ESTIMATION OF FUTURE VACANCY RATES THROUGHOUT JAPAN USING GOVERNMENT STATISTICAL INFORMATION

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ABSTRACT: The increase of vacant houses is a problem occurring in developed countries including Japan, potentially causing adverse effects on local communities and leading to imbalances in housing prices. In Japan, various measures have been taken to address this problem. However, conducting field surveys to understand the actual conditions of vacant houses is difficult to repeatedly implement across a wide area, due to the significant time and cost burden. In addition, in our interviews with several municipalities, we discovered a high demand for forecasts of future numbers of vacant houses, which are considered essential data in developing countermeasures for vacant house problems. Also, while most previous estimates primarily focused on the macro perspective of prefectural units, there has been a growing demand for estimates at a more micro scale, specifically at the municipality units. In this study, we utilized open data from the Population Census and the Housing and Land Survey, uniformly aggregated at a national level, to develop a machine learning model using LightGBM for predicting future proportions of poorly managed vacant houses at the municipal level throughout Japan. Specifically, we adopted variables such as population, age, and housing structure data obtained from the Population Census as explanatory variables, and we identified the 'other residences' from the Housing and Land Survey, likely to be poorly managed, as our dependent variable. This model enables us to predict with high precision the vacancy rates for each municipality three and eight years into the future, extending our predictions up to 2028. In addition, the Housing and Land Survey is a sample survey, and for municipalities with a population of less than 15,000, the survey results have not been disclosed due to the small sample size. Therefore, there is almost no statistical data on vacant houses in these municipalities. However, by extrapolating the explanatory variables of these municipalities into our prediction model, we can estimate current and future vacancy rates in all municipalities nationwide including these municipalities with small populations. We also developed an environment where various stakeholders and researchers can view and use our estimation results by publishing these estimation results on WebGIS. It is expected that the environment will provide important reference information that can assist in formulating measures against the vacant house problem in municipalities throughout Japan.

1. INTRODUCTION

1.1 Background and Objective

The emergence and increase of vacant houses is currently a problem in many developed countries, including Europe, the United States, and Japan (Baba and Asami, 2017; Bernt, 2009; Couch, 2013; Silberman, 2013). It has been pointed out that the reasons for the occurrence of this problem are due to the shrinking of cities, oversupply of housing, and social backgrounds such as low birthrate, aging population, and population shift to large cities (Haase, 2013; Zou and Wang, 2020). In Japan, the number of vacant houses reached a record high of about 8.49 million (about 13.6%) in 2018, especially about 3.49 million (about 5.6%) vacant houses with no residential purpose that are possibly mismanaged (Ministry of Land, Infrastructure, Transport and Tourism Housing Bureau, 2022), and this situation is expected to continue. There are various types of vacant houses, ranging from houses for secondary use, houses in circulation, and houses at risk of collapse. Therefore, it is not possible to treat them all in the same way. However, vacant houses, especially those that are not properly managed, pose the risk of deteriorating the living environment of the surrounding residents, such as risk of collapse in the event of a disaster due to aging, deterioration of public health, obstruction of the landscape, and deterioration of public safety and may also lead to a decline in the attractiveness of the entire community (Baba and Hino, 2019). Therefore, local governments have long been aware of the condition and geographical distribution of vacant houses and have had to take some measures to deal with them.

Therefore, the national and local governments in Japan have been promoting various efforts to address the problem of vacant houses. A representative example is the enforcement of the “Act on Special Measures concerning Promotion of

Measures for Empty Houses” in May 2015 (Ministry of Internal Affairs and Communications, 2019). The Law defines vacant houses that are not properly managed as "specified vacant houses" and allows for advice and recommendations to the owners for proper management, and in some cases, administrative enforcement. In addition, the Law requires local governments nationwide to formulate plans for vacant houses and promote measures comprehensively and systematically. The enforcement of this law has resulted in an increased interest in vacant house countermeasures by local governments, which have begun to confirm the location and condition of vacant houses, require owners to take appropriate measures, and promote the use of vacant houses.

