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Development of downscaling method using the RBF network assessing the hourly population inflow: A case study of the Sapporo urban area

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A R T I C L E I N F O

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A B S T R A C T

In Japan in recent years, policies for compact cities have been promoted as the population has decreased, and the use of micro-geo data has attracted attention in urban planning. Therefore, when considering a compact city, it is important to know the relationship between the urban facility layout and the population flow. In this research, we created a data set using demographic data, location information of mobile phones, and detailed building data and used a radial basis function (RBF) network. In short, the purpose of this study was to develop a method to reduce the estimated area of population inflow per hour. Population inflow is expressed as the visiting population, which is defined by the difference in the staying population in the time of two sections. By spatially visualizing the results, we were able to downscale the population flow data on a 500 m grid.

1. Introduction

Japan has a declining birth rate and an aging population. In May 2018, the population was 126.47 million (Statistics Bureau, 2019). However, according to government reports, the population is predicted to decrease to 110.992 million in 2040 and further to 88.08 million in 2065 (National Institute of Population and Social Security Research, 2019). Regarding the reconstruction of sustainable cities in response to such social change, measures of compact cities and networks have been proposed. Compact city plans and strategies have been proposed to deal with the decreasing population problems and also focus on sustainable city development to respond to social impact. However, the most critical consideration is a compact city identification. This concentrates various functions, such as houses, public facilities, and commercial facilities, in the center of the city, creates an easy-to-move environment by walking, bicycle, or public transport, and forms an urban area (Waddell et al., 2007). For example, when considering such measures in local cities, we have to consider which types of urban facilities and buildings are to aggregate in which area and building. As a result, it is necessary to predict population flow. Besides, the amount of change in the spatial distribution of the visiting population in the case of assuming a new urban structure is essential. In this study, the visiting population is defined as the difference between the nighttime population and the population at a certain time.

On the other hand, the application of micro-geo data is demanded in the field of urban planning studies. There are several cases of research on population prediction using micro-geo data (Ballas et al., 2005; Rogers et al., 2014). One study also extracted personal and household micro-geo data from questionnaire results and constructed a model to predict the future population distribution from changes in household structure and migration place by the occurrence of life events (Sugiki et al., 2016). Another study conducted a spatial microsimulation in a suburban New Town area to predict future population from the household structure (Suzuki et al., 2016). There is also an example of research that rationally estimates agent-based households from the microsimulation of land use (Sugiki et al., 2012). These studies represent the effectiveness of micro-geo data for the future prediction of the resident population. However, there are a few cases where the subject of population flow analysis is dynamically changing in time–space and the area is subdivided. Focusing on that point, the authors estimated the visiting population by integrating multiple micro-geo data. Mainly, the visiting population in each grid, which was the objective variable determined by the mobile spatial statistics provided by NTT Docomo (2019), and the total floor area by the application, which was an explanatory variable determined by the city planning survey. For example, for the area size, the model creation was a 1 km grid and the downscaling estimation was a

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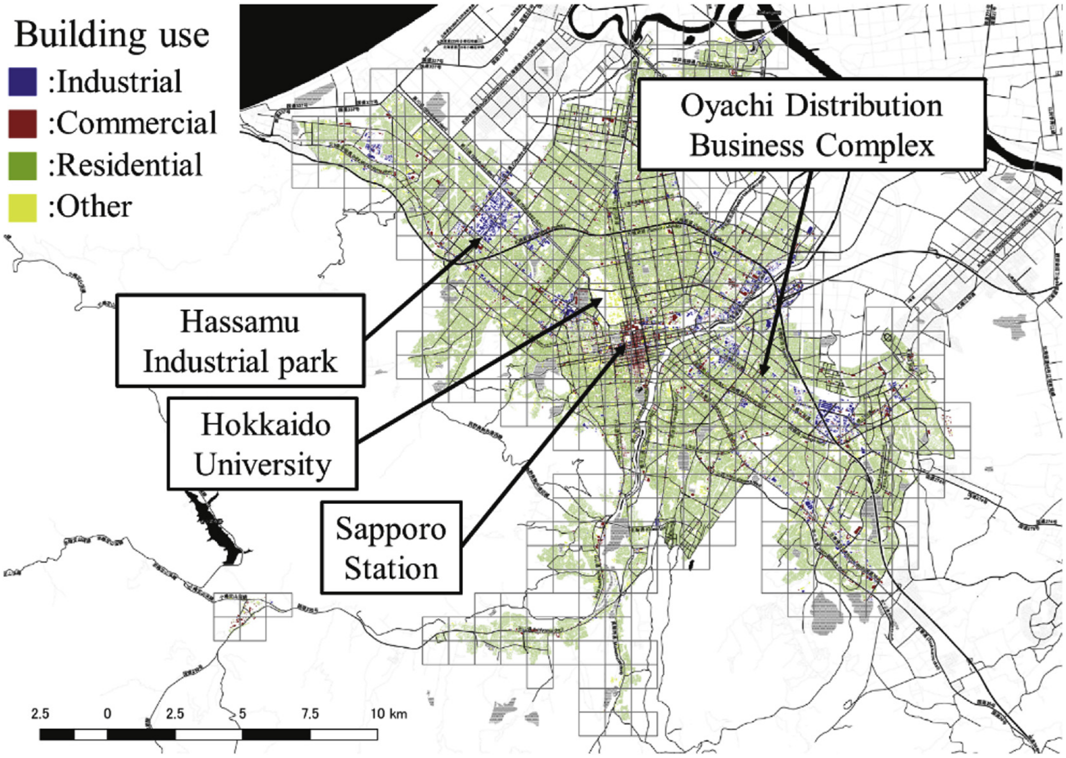

Fig. 1. Distribution of buildings in Sapporo city.

square grid of about 500 m.

In addition, multiple regression analyses have been used to clarify the types of buildings that will change the visiting population (Arimura et al., 2016). Nonetheless, in the research, multiple regression analysis was used, and only statistically significant building attributes were adopted as explanatory variables. Many attributes were discarded, and an interaction of building attributes in the grid was not taken into consideration; thus, this meant that there was a limit to the accuracy of the estimation. In addition, because detailed data of each building are recorded in the city planning survey data, it was possible to analyze these data in a more detailed area, the estimated area of the study being a 1 km grid. The purpose of our study was to estimate the visiting population in a

