Lat, latitude; Elv, average elevation; Slp, average slope increment; Rlf, relative relief; Gm, geomorphologic class; Pop1, population within focal TMU; Pop1_p, population within focal TMU in previous time step; Pop5, population within a 5-km radius; Pop5_p, population within a 5-km radius in previous time step; Pop10, population within a 10-km radius; Pop10_p, population within a 10-km radius in previous time step; and pEx, proportion of excessively artificialized land use in the previous time step.
The proportions of built-up area and other artificial land were most strongly determined by population, followed by legacy effects (Figure 2). Topographical and spatial factors had almost no effect on these two land use types (Figure 2). Built-up area increased as population increased and also increased as the proportion of excessively artificialized land use in the previous 5 years increased. The proportion of other artificial land decreased as the population increased but increased as the proportion of excessively artificialized land use in the previous 5 years increased (Figure S1).

### 3.3 Future projection of land use change

We projected our model results using two different scenarios for the population distribution: a centralization scenario and a decentralization scenario. Paddy field and other agricultural land were predicted to decrease over time until 2050. Both land use types decreased to a greater degree in the centralization scenario than in the decentralization scenario (Figures 3a and d). In the centralization scenario, the total area of paddy field decreased by 23.5% and other agricultural land decreased by 17.1% in 2050 compared to the observed total area in 2010.

**FIGURE 3** Observed and predicted total areas of five land use types from 1985 to 2050: (a) paddy field; (b) forest and wasteland; (c) built-up area; (d) other agricultural land; and (e) other artificial land. X, observed value; closed circle, predicted value in the centralization scenario; and open triangle, predicted value in the decentralization scenario.
(Figures 3a and d). In the decentralization scenario, the total area of paddy field decreased by 15.0% and other agricultural land decreased by 11.9% in 2050 compared to the observed total area in 2010 (Figures 3a and d). Forest and wasteland were predicted to increase until 2020 in both scenarios and then to diverge between the scenarios (Figure 3b). The total area of forest and wasteland increased in the centralization scenarios and was 1.4% higher in 2050 compared to 2010. However, in the decentralization scenario, the total area of forest and wasteland started to decrease after 2020 and decreased by 0.2% in 2050 compared to 2010 (Figure 3b). Total built-up area increased until 2025 in both scenarios. Therefore, it decreased in the centralization scenario but continued to increase until 2030 in the decentralization scenario. The centralization scenario showed a greater decrease (Figure 3c). The total built-up area decreased by 6.0% in 2050 compared to the observed total area in 2010 in the centralization scenario and decreased by 4.4% in 2050 in the decentralization scenario (Figure 3c). Other artificial land increased during 2010 and continued to increase over time in both scenarios. The increase was greater in the centralization scenario than in the decentralization scenario (Figure 3e). The total built-up area increased by 192.1% in 2050 compared to the observed total area in 2010 in the centralization scenario and increased by 185.6% in 2050 in the decentralization scenario (Figure 3e).

When we evaluate the change in land use at a more local scale, we can see the difference in the spatial distribution of each land use type between the two population scenarios. In Toyota city, where the total population is predicted to remain constant, built-up area expanded, especially in the decentralization scenario (Figure 4). Simultaneously, the proportion of paddy fields surrounding the densely inhabited district declined. Forest and wasteland decreased at the grid cell scale in which built-up area expanded. These trends were also obvious in the decentralization scenario. In Joetsu city, however, paddy fields decreased not only in the area surrounding the densely inhabited district, but also in the area dominated by forests, especially in the centralization scenario (Figure 5). In these areas, forest and wasteland expanded in the centralization scenario, while land use types related to human activity (such as paddy fields, other agricultural land, and built-up area) remained steady (or even increased) in the decentralized scenario.

4 | DISCUSSION

In this study, we applied a machine-learning method to construct a predictive land use model and applied it to two distinct scenarios for future spatially explicit population projections: centralization and decentralization scenarios. Our model successfully predicted land use changes in 1985–2010 in Japan with high performance (Table 2), indicating the effectiveness of the machine-learning method for predicting land use change. Land use models usually combine remote sensing data, socioeconomic data, and other parameters to obtain high accuracy (e.g. Li et al., 2015). However, our PPAP-LM approach enabled us to obtain high accuracy with comparatively simple variables. This might be attributable to the use of the CART model based on if–then rules, which can capture qualitative aspects of human knowledge and reasoning processes underlying decisions contributing to land use change (Sadok et al., 2009).