Several years passed since the enforcement of this law, and the authors conducted interviews with several municipalities to understand the status of measures against vacant houses. All of the municipalities were reportedly pressed to respond to complaints about vacant houses from residents due to a decrease in the number of staff members in charge and a rapid increase in the number of vacant houses. In addition, the surveyors conduct periodic visual inspections of vacant houses to ascertain their actual condition, but this is a costly and time-consuming process. In other words, it is clear that inefficient and only symptomatic measures are being taken.

The estimation of future changes in the number of vacant houses and their spatial visualization in GIS may be useful in formulating concrete plans based on the estimation results and in guiding the selection of priority areas for vacant house countermeasures. In other words, it is expected to be very useful in preventing the number of buildings in danger of collapse. According to local government officials, this product has been positively evaluated for its ability to improve operational efficiency. In addition, the product is suggested to be useful as a method to promote EBPM (Evidenced Based Policy Making), which facilitates urban planning by proposing policies based on the data obtained from the estimation results and proposes areas to be addressed based on the understanding of residents, whereas inefficient surveys have been conducted so far based on all-count surveys or individual experiences.

Based on the above, the objective of this study was to construct an estimation model of the vacant house rate for the future in three years and eight years in each municipality in Japan, utilizing the Population Census and the Housing and Land Survey, targeting vacant houses that are not intended for habitation with the possibility of mismanagement, and to clearly indicate areas where priority should be given to vacant house countermeasures. In addition, by analyzing the features that contributed to the prediction of the machine learning model and understanding the spatial distribution of the importance of countermeasures, it was possible to visualize the influence of which features and to what extent, and to understand and discuss the characteristics of areas where vacant houses are likely to occur. These efforts are expected to contribute not only to improving the operational efficiency of local governments, but also to solving various social issues such as crime prevention and disaster prevention.

1.2 Previous Studies

As awareness of the vacant house problem grows, research is being conducted to efficiently identify and predict the location and increase in the number of vacant houses by utilizing various types of data. For example, Yamashita and Morimoto conducted a logistic regression analysis to predict vacant houses in Utsunomiya City, Tochigi Prefecture, using fixed asset registers and water usage data (Yamashita and Morimoto, 2015). However, this method defined all properties that were discontinued or suspended in water usage data as vacant houses. These conditions might change over time, necessitating verification of whether they were appropriate. Moreover, sufficient discussion relatively was not made regarding the accuracy of vacant house prediction. Sayuda et al. (2022) and Tomita et al. (2022) have conducted a study on the estimation of vacant houses by building using water consumption data and basic resident registers owned by local governments. In these reports, although the technology for accurately predicting vacant houses per building was established, some municipalities found it difficult to provide their own data, including basic resident registers, for the protection of personal information, making it difficult to deploy the technology horizontally in other municipalities.

On the other hand, there are also some cases that have analyzed the trends in the number of vacant houses in each municipality in the target area and the factors that have contributed to the occurrence of vacant houses, utilizing existing national and municipal statistics that are publicly available. For example, Nam et al. (2016) conducted a study in Korea's Gyeonggi province and Miyazawa (2019) conducted a study in the Tama region of Japan. These studies also refer to regional characteristics such as the mechanism of vacant house generation and the factors that increased the number of vacant houses in the targeted areas. However, these studies are limited in their target areas and do not assess how important the issue of vacant houses in those areas is nationally or internationally.

In recent years, some studies have estimated the number of vacant houses using satellite images (Pan and Dong, 2021; Zou and Wang, 2020). However, the number of target buildings is small, and there are still many issues to be solved in terms of social implementation.