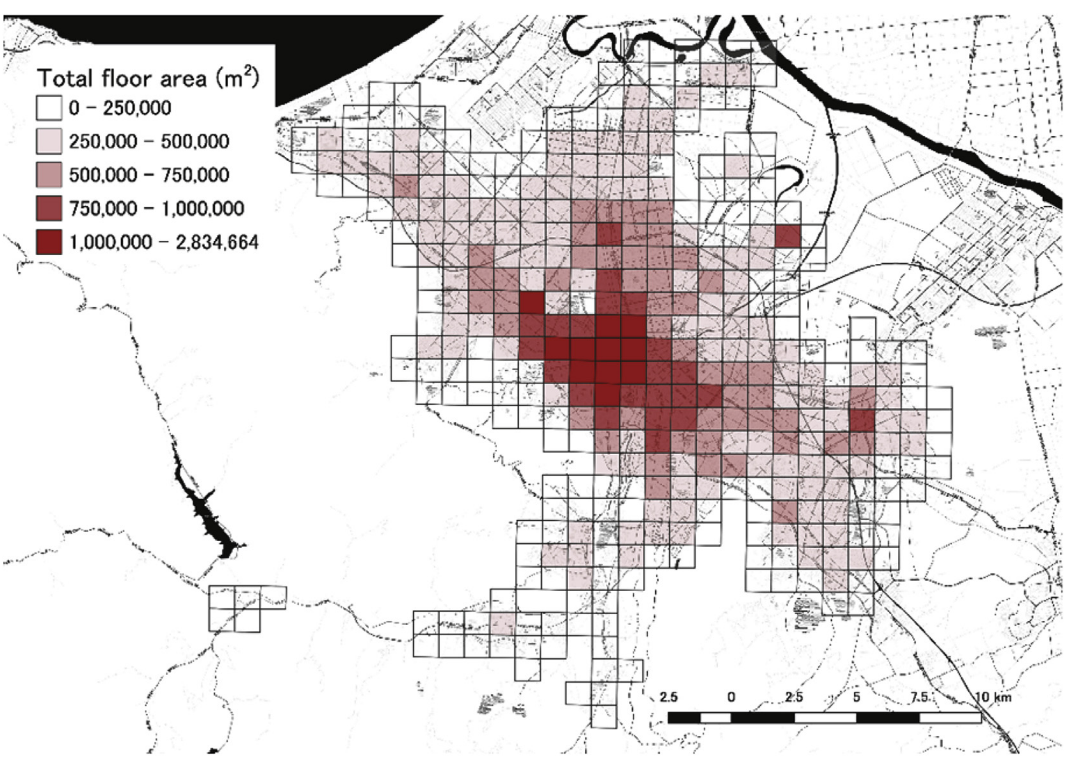

Fig. 2. Total floor area per grid.

Table 1
Building types for analysis.

Primary Classification	Secondary Classification
Commerce	Local state facilities, Local government facilities, Business facilities, Collective sales facilities, Accommodation facilities, Entertainment facilities, Club and restaurant business facilities, Amusement facilities, Sports facilities, Special store facilities
Residence	Exclusive housing, Common housing, General shop combined housing, Office combined housing, Eating and drinking shop housing, Combined with workshop housing
Industry	Light industrial facilities, Service industrial facilities, Communication facilities Domestic industrial facilities, Heavy chemistry industrial facilities, Supply processing facilities, Transportation warehouse facilities
Other	Educational facilities, Cultural facilities, Religious facilities, Medical facilities, Exercise facilities, Social welfare facilities, Welfare facilities, Memorial facilities, Agricultural facilities, Fishery facilities, Research facilities

more detailed area from building data according to use for these reasons. Hence, this research improves the estimation of the visiting population using the radial basis function (RBF) network. The visiting population estimated by constructing a model using the building on the 1 km grid was used as learning data. In other words, rather than the specific type of building, the visiting population can be estimated according to the composition pattern of all the buildings in the area. In addition, to create information in more detailed areas, the estimated value of the square grid of about 500 m adds the numerical values of corresponding four areas and compares it with the actual value of the original square grid of about 1 km to check the accuracy.

In this paper, Section 1 describes the background and purpose of this research. Section 2 explains the outline of the target city, the mobile spatial statistics, the urban planning, and the initial survey of the micro-geo data for analysis. Section 3 details the estimation model of the entrance population by time using accurate data. In addition, the downscaling of the spatial analysis and the validity of the method, which verifies the application result, are examined. Finally, Section 4 provides the conclusions of the study.

2. Data overview

2.1. Target area

The city of Sapporo, Hokkaido is a target area because it is a large city with a population of about 1.9 million people, and it is also easy to understand the movement of people. The formation of urban areas is a grid pattern, so it is easy to understand the distribution of buildings and the center of the business district area. The city of Sapporo is expected to have a declining population in the future and changes in urban structure accompanying it are also assumed (Sugiki et al., 2005). Thus, the urban planner aims to create a sustainable and compact city and, specifically, to accumulate residential and urban functions around public transport stations, such as subways and trams. It is compact city planning that makes it easy to use urban services smoothly and support the aging society movement.

2.2. Urban planning basic survey data

The urban planning basic survey is conducted and renewed approximately every five years about the items specified by Japanese laws, such as population, industry, and building. Recently, in the target area of Japan, it has mostly recorded information about building use, structure, age, total floor area, etc., and it can be used to understand the current situation and future (MLIT, 2013). It is actively used for the operation of urban planning, the land-use situation, building condition, and urban land improvement. In this research, city planning basic survey data of Sapporo city in 2017 were used for analysis.

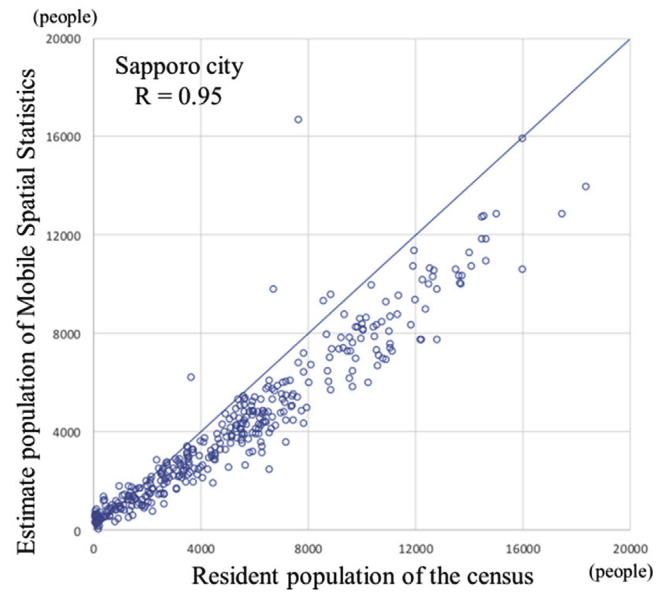

Fig. 3. Relationship between census and mobile spatial statistics.

Sapporo city is densely populated with large shops near Sapporo Station, as shown in Figs. 1 and 2. To the northwest of Sapporo Station is the Hassamu Industrial Park, which is a large industrial area, and to the southeast, there is the Oyachi Distribution Business Complex. Moreover, the data confirmed that residential buildings surround them. In this way, we could understand the structure of Sapporo from the total floor area and the different building uses. With these data, the visiting population could be estimated from the total floor area of various buildings. Therefore, the building information was compiled in the 1 km grid, which had the same scale as the mobile spatial statistics, and is described below. Table 1 shows the buildings used to estimate the visiting population. When creating a data set, we used 34 secondary classifications in the buildings using the code table of the city planning basic survey data of Sapporo city.

