Future Prediction of Regional City based on Causal Inference using Time-series Data

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Abstract: Regional cities in Japan have a lot of social issues. Various measures are being considered to solve these social issues, but it is difficult to ascertain and implement practical and effective measures to address them. In this study, we proposed a method for selecting indicators that have a causal relation to solve the social issues based on a causal inference. If there was a causal relation between two sets of time-series data, the slope of the approximation line of the time-shifted correlation coefficients at the base time returned a negative value. The causal inference was verified by using samples of time-series data and we constructed a network of the causal indicators based on the causal inference. In addition, we achieved future predictions via the vector autoregressive model using the network of causal indicators. The model was verified using the actual time-series data of the 87 regional cities. As a result, it was possible to simulate future predictions by introducing practical and effective measure that originated from the social issue.

1 INTRODUCTION

Regional cities in Japan have a lot of social issues such as depopulation, a decreasing birth rate and aging populations, and decline of regional industries. Various measures are being considered to solve these social issues, but it is difficult to ascertain and implement practical and effective measures to address them. If indicators related to the measures that have a causal relation with these issues can be determined through data-based analyses, more practical and effective measures can be employed. Though several causal inferences using statistical analysis have been proposed so far, they prove the causal relations of already-known incidents based on hypothesis (Rubin, 1974; Pearl, 1985; Shimizu, 2005).

In this study, our objectives are to propose a method for selecting indicators that have a causal relation to solve social issues and to achieve future predictions for regional cities using the causal indicators and quantifying the effects of the measures introduced. As a result, it is possible to plan the practical and effective measures that originate in the causal indicators obtained using this method. In addition, we are able to make predictions regarding regional cities in the future according to a model using the indicators that have a causal relation with various social issues.

2 CAUSAL INFERENCE USING TIME-SERIES DATA

We considered that time-series data were useful to determine causal relations because the causal indicators and the effect indicators were distinguished easily by shifting the time of two time-series data sets. The Granger causality concept is already well-known for determining causality using time-series data (Granger, 1969). However, it is difficult to explain the causal relation between two time-series data sets for a short term.

"e-Stat", a portal site in Japan, releases various time-series data for 1,742 Japanese regional cities (Ministry of Internal Affairs and Communications, 2016). The term of the time-series data investigated every year is mainly from 2000 to 2013, and we need a new causal inference using the time-series data for the short time period to discover various indicators that have a causal relation with social issues.

In this work, we propose a causal inference using time-series data to plan practical and efficient

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measures for regional cities and to carry out future prediction via models using indicators that have a causal relation. The following hypothesis of the causal inference was conceived in this study.

2.1 Hypothesis of Causal Inference using Time-series Data

We proposed a method to find out the causal relations from the variation of correlation coefficients between two indicators by shifting the time of two sets of time-series data.

According to the Pearson product-moment correlation coefficient (Rodgers and Nicewander, 1988), the correlation coefficient R of Indicator X and Indicator Y is calculated from the following equation (1):

$$R = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}} \tag{1}$$

where x indicates the time-series data of Indicator X and y indicates the time-series data of Indicator Y.

Expressing this with the average equation (2) of the time-series data of indicator X and the average equation (3) of the time-series data of indicator Y gives us following equation (4).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{3}$$

$$R = \frac{\sum_{i=1}^{n} x_i y_i - \frac{1}{n}\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 - \frac{1}{n}(\sum_{i=1}^{n} x_i)^2}\sqrt{\sum_{i=1}^{n} y_i^2 - \frac{1}{n}(\sum_{i=1}^{n} y_i)^2}} \tag{4}$$

Then, expressing equation (4) with equation (5), (6), (7), (8) and (9) respectively, gives us equation (10).