The total areas of paddy field and other agricultural land were predicted to decrease over time, especially in the centralization scenario (Figures 3a and d). In Japan, ownership transfer of agricultural land is restricted by the Agricultural Land Act, and efforts aimed at the relocation and accumulation of agricultural land are insufficient, although the area of agricultural land per farmer is small. Therefore, if a farmer leaves and becomes an absentee landowner, their lands tend to become abandoned (Kubo, 2011; Suginaka, 2005). These specific problems in the Japanese land system may promote land abandonment at a large scale, especially in rural areas. In these areas, promoting further migration from rural to urban areas (the centralization scenario) may cause a rapid decrease in land use related to agricultural activities in rural areas. Conversely, promoting backward migration from urban to rural areas (the decentralization scenario) may prevent the decline in land use related to agricultural activities in rural areas.
FIGURE 4 Example of results for Toyota city, Japan. Proportion of land use in 2010 (left panel), 2050 in the centralization scenario (middle-left panel), difference between 2050 in the centralization scenario and 2010 (middle panel), 2050 in the decentralization scenario (middle-right panel), and difference between 2050 in the decentralization scenario and 2010 (right panel). (a) Paddy field; (b) forest and wasteland; (c) built-up area; (d) other agricultural land; and (e) other artificial land. Maps were generated using QGIS v.2.10.1-Pisa (http://qgis.org/ja/site/)
While forest and wasteland increased in areas with a low proportion of excessively artificialized land (like typical rural landscapes), other artificial land increased in areas with a high proportion of excessively artificialized land (like typical urban landscapes). These asymmetric changes suggest a “legacy” effect of artificial land use under a population decline, as expressed by the effect of the proportion of excessively artificialized land use in the previous 5 years in our model. The proportions of paddy fields, forest and wasteland, and other agricultural land were negatively correlated with this variable, while the proportions of built-up area and other artificial land showed positive correlations (Figure S1). Generally, agricultural land and forest in urban fringes are exposed to severe development pressure and tend to be converted into non-agricultural land use (Nakahara & Hoshino, 2006). Previously (during population growth periods), built-up area increased as the population increased in urban areas, and this increment was associated with a decrease in other land use types in surrounding areas. When the population starts to decrease, a “legacy” effect of previous artificial land use may remain; “rewilding” may not occur naturally in areas that experienced intense artificial modification.

Although the total population was the same in the two scenarios, the total built-up area became smaller in the centralization scenario than in the decentralization scenario (Figure 3c). This result may reflect the efficient use of built-up area by a concentrated population in the centralization scenario, which supports the longstanding compact city theory (Holden & Norland, 2005). Therefore, the centralization scenario may be more effective for the prevention of the loss of agricultural land and forest due to sprawl in the fringe regions of urban areas, such as Toyota city.
FIGURE 5  Example of results for Joetsu city, Japan. Proportions of land use in 2010 (left panel), 2050 in the centralization scenario (middle-left panel), difference between 2050 in the centralization scenario and 2010 (middle panel), 2050 in the decentralization scenario (middle-right panel), and difference between 2050 in the decentralization scenario and 2010 (right panel). (a) Paddy field; (b) forest and wasteland; (c) built-up area; (d) other agricultural land; and (e) other artificial land. Maps were generated using QGIS v.2.10.1-Pisa (http://qgis.org/ja/site/)
On the other hand, in agricultural areas, such as Joetsu city, centralization may also accelerate the abandonment of agricultural land (Figures 5a, b, and d). In this situation, promoting the expansion of agricultural land per farmer might be necessary to maintain agricultural productivity and ensure future food security.

Our model did not consider the effects of future economic and climatic changes. Incorporating our land use model with a top-down approach that accounts for economic change (e.g., Hasegawa, Fujimori, Ito, Takahashi, & Masui, 2017) may be useful for forecasting land use change under a shrinking population in the future.

**CONCLUSIONS**

Previous studies related to population distribution have focused on social aspects, such as the cost of public transportation or the amount of CO$_2$ emissions. In this study, we examined an additional aspect of the effect of population distribution: effects on land use change. Our results illustrated that the spatial distribution of a population may affect various land use types, not limited to urban areas. During a population decline, the proportions of each land use type showed complex responses according to the “legacy” of excessively artificialized land. Population
centralization may improve the expansion of forest areas and enhance carbon storage, while population decentralization may contribute to the maintenance of the cultural landscape with a mixture of forest and agricultural land use. Our results can be used to analyze the effect of future population distributions via land use changes, such as effects on wildlife or ecosystem services. Further studies are required to reveal the effects of changes in population distribution via land use change, which can provide a basis for comprehensive planning to balance rural and urban development.

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