2.3. Estimation of visiting population by mobile spatial statistics

Mobile spatial statistics are used to estimate the population (current population) staying at certain times by area, using NTT Docomo's (NTT Docomo, 2019) mobile phone network operational data. This method is drawing attention to provide new data that can dynamically capture the population distribution by time zone. Today, the entire population of our country is about 127 million, and the entire number of subscribers of all three service providers is about 171 million. Besides, the number of NTT Docomo subscribers accounts for more than 40% of the entire 77 million cases (TCA, 2019). Because of the high penetration rate of such mobile phones and the large share of NTT Docomo, it is possible to obtain a reliable distribution of the current population. Regarding the reliability of the mobile spatial statistic method, the authors' previous research (Arimura et al., 2016) compared and verified it with the census (permanent population). This research aims to estimate the current population rather than the permanent population. Moreover, because the aggregation method differs between mobile spatial statistics and the national census, the population values do not necessarily match. However, a high correlation ($R = 0.95$) was confirmed between the census and mobile spatial statistics, as shown in Fig. 3.

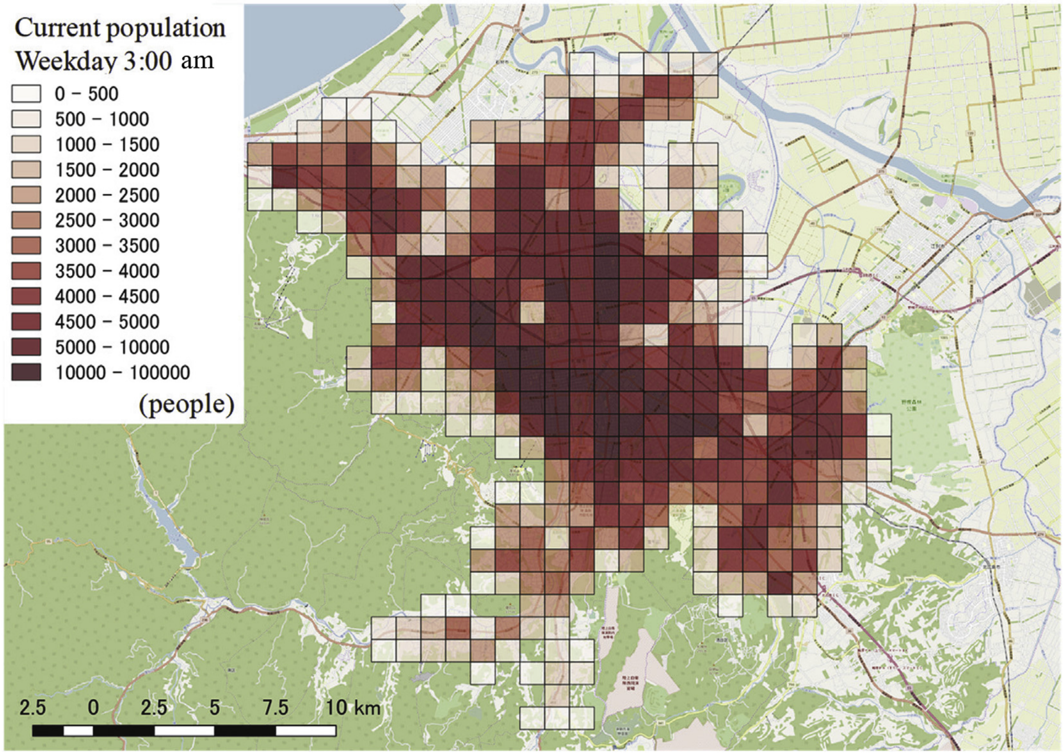

Fig. 4. Current population distribution at 3:00 am.

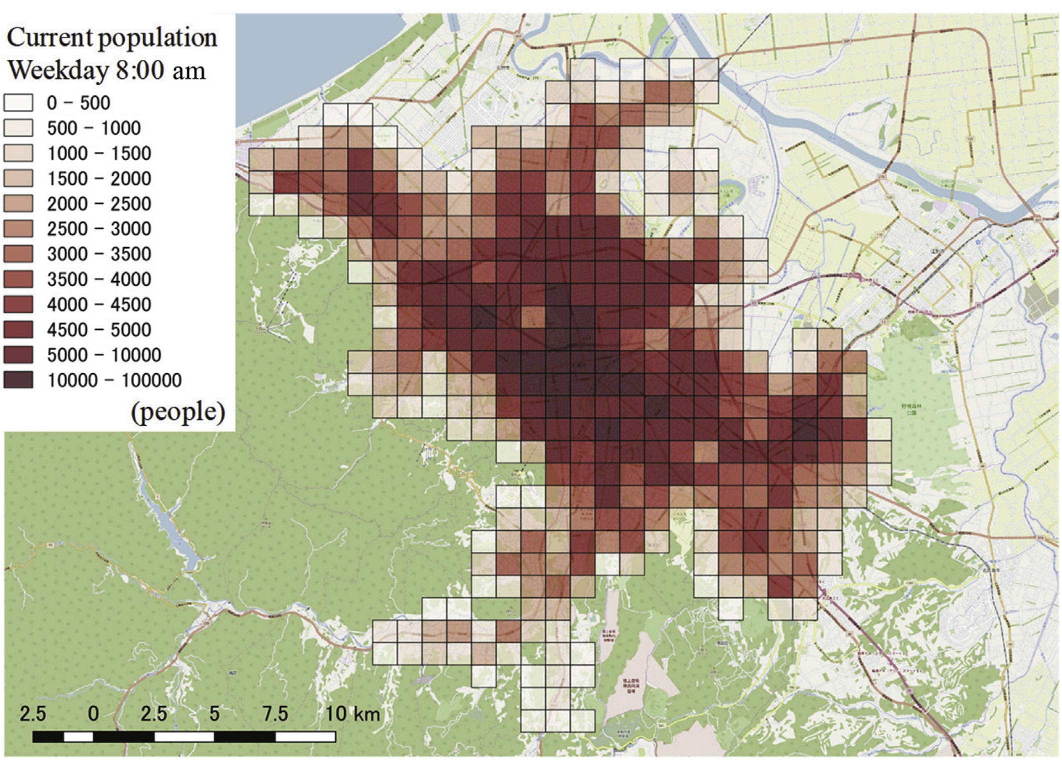

Fig. 5. Current population distribution at 8:00 am.