$$S_X = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{5}$$

$$S_Y = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{6}$$

$$S_{XX} = \frac{1}{n}\sum_{i=1}^{n} x_i x_i \tag{7}$$

$$S_{YY} = \frac{1}{n}\sum_{i=1}^{n} y_i y_i \tag{8}$$

$$S_{XY} = \frac{1}{n}\sum_{i=1}^{n} x_i y_i \tag{9}$$

$$R = \frac{S_{XY} - \frac{1}{n}S_X S_Y}{\sqrt{S_{XX} - \frac{1}{n}S_X^2}\sqrt{S_{YY} - \frac{1}{n}S_Y^2}} \tag{10}$$

Simple time-series data of Indicator X shown in Table 1 were prepared to prove the hypothesis. These time-series data A, B and C change in three patterns from Time T1-2 to Time T1+1.

Table 1: Time-series data of Indicator X.

t	T1-2	T1-1	T1	T1+1
A	x-1	x	x+1	x+2
B	x	x	x	x
C	x+3	x+2	x+1	x

If Indicator Y has a causal relation with Indicator X completely (R=1.0), the time-series data of Indicator Y are shown as per Table 2 according to the regression line: Y(t) = aX(t-1) + b (a>0). We assumed simply that Indicator X influences Indicator Y at the next unit time.

Table 2: Time-series data of Indicator Y.

t	T1-1	T1	T1+1
A	a(x-1)+b	ax+b	a(x+1)+b
B	ax+b	ax+b	ax+b
C	a(x+3)+b	a(x+2)+b	a(x+1)+b

From Table 1 and Table 2, when Indicator Y is fixed at Time T1 and Indicator X is shifted at each Time T1-1, T1 and T1+1, equations (5), (6), (7), (8) and (9) are shown in Table 3.

Table 3: Expressions of Indicator X and Indicator Y when Indicator Y is at Time T1 and Indicator X is at each Time T1-1, T1 and T1+1.

t for X	T1-1	T1	T1+1
S_X	(3x+2)/3	(3x+2)/3	(3x+2)/3
S_Y	(3y+2a)/3	(3y+2a)/3	(3y+2a)/3
S_{XX}	$(3x^2+4x+4)$ /3	$(3x^2+4x+2$) /3	$(3x^2+4x+4)$ /3
S_{YY}	$(3y^2+4ay+4a^2$)/3	$(3y^2+4ay+4$ $a^2)$ /3	$(3y^2+4ay+4a^2$)/3
S_{XY}	(3xy+2y+2ax +4a)/3	(3xy+2y+2a x +2a)/3	(3xy+2y+2ax) /3

Equation (10) provides the correlation coefficient by substituting the equations of Table 3. Figure 1 shows the correlation coefficient of Indicator X to Indicator Y at Time T1. This is the representative result as it is not dependent on the values of a and b. From this result, we can build the following hypothesis: if Indicator Y has a causal relation with Indicator X and Indicator X is the causal indicator of Indicator Y, R t-1 > R t > R t+1 is completed.

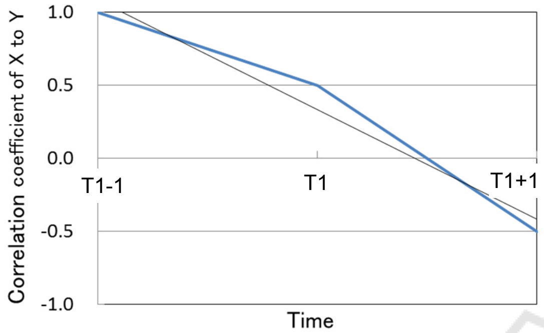
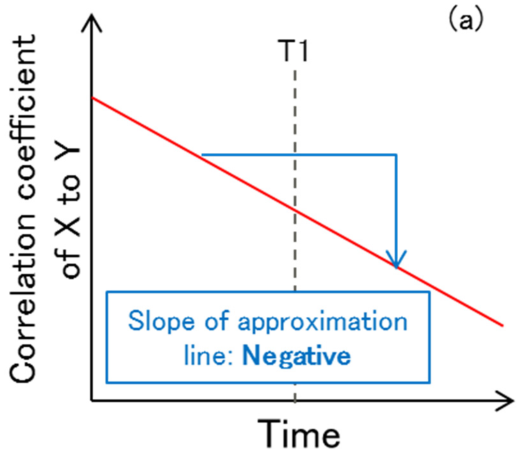


Figure 1: Correlation coefficient of Indicator X at each time to Indicator Y at Time t.