As mentioned above, most studies focus on past and present estimates of vacant houses and their factor analysis. However, to solve the fundamental problem of vacant houses, it is important to estimate the future number of vacant houses and develop proactive countermeasures Kanamori et al. (2015) constructed a regression model of the vacant house rate based on housing stock count data and Population Census data at the prefectural level throughout Japan. Akiyama (2015) also estimates how much vacant houses will increase in the future based on the difference from the number of dwelling units at a certain standard time based on population data until 2040. However, both studies estimated the number of vacant houses as a whole and did not focus on vacant houses with the potential for mismanagement, which should be addressed by local governments.

Finally, Akiyama and Mizutani (2023), a direct previous study of this research, used publicly available government statistics (Population Census and Housing and Land Survey) and machine learning to accurately estimate the percentage of vacant houses in each municipality eight years later. In addition, by publishing the research results on its website, the company has established a foundation for making the results widely available to the public. However, the study did not consider the effects of the nationwide consolidation of municipalities in Japan, which will be discussed in detail in Section 2.3, and did not accurately track the actual conditions in many areas. Therefore, in this study, we developed a future estimation model of the percentage of vacant houses that are likely to be unmanageable up to eight years later, taking these effects into account, and based on the actual conditions of administrative districts in Japan.

2. METHOD

2.1 Data

2.1.1 Population Census

The Population Census is conducted once every five years to assess the actual status of the population and households in Japan. We used this survey conducted in 2000, 2005, 2010, 2015, and 2020. The data obtained from this census include information on household units, such as the building and the number of children, as well as data on individual units, such as age, gender, and occupation. Since the information available to the public differs from year to year, this study is limited to the variables common to the five time points. Since the tabulation method also differs, some variables were recounted here in a format that can be used at any point in time. In addition, the census is further divided into a total number of items and multiple items within each item. Therefore, in this study, we calculated the percentage of each total number of available variables and used it for model building. For some items, there are no corresponding record in the municipality. In such cases, the missing values were complemented by 0 as not applicable. The information on how many households or persons of each attribute exist in each municipality is used as an explanatory variable. Table 1 shows the list that were finally used as explanatory variables in the machine learning model.

Table 1. List of explanatory variables on the population census in the machine learning model

Statistics	Data columns
Population and households by gender	Total population
	Total number of households
	Male ratio
Age group	Proportion of under 15 years old
	Proportion of 15 to 64 years old
	Proportion of 65 years and over
	Proportion of 75 years and over
Number of general households by the number of household members	Proportion of 1-person household
	Proportion of 2-person households
	Proportion of 3-person households
	Proportion of 4-person households
	Proportion of 5-person and above households
	Number of persons per household
Number of general households by family type (6 categories), number of persons in general households and persons per household	Proportion of households consisting only of relatives
	Proportion of nuclear family households consisting only of couples
	Proportion of nuclear family households consisting of couples and children
	Proportion of non-nuclear family households
	Proportion of households with members under 6 years old
	Proportion of households with members under 18 years old
	Proportion of households with members 65 years and over
Number of ordinary households by type of dwelling and relationship of house ownership	Proportion of households living in owned houses
	Proportion of general households living in private rentals
Number of households by construction method	Proportion of households living in detached house
	Proportion of households living in row houses
	Proportion of households living in 1-2 story apartment buildings
	Proportion of households living in 3-5 story apartment buildings
	Proportion of households living in 6-10 story apartment buildings
	Proportion of households living in apartment buildings with 11 stories or more
	Proportion of households living in other types of housing
Number of general households by economic composition	Proportion of households with agriculture, forestry, and fisheries workers
	Proportion of households with mixed agriculture, forestry, fisheries and non-agriculture workers
	Proportion of households with non-agriculture, forestry, and fisheries workers
	Proportion of households with unemployed members