It can be seen in the figure that there is a grid in which there is a significant error in the current population and permanent population. It seems that the unique building of that area is affecting the cause. For example, there is a big entertainment area in front of the station. In this research, the current Sapporo city population data by the time zone of the 1 km grid on a scale (374 grids) in the range, where building information exists, were used. The data include the population at 3:00 a.m. and 8:00 a.m. on 19 October (a weekday). Figs. 4 and 5 show the current population distribution at the target time. They show that the current population was widely dispersed at 3:00 a.m., while at 8:00 a.m. it was

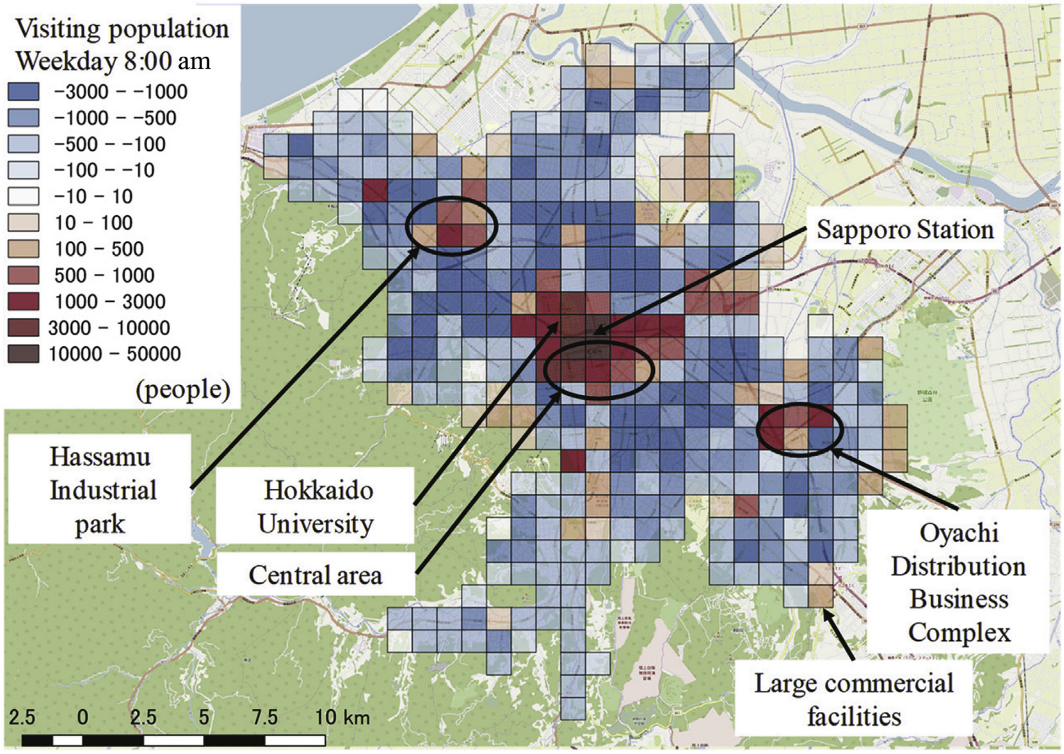

Fig. 6. Visiting population distribution at 8:00 am.

concentrated in the commercial district. The current population increased significantly from 3:00 a.m. to 8:00 a.m. in the commercial area near JR Sapporo Station. On the other hand, the area where there was little change in the current population has many residences and is occupied by buildings with a small total floor area. The difference from the current population in the late-night time zone as described above can be thought of as the visiting population at that time.

Fig. 6 shows the distribution of the visiting population, which is the difference between 3:00 a.m. and 8:00 a.m. With these data, you can understand how much the current population grows in the commercial area in the morning and moves between grids. In other words, by visualizing the visiting population, we can infer the bustle of the city according to the purpose and size of the buildings.

3. Method and result

In this study, we constructed a model to estimate the population from the total floor area data of each building, using the urban planning basic survey, and further considered the downscale method that enables estimation in more detailed space units. Then, an estimation model of the visiting population was constructed using the building data for each area and the RBF network of machine learning (Wang et al., 2014). Next, the applicable range of the model was divided by the estimation method of the visiting population using the 500 m grid.

3.1. Overview of the RBF network

The RBF network is one of the neural networks proposed as a method to complement a finite number of input and output data (Orr, 1996). The structure is composed of three layers, namely, an input layer, a hidden layer, and an output layer, and it is possible to approximate an arbitrary nonlinear function by adding weight to a plurality of the RBF network corresponding to the hidden layer (Fuchida et al., 2000). Furthermore, the RBF network has the advantage that there is no local minimum problem frequently mentioned in the multilayer perceptron and the like,

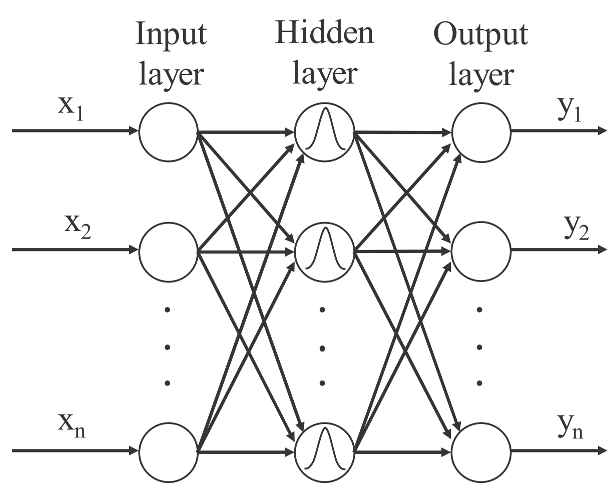

Fig. 7. Overview of radial basis function (RBF) network.

and it is possible to derive the best approximation method of arbitrary nonlinear function by the least-squares method (Yingwei et al., 1997). Besides, it has been reported that learning efficiency is superior due to the simplification of the structure, such as being able to set a smaller number of hidden layers than the sigmoid function type neural network (Moody and Darken, 1989; Hachino et al., 2008). Fig. 7 shows the structure of the RBF network. When n finite input and output data sets $[(x_1, y_1), ..., (x_n, y_n)]$ are given to the RBF network, the aim is to determine a function $y = f(x)$ that satisfies these. As an RBF of the hidden layer, Gaussian function, multiquadric, thin plate spline, etc. can be set, but in this research, the Gaussian function was adopted, which is generally used in RBF network studies (Billings et al., 2007).

Naturally, the advantages of applying the RBF network to the estimation of the population from the building attribute data in the grid are

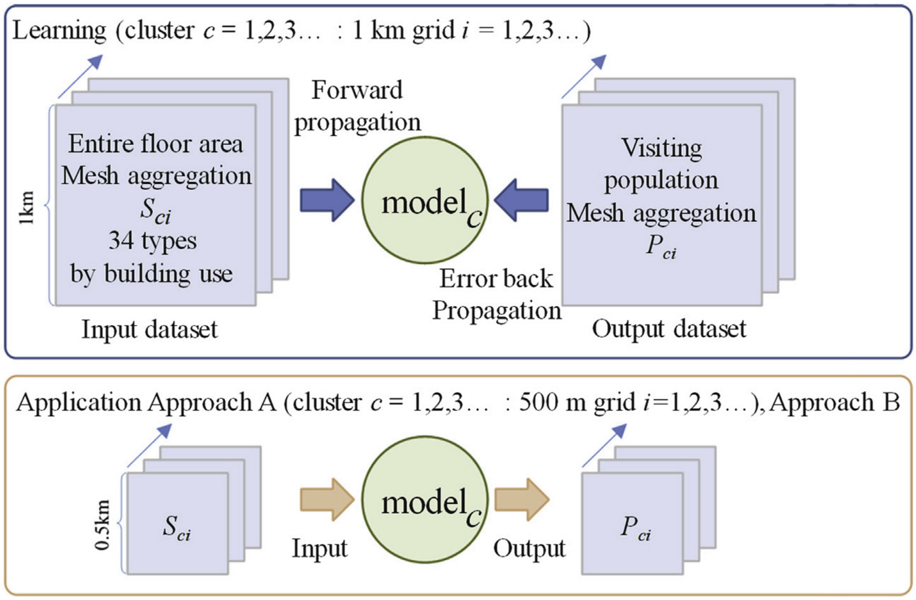

Fig. 8. Model estimating visiting population and downscaling procedure.