In other words, the correlation coefficients of Indicator X to Indicator Y at a base time: T1 become lower as shown in Figure 2 (a), and the slope of the approximation line has a negative value. Similarly, the correlation coefficients of Indicator Y to Indicator X at a base time: T2 rise, as shown in Figure 2 (b) if Indicator X is the causal indicator of Indicator Y, and the slope of the approximation line has a positive value.



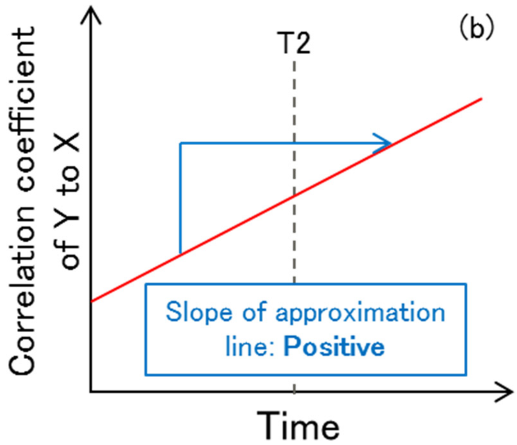


Figure 2: Correlation coefficient of Indicator X to Indicator Y at base time (a) and correlation coefficient of Indicator Y to Indicator X at base time (b) when Indicator X is a causal indicator of Indicator Y.

2.2 Verification of Causal Inference using Samples of Time-Series Data

The causal inference was applied to samples of time-series data with an already-known causal relation to confirm the above-mentioned hypothesis. The samples of time-series data in this verification are shown in Figure 3.

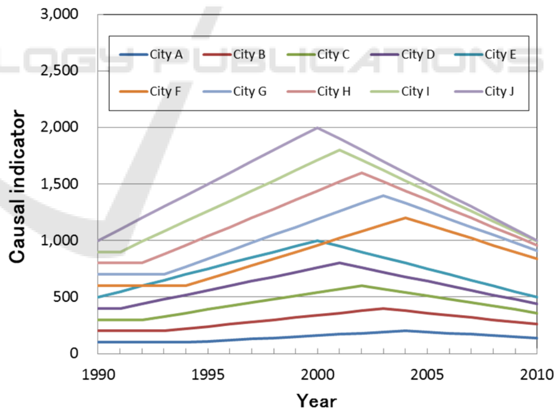


Figure 3: Causal samples of time-series data for 10 cities between 1990 and 2010.

We assumed and prepared the samples of time-series data for 10 cities from City A to City J between 1990 and 2010. The data of each city increased 10% per year for 10 years and decreased 10% per year for 10 years, and the changing years and the initial values of the 10 cities were different respectively. Next, we assumed that the causal samples of time-series data affected effect samples of time-series data in the next year by 30%. And the influence of the causal samples of time-series data gradually decreased by 3% every year, which lasted for 10 years. The effect samples of time-series data for 10 cities from City A to City J between 2000 and 2010 in this verification are shown in Figure 4.

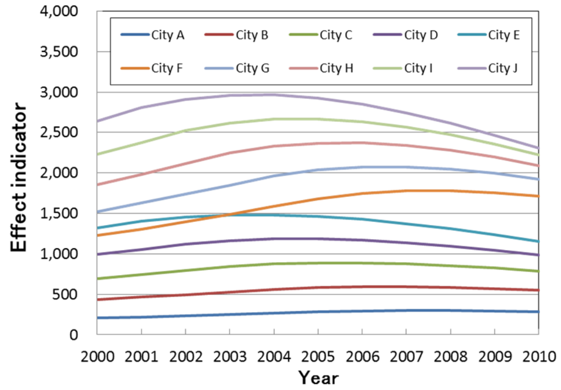


Figure 4: Effect samples of time-series data for 10 cities between 2000 and 2010.