2.1.2 Housing and Land Survey

The Housing and Land Survey is conducted once every five years to assess housing and residential conditions in Japan, covering all cities, wards, and towns and villages with a population of 15,000 or more. We used this survey conducted in 2003, 2008, 2013, and 2018. This survey contains the number of houses with occupied households, the number of houses without occupied households, and the number of houses under construction in each municipality, and the number of vacant houses is included among the houses without occupied households. This survey categorizes vacant houses into secondary residences, rental properties, properties for sale, and “other vacant houses”. Secondary residences are vacation houses, such as resort condominiums, and are not usually occupied, but are intended to be used temporarily during a certain period. Rental properties or properties for sale are houses that have a definite manager and are expected to be used or checked by the manager as necessary during a certain period. On the other hand, “other vacant houses” are houses that have not been occupied for a long time, are not planned to be distributed or utilized, and have been left unoccupied. In addition, when a house has been vacant for an extended period, the owner is often difficult to identify. These houses pose risks such as structural collapse and overgrowth of weeds, which can negatively impact surrounding areas. The aim of this study is to estimate the number of vacant houses that are at high risk of requiring municipal intervention, such as regulatory action or demolition, due to mismanagement. For this analysis, the vacancy rate is defined as the percentage of other vacant houses among the total number of residences. This vacancy rate serves as the target variable in the machine learning model developed in this study.

2.2 Prediction Flow

The survey years for the Population Census and the Housing and Land Survey differ by three years. Leveraging this gap, we construct a database for each municipality. This database integrates tables of vacancy rates, calculated from the Housing and Land Survey at 3- and 8-year later, with data from five time points in the Population Census. Based on the database, machine learning models are used to make forecasts as shown in Figure 1. The models are created at each point in time, 3 or 8 years in the future. If the mechanism of the occurrence of vacant houses does not change significantly, the estimated rate of vacant houses in 3 and 8 years is calculated by extrapolating the Population Census several years into the future to these models. This study evaluates the accuracy of the models by comparing the results obtained by extrapolation of the Population Census in previous years with the error in the vacancy rate obtained from the Housing and Land Survey.

2.3 Dataset Construction

The dataset for the estimation was constructed by combining the Population Census with the corresponding Housing and Land Survey after 3 and 8 years later. However, to combine both datasets, it was necessary to construct a dataset that considered the unique circumstances of mergers and divisions of municipalities in Japan. The scope of municipalities has been changing year by year due to the nationwide merger of municipalities called “Heisei no Daigappei (The Great Merger of the Heisei Era)”, which was implemented after 1999 for the purpose of establishing administrative and fiscal foundations, and the establishment of administrative districts because of the shift to ordinance-designated cities. According to the National Bureau of Statistics, the number of municipalities has increased from 3,229 in 1999 to 1,718 today (Ministry of Internal Affairs and Communications, 2010).