that the structure is simple and the learning efficiency is high. In addition, the most significant advantages are that it has a strong resistance to input noise and has an online learning ability (Yu et al., 2011). It also has the potential to learn the input data of all 34 types of building attributes recorded in the city planning basic survey data shown in Table 1, and the input data obtained by mobile spatial statistics as output data are also there. It is possible to analyze the relationship between the composition of the total floor area for all buildings in the grid and the visiting population. In the multiple regression analysis in the existing study, only the building use selected as an explanatory variable was considered. However, using the RBF network, it is possible to analyze the utilization of the total floor area of all the buildings in the grid.

3.2. Estimation of visiting population

Fig. 8 shows the outline of the estimation of the visiting population using the RBF network. First, learning of the RBF network is performed using the input data as the total area for buildings on the 1 km grid and the output data as the visiting population. In the configuration of the middle layer, it is necessary to set the number of neurons, alpha (learning rate parameter), the number of trials, etc. These settings were referenced by the authors' previous research (Asada et al., 2015) and the results of prelearning in advance. After trying various patterns, the network confirmed that the influence on accuracy was minimal, the number of trials was fixed to 1000, the learning rate parameter to 0.1, and the data were analyzed with several multiple neurons. Then, the number of neurons was determined by calculating the Akaike Information Criterion for each model.

The composition of the total floor area by building used input data that greatly varied from district to district. Therefore, it is possible that accuracy cannot be obtained satisfactorily in a model that collectively covers all districts (374 grids). For that purpose, cluster analysis (Ward's method) was applied to the total floor area data by building use areas with similar building structures clustered, and a model was constructed for each cluster.

In this research, Approach A is a method of performing, by clustering, downscaling for clusters that have similar grid characteristics, and Approach B is a method of constructing a model using whole learning data without performing clustering and downscaling (Fig. 8). They were compared, and the results for these two approaches were examined. Moreover, Approach B uses the entire training data to build the model, so

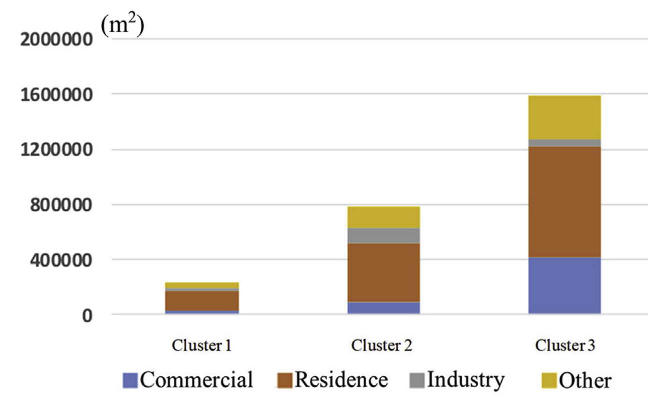

Fig. 9. The average total floor area by building for each cluster.

it takes a very long time to calculate the results.

Fig. 9 shows the average value of the total floor area for each building in each cluster. Cluster 1 is mostly residential building use and is expected to be a suburban residential area because of the small amount. Cluster 3 shows that it is the center of Sapporo city because of the large proportion of commercial buildings used compared with Clusters 1 and 2 and because of other clusters. Fig. 10 shows the geographical distribution of these clusters, i.e., the distribution of the entire large amount of buildings. Cluster 2 characterized industrial buildings more than the area roughly gathered for each cluster in the construction of the grid. Cluster 3 was found to be a commercial area around Sapporo Station. Cluster 2 was gathered from surrounding the periphery of Cluster 3, and Cluster 1 was arranged around Cluster 2. In this way, by making clusters and visualizing the spatial distribution, it was possible to confirm the formation and features of the city. In the 1 km grid, Figs. 11 and 12 show the relationship between the observed value of the mobile spatial statistics and the estimated value by the RBF network.

In Cluster 2 of Approach A, there were some areas where the area greatly deviated, but because the correlation coefficient was approximately 0.9, it can be said that the learning of the model had converged. Approach B had a high correlation coefficient of 0.97. Therefore, because the model accuracy of the tertiary scale was a high correlation between Approaches A and B, the learning converged with high accuracy.

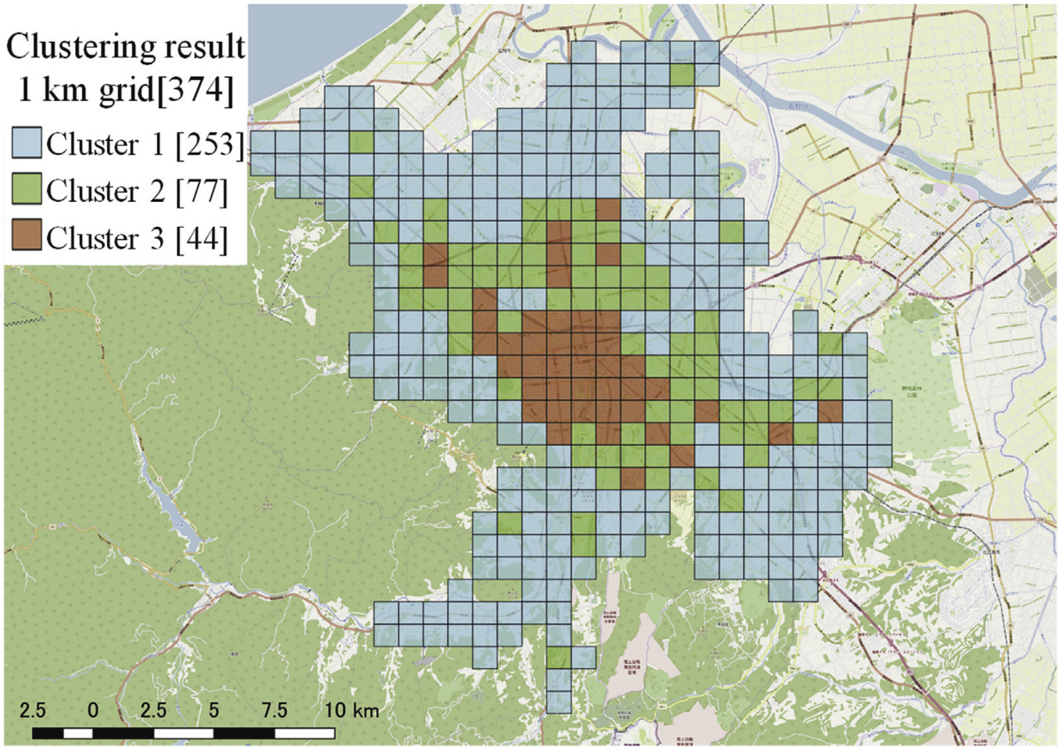

Fig. 10. Spatial distribution of each cluster.