We calculated the correlation coefficients using the effect sample data based on 2005 and the causal samples of time-series data between 2000 and 2010, and Figure 5 shows the result. From this result, if there is a causal relation between two sets of time-series data, the slope of the approximation line of the correlation coefficients at the base time returns a negative value, and our hypothesis could be proved by using samples of time-series data.

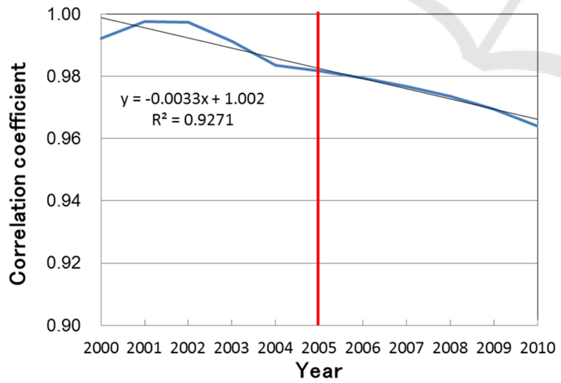


Figure 5: Correlation coefficients using the effect sample data based on 2005 and the causal samples of time-series data between 2000 and 2010.

3 SIMULATION MODEL FOR FUTURE PREDICTION

We considered that future predictions of regional cities could be conducted by selecting an appropriate model using the causal indicators. As mentioned below, a number of simulation models for the future predictions were verified, and the most suitable model was selected.

3.1 Selecting Simulation Models using Causal Indicators

The model selection was considered using the following simulation models, time-series data, and a verification method.

3.1.1 Simulation Model

As models in which plural causal indicators as explanatory variables were available, the following 3 types of regression model - the multivariate regression model (MR model), the stepwise regression model (SW model), and the vector autoregressive model (VAR model) - were verified in this study (Sims, 1980).

3.1.2 Time-series Data

First, we constructed a network of causal indicators based on the above-mentioned causal inference. 238 kinds of time-series data between 2000 and 2013 for 1,742 regional cities in Japan were included in this network and the causal relations were mutually calculated using the causal inference. Causal indicators can be easily selected using this network.

Population issue is a common significant target for a lot of regional cities in Japan. The following 6 kinds of time-series data - live births (person), in-migrants from other prefectures (person), kindergarten pupils (person), marriages, taxable income (thousand yen), and tax debtors per income levy (person) - were selected as the causal indicators of total population from the network of causal indicators. We also conducted the verification using time-series data that directly influenced total population such as deaths (person) and out-migrants to other prefectures (person) in addition to live births and in-migrants. The time-series data in this verification are shown in Table 4.

Table 4: Time-series data of causal and direct indicators from 1985 to 1999 for verification of each simulation model.

Year	Population (person)	Live births (person)	In-migrants (person)	Marriages (couple)	Taxable income (thousand yen)	Tax debtors (person)	Kindergarten pupils (person)	Deaths (person)	Out-migrants (person)
1985	1,088,624	14,003	83,718	8,697	1,317,664,207	443,164	21,452	4,477	78,451
1986	1,106,148	13,773	87,562	8,522	1,410,421,764	455,918	21,317	4,523	78,085
1987	1,126,485	13,999	90,742	8,885	1,521,779,615	471,283	21,790	4,753	80,193
1988	1,142,953	13,920	88,421	9,166	1,696,876,283	487,709	22,004	5,060	81,131
1989	1,157,005	13,090	91,848	9,484	1,793,159,486	496,645	21,918	5,038	85,576
1990	1,173,603	13,279	93,797	9,696	2,030,951,252	505,254	21,515	5,346	86,633
1991	1,187,034	13,494	91,537	10,049	2,243,247,257	528,811	21,582	5,487	87,751
1992	1,195,464	13,356	91,587	10,226	2,407,042,715	545,002	21,254	5,736	91,665
1993	1,199,707	12,855	90,167	10,718	2,341,293,380	557,276	20,895	6,032	93,102
1994	1,202,069	13,476	89,639	10,857	2,378,227,721	561,607	19,952	6,153	94,026
1995	1,202,820	13,146	87,846	10,897	2,398,720,169	561,574	19,476	6,399	91,268
1996	1,209,212	13,309	88,284	11,147	2,381,925,353	564,303	19,673	6,265	88,317
1997	1,217,359	13,423	87,209	10,465	2,443,414,810	567,349	19,799	6,461	85,304
1998	1,229,789	13,756	88,702	10,759	2,459,854,574	572,562	20,565	6,783	83,223
1999	1,240,172	13,590	87,196	10,211	2,417,084,645	572,331	21,071	7,186	83,975