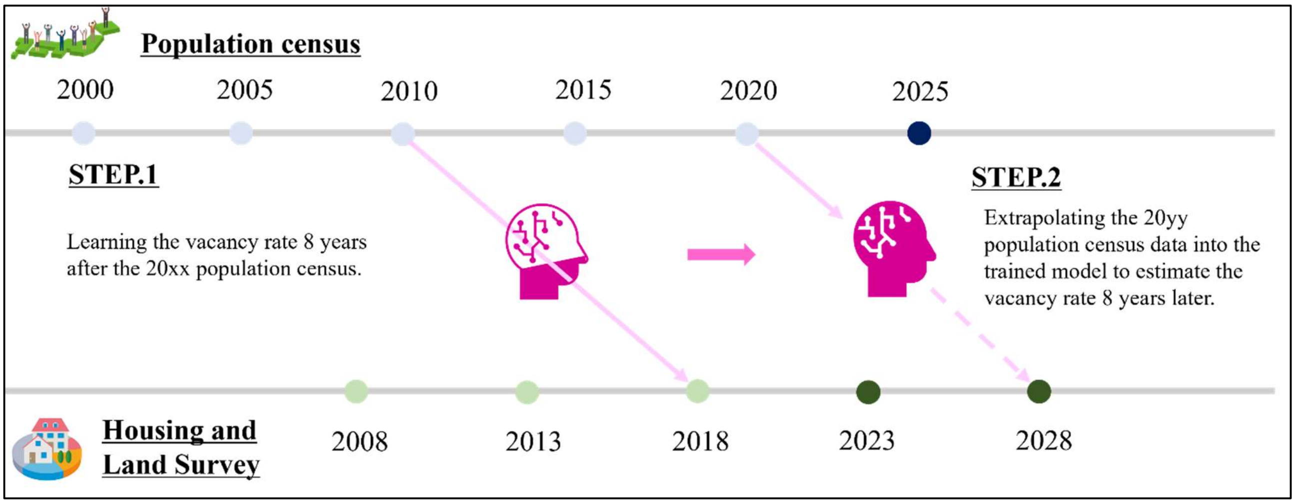

Figure 1. Building method of machine learning model and extrapolation

As shown in Figure 2, for example, the area that is currently Okayama City, the capital of Okayama Prefecture in western Japan consisted of five cities and towns in the early 2000s. By 2007, they were merged into Okayama City, which was designated as an ordinance-designated city in April 2009, and became the current city consisting of four wards. The data currently available are not updated to reflect such mergers and divisions of cities, wards, towns, and villages. For these reasons, it was difficult to make time-series estimates that were in line with actual conditions. Therefore, as shown in Table 2, we constructed an algorithm that compares the municipalities' classification as of the survey year of the targeted Population Census and the Housing and Land Survey and recounts the data at all time points and locations so that the aggregation unit includes all the municipalities. In the case in Table 2, the entire area of Okayama City as of 2008 was recounted so that it could be considered as one city district. Then, the data were combined to correspond to the Population Census and the Housing and Land Survey.

2.4 Prediction model

We used the LightGBM classification model proposed by Ke et al. (2017) for the prediction of this study. The LightGBM is a gradient boosting decision tree method that combines multiple weak learners and iteratively trains them to minimize errors; LightGBM is known to be more accurate and faster than other methods because it is “leaf-wise”, meaning it splits from the node with the lowest loss to tree by splitting from the node with the smallest loss, and to reduce computational cost by using only a portion of the data with the smallest residuals for training.

The main reason for using this method is that the gradient boosting decision tree method allows us to build more realistic predictive models. While analysis by regression analysis has the advantage of high interpretability, requiring a priori knowledge or hypotheses about the relationship between explanatory and objective variables for modeling, the tree-based algorithm has the advantage of being easy to handle because the learner makes decisions in a data-driven manner. For example, the relationship between the number of household and the number of vacant houses is not linear, and it has been shown that the probability of vacant houses differs significantly depending on whether there are more single-person households or households with two or more members (Mizutani et al, 2022). For tuning the hyperparameters, each model was explored using the Optuna (Akiba et al, 2019). Finally, predictions were made by cross-validation (3 partitioning), together with the estimation results of the respective validation data. MAE (mean absolute error), RMSE (mean squared error), and R2 (coefficient of determination) were used as evaluation indices.

3. RESULT

3.1 Evaluation

Table 3 shows the evaluation based on the 3-year forecast model and the evaluation based on the 8-year forecast model. If the year in the row and column headings in the matrix are consistent, this indicates the prediction accuracy of the data used to validate the training model. If they do not match, it indicates the prediction accuracy when extrapolated to the model constructed in the previous year. Since the purpose of this study is to estimate the future vacancy rate, no