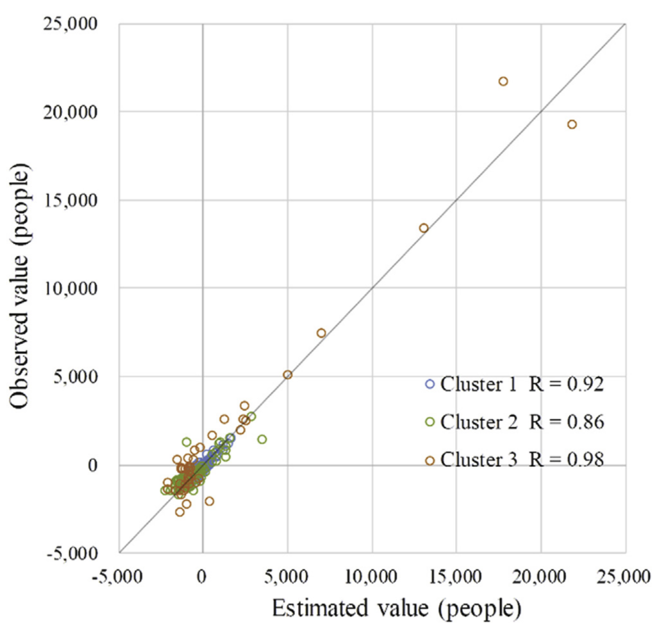

Fig. 11. Model accuracy in the 1 km grid on a side (Approach A).

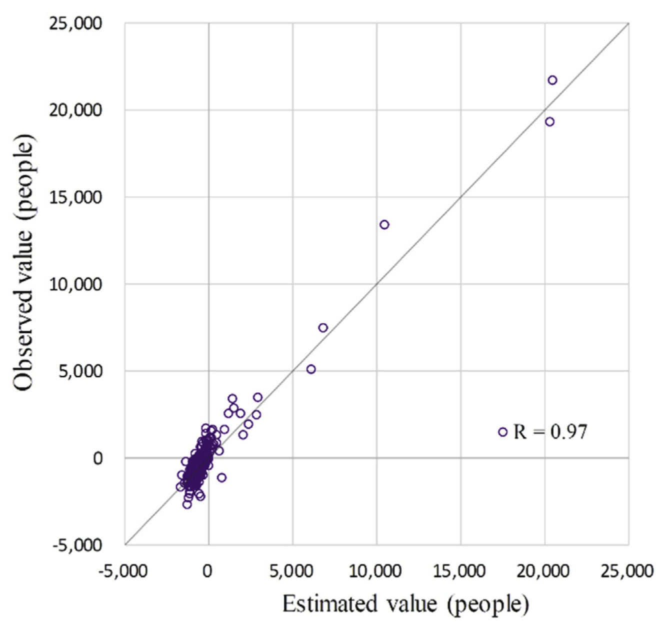

Fig. 12. Model accuracy in the 500 m grid on a side (Approach B).

3.3. Estimation of visiting population by downscaling

There is a problem with adapting the RBF network model learned with a 1 km grid to downscale to a 500 m grid. It is possible that values outside the range of the maximum or minimum floor area by building used in the 1 km grid learning data will be used as input data for the 500 m grid. In summary, it is a data extrapolation problem. To answer this question, the learning by the RBF network in this study was normalized by aligning the maximum value of the total floor area by 1 for the building and the minimum value of 0 for each cluster. The 500 m grid input data had a minimum floor area for each of the building uses of 0 square meters, and the target area was reduced to 1/4, so there was no extrapolation problem.

Next, the verification method of downscaling in this study is explained. We calculated the estimated visiting population in the 500 m grid. Noting that the 500 m grid is 1/4 of the 1 km grid, we added the visiting population of four grids corresponding to the 1 km grid and compared them. The accuracy of the estimated value was verified by the correlation coefficient between the sum and the observed value at the 1 km grid. It consisted of a 1 km grid of the data set, as seen in Fig. 13

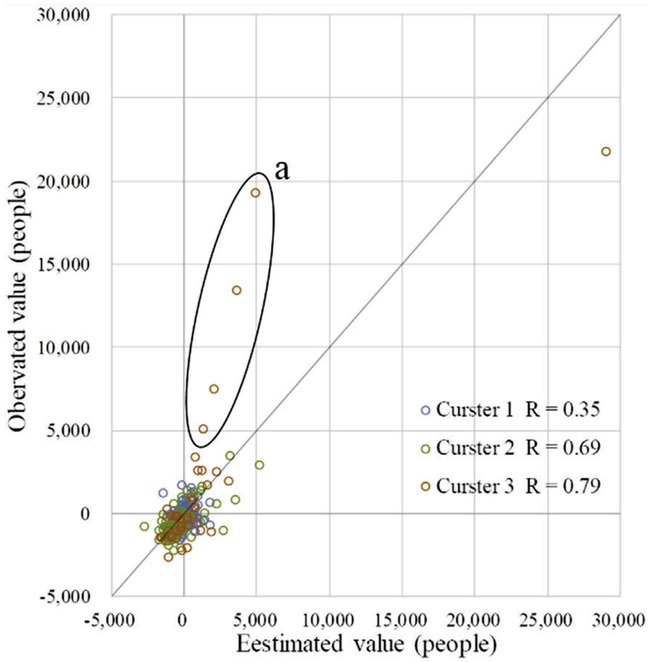

Fig. 13. Estimated accuracy of visiting population (Approach A).

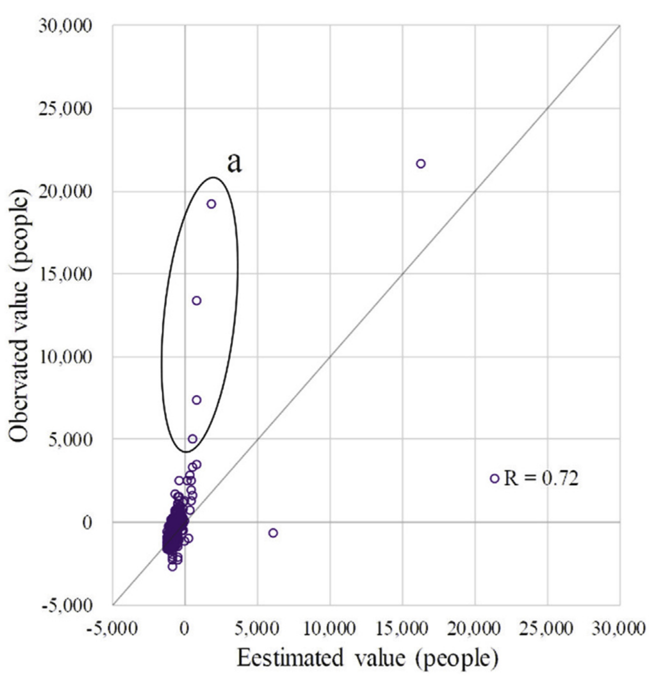

Fig. 14. Estimated accuracy of visiting population (Approach B).