3.1.3 Verification Method

We predicted the total population from 2000 to 2013 by 3 types of simulation models and the 8 kinds of time-series data from 1985 to 1999, compared with actual data from 2000 to 2013. In this verification, an actual city (City K) of 1.2 million population scale was targeted.

3.2 Verification of Future Prediction using Simulation Models

The verification result using 3 types of simulation models and using the 8 kinds of time-series data is shown in Figure 6. In this verification, we tried out 5 types of simulation: 1 VAR model using 6 kinds of causal indicators, 2 VAR model using 4 kinds of direct indicators, 3 MR model using 6 kinds of causal indicators, 4 MR model using 4 kinds of direct indicators, and 5 SW model using in-migrants, deaths, tax debtors, and kindergarten pupils that were chosen as effective explanatory variables. As a result, we observed that the simulations using a VAR model showed good coincidence with the actual data, especially in terms of selecting the causal indicators. The average rate of relative error for the actual data with the VAR model using the causal indicators was the lowest by 1.1 %/year. The next lowest simulation was the VAR model using the direct indicators, and the average relative error was 3.7%/year. The average relative errors in the other simulations were 5.6%/year at the same level.

The future population investigated by the cohort-component method is used as a bench mark in Japan (National Institute of Population and Social Security Research, 2013). We calculated the average rate of relative error for the actual data with the VAR model using the causal indicators, compared with the cohort-component method. In this comparison, 87 cities that were 5% cities divided into 10 categories on Japanese population scale were selected. The total population from 2007 to 2013 was predicted by the VAR model using time-series data from 2000 to 2006 of the 6 kinds of causal indicators. Figure 7 showed the number of cities in each relative error of the population prediction by both methods. It was confirmed that the population prediction via VAR model using the causal indicators was predictable in a smaller relative error.

We concluded that it was possible to predict regional cities in the future via the vector autoregressive model using the causal indicators that have a causal relation with social issues.

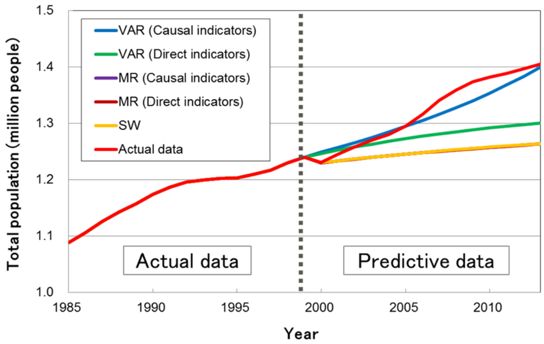


Figure 6: Verification of total population based on 5 types of simulations using different kinds of time-series data. The results using MR models are almost the same as the result using SW model.