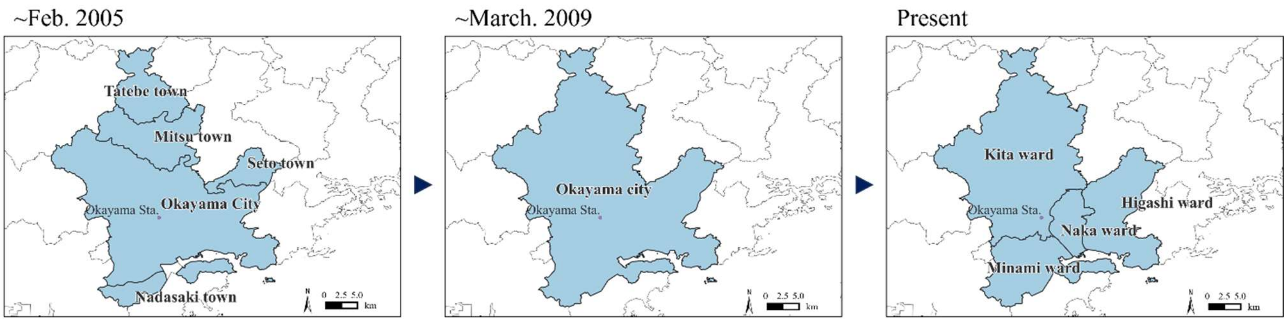

Figure 2. Changes in administrative boundary of Okayama city

Table 2. Data integration considering municipal mergers in Okayama city

2000		2008	
Municipality	Population	Municipality	Number of vacant house
Okayama city	626,642	Okayama city	21,120
Mitsu town	10,214		
Nadasaki town	15,823		
Tatebe town	6,989		
Seto town	14,707		

▶

2000		2008	
Municipality	Population	Municipality	Number of vacant house
Okayama city	672,375	Okayama city	21,120

Table 3. Result of model evaluation

3-year prediction

Learning \ Extrapo-lation	2000→2003			2005→2008			2010→2013			2015→2018		
	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE
2000→2003	**0.5386**	**0.0116**	**0.0167**	*0.6571*	*0.0134*	*0.0190*	*0.6210*	*0.0176*	*0.0251*	*0.4975*	*0.0242*	*0.0322*
2005→2008	-	-	-	**0.6863**	**0.0128**	**0.0182**	*0.7373*	*0.0148*	*0.0209*	*0.6526*	*0.0205*	*0.0268*
2010→2013	-	-	-	-	-	-	**0.7669**	**0.0139**	**0.0197**	*0.7490*	*0.0174*	*0.0227*
2015→2018	-	-	-	-	-	-	-	-	-	**0.8071**	**0.0141**	**0.0199**

8-year prediction

Learning \ Extrapo-lation	2000→2008			2005→2013			2010→2018		
	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE
2000→2008	**0.6767**	**0.0130**	**0.0184**	*0.7483*	*0.0144*	*0.0205*	*0.6686*	*0.0201*	*0.0262*
2005→2013	-	-	-	**0.7912**	**0.0132**	**0.0187**	*0.7561*	*0.0173*	*0.0224*
2010→2018	-	-	-	-	-	-	**0.8122**	**0.0141**	**0.0197**

Note.1 : XXXX→YYYY: where XXXX is the year of the population census and YYYY is the year of the prediction.
Note.2 : **Bolded values** indicate the prediction accuracy of the validation data, and *italicized values* indicate the accuracy of the extrapolation.

extrapolation back to previous years is performed. Therefore, there are some blank fields. The estimation accuracy is generally high for all models, and the extrapolation results are not significantly inferior, indicating that we were able to construct a model with superior versatility.

3.2 Analysis of estimated factors

Determining the contribution of the features in our model, we employed a method called "Shapley Additive exPlanations (SHAP)" (Lundberg and Lee, 2017) to determine the importance of the features in determining whether a house is vacant or not, and to provide support for the prediction of why the model produced such a predictive value. Figure 3 shows a beeswarm diagram of the top 10 features ordered by feature importance based on the Shap values (contribution of each feature) obtained when learning the vacancy rate from the 2010 Population Census to the 2018 Housing and Land Survey. In a beeswarm diagram, each point is an instance (each city/town/village). The more cases where the SHAP value of an instance with a high feature value (red) is positive and large, the greater the vacancy rate in the municipality where the feature value is large, while the more cases where the blue instances have positive SHAP values, the greater the vacancy rate in the municipality where the feature value is small.