(Approach A) and 14 (Approach B). Figs. 15 and 16 show histograms of the absolute error. Other statistical indicators, such as absolute mean error and root mean square error, are listed in Table 2. From there, it can be seen that Approach B had an underestimated value as a whole and that Approach A is superior for any index.

Clusters 2 and 3 of Approach A had correlation coefficients of 0.69 and 0.79, respectively, and because both were about 0.7, learning converged with high accuracy. However, Cluster 1 represented a low correlation coefficient of 0.35. The reason for this may be the influence of the composition ratio of the buildings in the grid classified as Cluster 1. As shown in Fig. 9, the entire number of buildings in Cluster 1 was

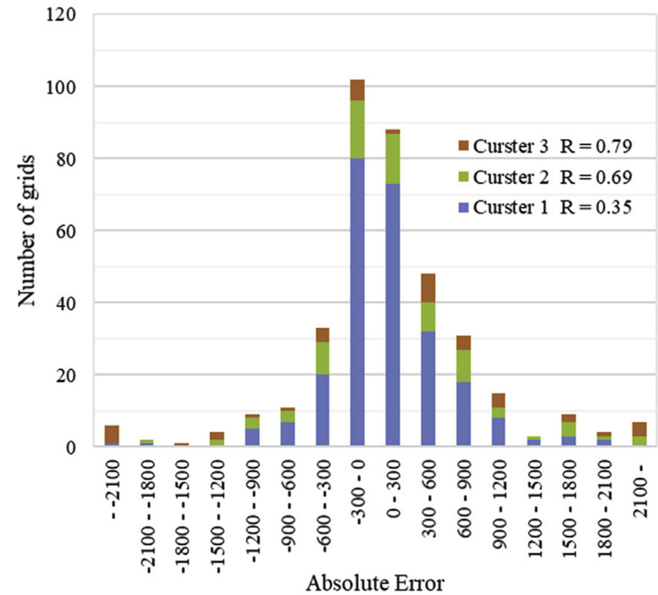

Fig. 15. Absolute error of estimate (Approach A).

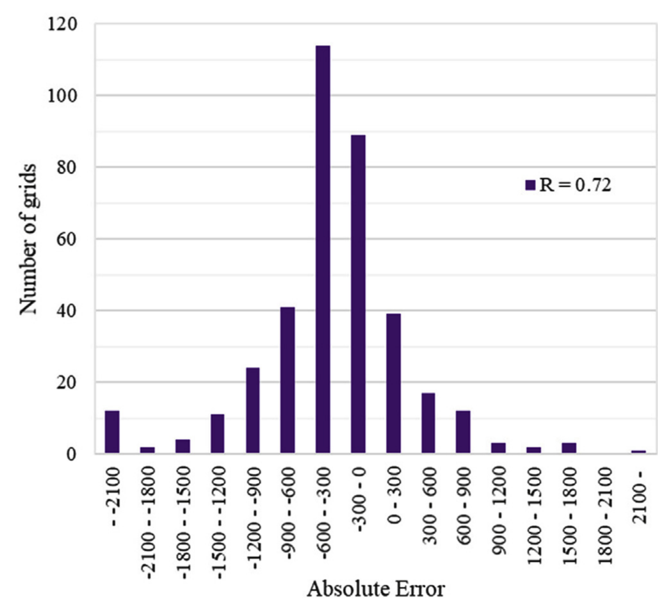

Fig. 16. Absolute error of estimate (Approach B).

Table 2
Estimated accuracy of visiting population.

	R	Average	Median	MAE	RMSE
Approach A	0.763	−65.3	−198.6	576.7	1261.4
Approach B	0.713	−611.9	−739.2	667.9	1452.5

smaller than that in other clusters, and there were many houses in the grid. For this reason, many of the visiting populations in this cluster were negative and small, so it is possible that learning was not successful with good accuracy. Because the purpose of this research was to estimate the visiting population (the difference with nighttime population) and to understand the part where the movement is significant, the error in a small range is not a big problem. However, regarding the large errors existing in both Approaches A and B, we need to investigate the composition of the building's use of the grid to improve it in the future. In

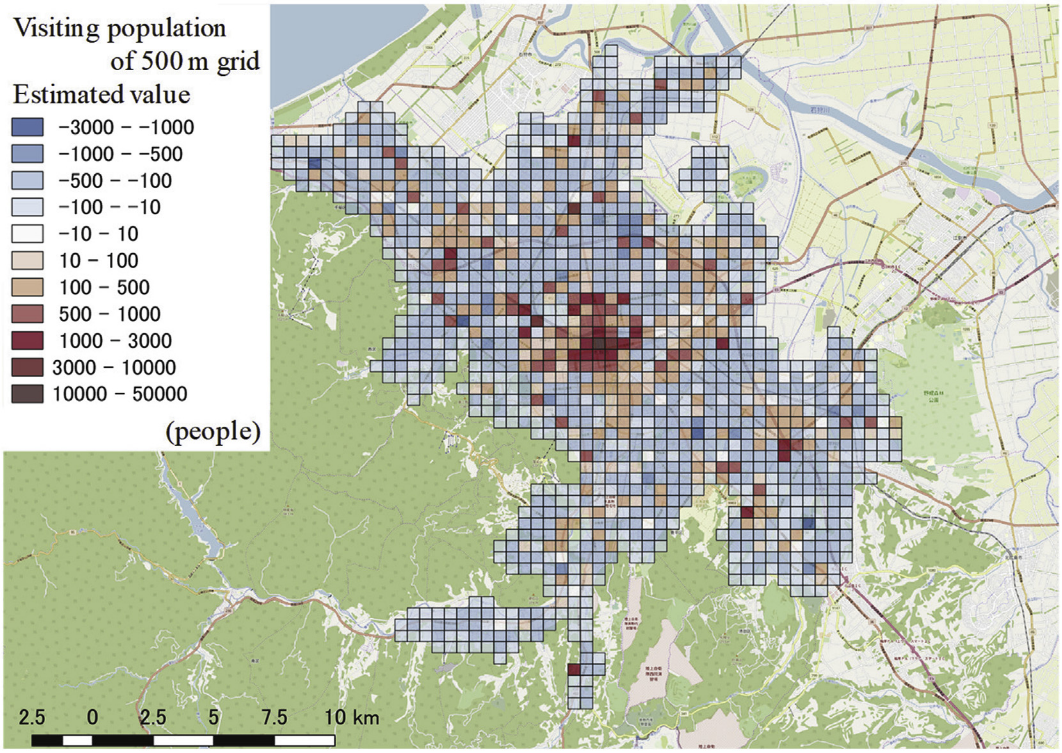

Fig. 17. Distribution of the estimated visiting population (Approach A).