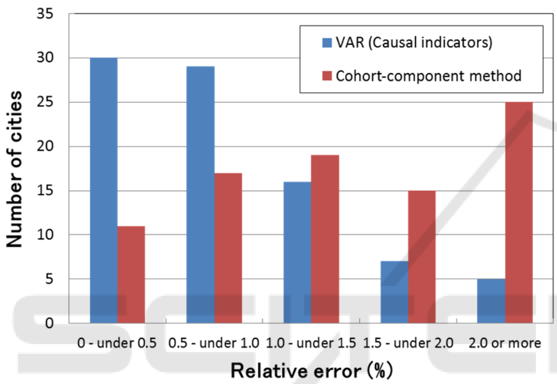


Figure 7: The number of cities in each relative error of the population prediction by VAR model and cohort-component method.

4 FUTURE PREDICTION OF REGIONAL CITY USING CAUSAL INDICATORS

We predicted a regional city in the future using the network of causal indicators. A lot of regional cities in Japan are experiencing depopulation issues as described above, and the future population of the regional city was simulated using the causal indicators.

4.1 Future Prediction for Regional City in the Future

We selected the causal indicators of live births, in-migrants, kindergarten pupils, marriages, taxable income, and tax debtors per income levy that have a causal relation with total population. Figure 8 shows the causal relation diagram of total population and the causal indicators. These causal indicators that have correlation coefficients of 0.9 or more based on the total population data in 2006 were selected from the network of causal indicators. We predicted the total population from 2014 to 2050 via the VAR model using actual time-series data for the causal indicators from 2000 to 2013. In this future prediction, City L with a population of 275,000 was targeted.

The future prediction of total population in City L is shown in Figure 9. As a result, we predicted that the population of City L would decrease from 276,000 people to 258,000 people between 2014 and 2050 (the population decrease rate being 6.3%). It was suggested that population decrease was the social issue for City L as well as a lot of regional cities in Japan.

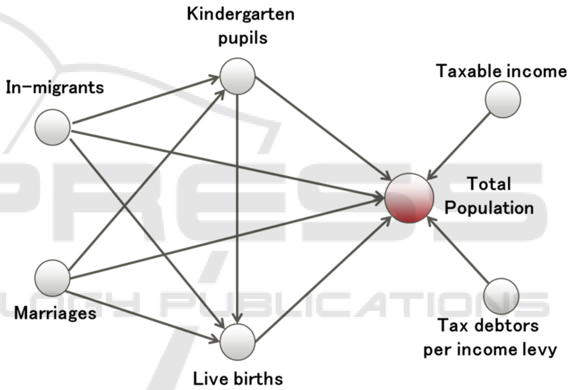


Figure 8: Causal relation diagram of total population selected from network of causal indicators.

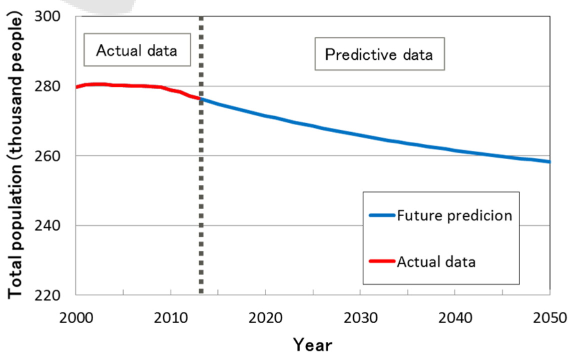


Figure 9: Future prediction of total population in City L from 2014 to 2050.