We determined the correlation between the SHAP value and the size of the feature value. As a result, the figure indicates that areas with a high proportion of elderly people, areas with a high proportion of detached houses, and areas with a high proportion of one-person households tend to have a high vacancy rate. This result is consistent with the characteristics of factors contributing to the occurrence of vacant houses, which have also been identified in previous studies (Baba, 2022; Sayuda et al, 2022).

Figure 3. Beeswarm diagram of the SHAP values of the top 10 most important features

3.3 Analysis of estimated vacancy rates throughout Japan

Figure 4 shows the estimation result of the vacancy rate in each municipality in 2018, 2023, and 2028. For the estimation of the 2018 vacancy rate, the 2015 Population Census and the 2018 Housing and Land Survey were utilized. Subsequently, to project the vacancy rates for 2023 and 2028, models were constructed using two separate datasets: one with the 2015 Population Census and the 2018 Housing and Land Survey, and another with the 2010 Population Census and the 2018 Housing and Land Survey. The 2020 Population Census data was then extrapolated into each model for these estimations. According to these results, the vacancy rate is increasing in many areas in Japan. The average vacancy rate per municipality was 9.44% in 2018 and will be 12.86% in 2028, an increase of about 3.42 points. The number of municipalities with an estimated vacancy rate of 20% or more was 81 (4.27%) in 2018. However it will be 181 (9.55%) in 2028. In particular, the vacancy rate is expected to increase not only in the mountainous areas in the Chugoku, Shikoku, and Kyushu regions, where the vacancy rate is already high as of 2018, but also nationwide, excluding metropolitan areas such as Tokyo and Osaka, suggesting that nationwide measures will be necessary.

These predictions can be applied to towns and villages with a population of less than 15,000, which are outside the scope of the Housing and Land Survey. As a result, these predictions can estimate the relative vacancy rate for unsurveyed towns and villages, both in the present time and in the future.

4. CONCLUSION AND FUTURE WORKS

In this study, we constructed models using publicly available open data from both the Population Census and the housing and land survey. These models enable estimates up to the year 2028 for each municipality. Moreover, this study enables the extrapolation of the machine learning model to areas not covered by the Housing and Land Survey. This enabled us to not only estimate the state of target areas but also acquire information on vacant houses in areas where no prior data existed.

The major challenges for us include extending the estimation period, refining the granularity of estimation targets, and implementing the findings in society. At first, we aim to construct a dataset and a machine learning model that combines the 2000 Population Census with the 2018 Housing and Land Survey. We will then extrapolate the 2020 Population Census results to this model to extend our estimations to as far as the year 2038. The second is that the Population Census is currently available only at the municipal level, but the Population Census is also available at a more detailed city block level. By downscaling the Housing and Land Survey to city block levels through the Population Census and other statistical surveys, we plan to construct of a model to estimate vacant houses in city block levels throughout Japan in the future. In addition, the Statistics Data Utilization Center of the Ministry of Internal Affairs and Communications provide us with the Population Census and the Housing and Land Survey for all of Japan at basic survey level. By utilizing these data, detailed and highly versatile estimates of the future number of vacant houses throughout Japan will be realized. The third is to promote measures against vacant houses and national land planning based on the results of this estimation. As a specific initiative, we are developing a dashboard system that allows stakeholders, mainly from industry, government, and academia, to view these results on a digital map. In addition, we plan to accelerate actions to promote measures for vacant houses using the results of this study by continuing interview surveys with local governments and clarifying on-site demands. Finally, since similar statistical surveys have been conducted outside of Japan, we expect to expand the survey to other developed countries and Asian countries where the number of vacant houses is expected to increase as the population decline becomes more apparent in the future. In the future, we aim to expand the survey to regions outside of Japan where the problem of vacant houses is becoming more serious.