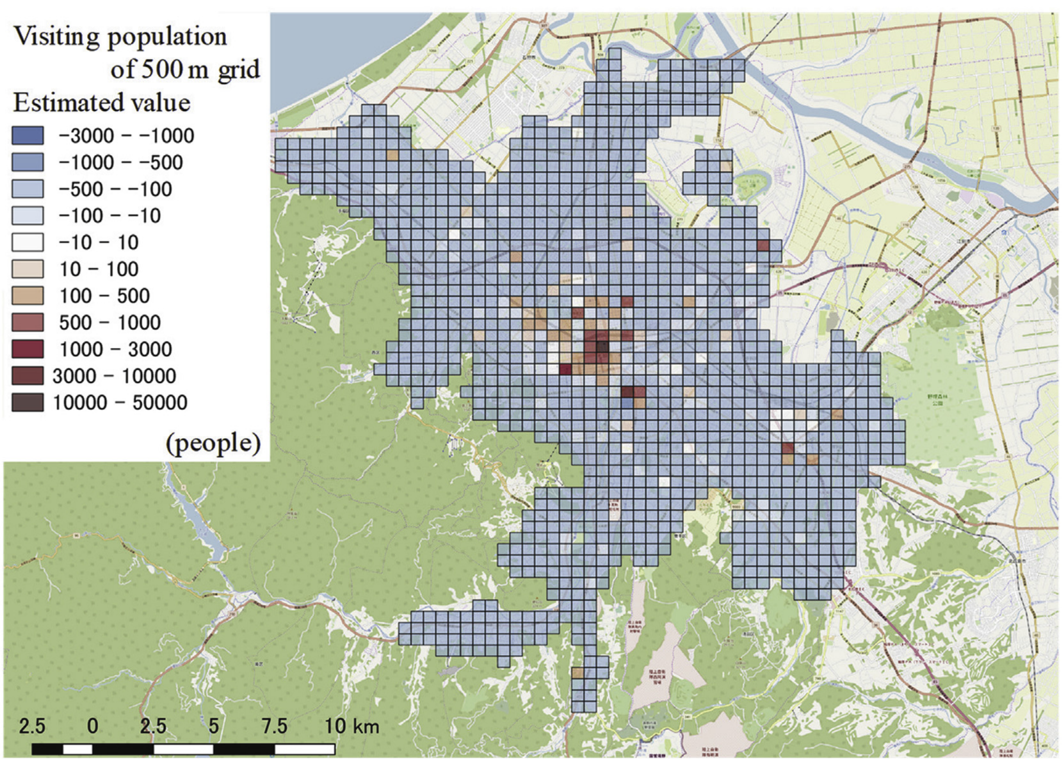

Fig. 18. Distribution of the estimated visiting population (Approach B).

particular, there are the grids concerning "a" shown in Figs. 13 and 14. Because these are the commercial districts around Sapporo Station and the central city, the difference in the staying population was very large and the estimation accuracy was low. In addition, the correlation coefficient of Approach B was 0.7 or higher, and the accuracy was very high. Furthermore, unlike Approach A, it can be seen that the estimated value was output as a negative value overall. Therefore, it is understood that learning was incomplete.

Next, Figs. 17 and 18 show the distribution of the estimated values for Approaches A and B, respectively. Approach A has almost the same color tendency compared with the 1 km grid observation (Fig. 6). In the 500 m grid, which is finer than the 1 km grid, it was possible to show the increase and decrease of the population in a smaller area that could not be previously expressed.

On the other hand, the result of Approach B shows that the visiting population overall decreased. In addition, despite the increase in the visiting population in the 1 km grid, there was an area represented by only a decrease in the 500 m grid, so consistency could not be confirmed. From the above, the correlation coefficient shows that there was only a tiny difference between Approach A and Approach B; besides, the time required for building a model is much less in Approach A than in Approach B. Therefore, it is better to adopt Approach A when applying it to another city in the future. In this research, we devised a spatial coverage of the model to obtain a method that enabled the estimation of the visiting population on a more delicate scale. Using this method, it is possible to predict even on a small scale (500 m grid) where data acquisition becomes difficult due to the protection of personal information and the like.

However, the accuracy of prediction was not satisfactory because the correlation coefficient was about 0.7. Future discussion could improve by adding other information to explanatory variables. For example, not only information on buildings but also transportation networks, terrain, and the like could be used. In Approach A, cluster analysis was conducted on the composition of building use in each area to improve the accuracy of the model and a model was constructed for each. Nonetheless, Cluster 1 was considered to have a low correlation coefficient because it contained extreme grids as described above. In this solution, it was necessary to reconstruct the model by performing clustering to reduce the bias in the types of building applications. For example, there were changes in the number of clusters and classification methods. Thus, solving these problems and improving accuracy are future issues.

4. Conclusions

In this research, we used the urban planning basic survey and mobile spatial statistics of micro-geo data, utilizing the RBF network of machine learning as the major analysis method. Hence, an estimation of the visiting population time-based model constructed from the total floor area of each building type (34 types) was carried out, and a downscaling method was carried out in which the estimation was performed in more detailed spatial units.

With the model that summarizes all the districts, there is a possibility that good accuracy cannot be obtained because the building distribution differs for each district. Therefore, Approach A is for clustering with the building type of the target area and constructing a model for each cluster, and Approach B builds the model using the entire learning data. Both are proposed for such downscaling methods.

In these approaches, the data set was created using explanatory variables for the total floor area for each building application and the output variable as the population to be learned, and learning was done in the RBF network of machine learning. The correlation coefficient between the observed value and the estimated value was about 0.9, and it confirmed that the learning had converged appropriately.

The authors found that the correlation coefficients between the estimated values and the observed values for Approaches A and B were both high. Moreover, by visualizing the estimated values spatially and comparing them with the observed values, we obtained a similar distribution. Approach A may be able to predict the visiting population of other cities in the future.

Finally, the hidden layer of the RBF network was determined based on the results of previous research and preliminary learning. A comparison of accuracy with neural networks by backpropagation using sigmoid-type perceptrons will be a future topic. There is a need to improve the accuracy of the model itself by tuning various hyperparameters of the hidden layer, applying other neural networks, and adding new information to explanatory variables. Besides, to make a dynamic estimation, using the staying population using mobile phone location information that can update data at an interval of 1 h, while increasing the time section to learn, accuracy by spatial resolution is a future issue. If these issues can be resolved, it is possible to estimate the population that changes with time, when changing the urban structure. By visualizing the spatiotemporal characteristics, the population becomes useful information for considering the compact city and network arrangement.

Declaration of competing interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

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