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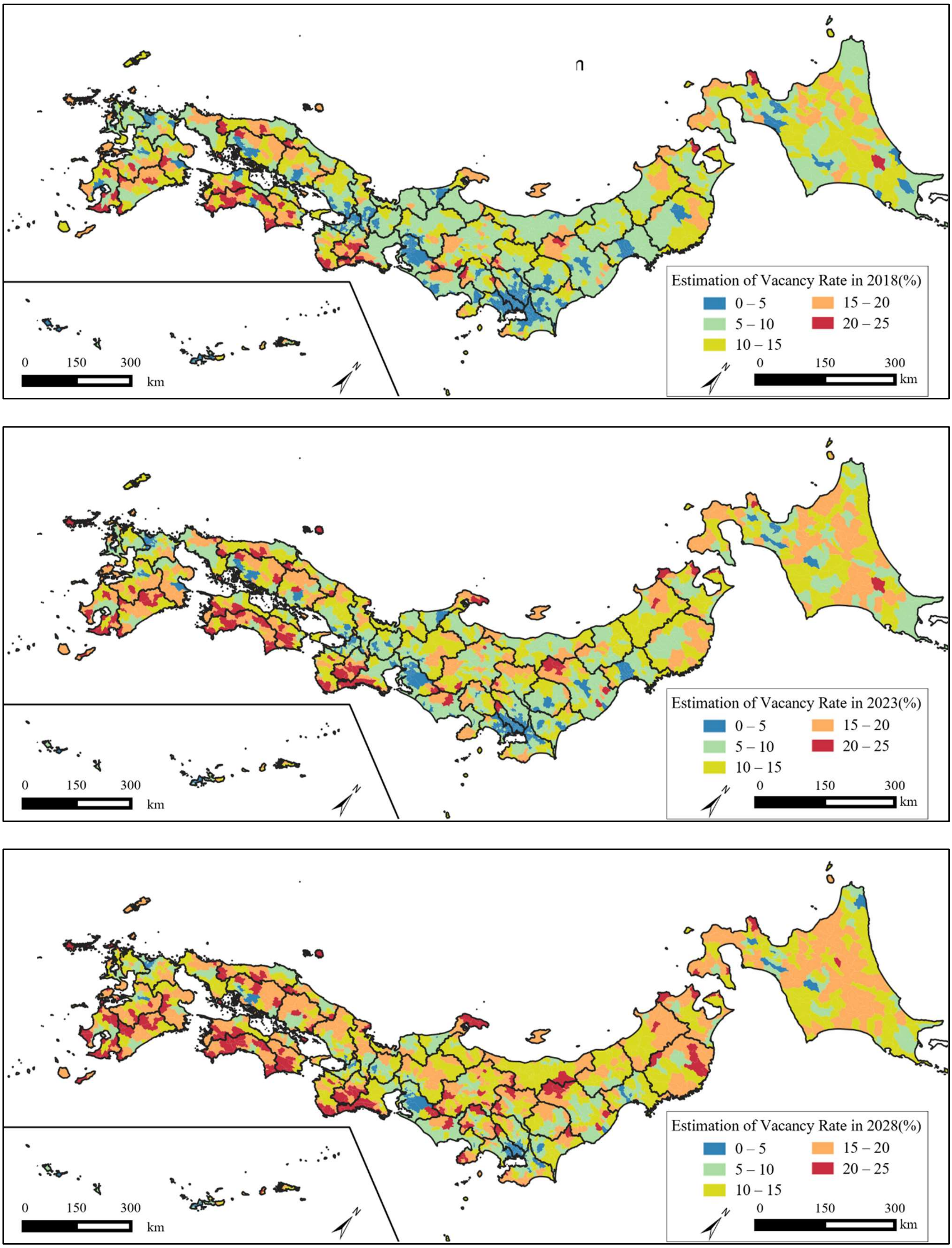

Figure 4. Estimation result of the vacancy rate in each municipality in 2018 (upper), 2023 (middle), and 2028 (lower)

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