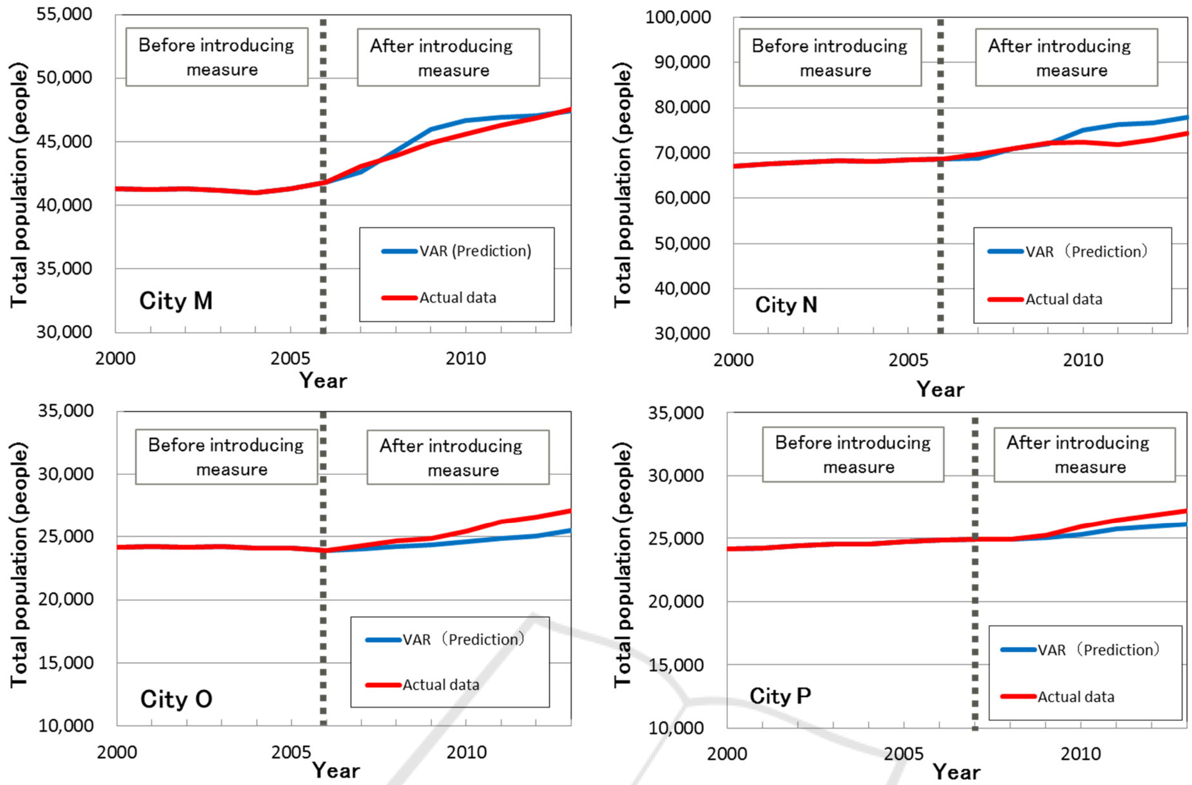


Figure 10: Verification of total population in 4 regional cities by introducing measure for in-migrants.

4.2 Future Prediction of Total Population by Introducing Measure

As shown in Figure 8, in-migrants were one of important causal indicators of total population from the viewpoint of population growth in the future. Then, we verified future predictions by actual case studies introducing a measure of in-migrants increase. 4 regional cities from City M to City P that introduced a measure to increase in-migrants were selected in this verification. In these cities, the measure that the residential area was increased by the land development was introduced in 2006 or 2007, and in-migrants consequently increased by 68%, 25%, 66% and 38% in 2013, respectively. The total populations from 2007 or 2008 to 2013 were verified via the VAR model using actual time-series data of in-migrants from 2007 or 2008 to 2013, compared with actual data. Figure 10 showed the verification results of 4 regional cities introducing the measure to increase in-migrants. Each average rate of relative error for the actual data was 1.2, 3.0, 3.6 and 2.6 %/year, and we confirmed the total population introducing the measure via VAR model was predictable in a smaller relative error.

Next, we assumed a measure for increasing in-migrants in City L, and set 5 types of scenario that increase in-migrants gradually from 2017 to 2025, and increase from 2026 to 2050 by 10% (Scenario 1), 20% (Scenario 2), 30% (Scenario 3), 40% (Scenario 4) and 50% (Scenario 5), compared with the BAU scenario. Figure 11 shows the simulation result for total population in each scenario. From this result, we confirmed that total population in City L increased by increasing in-migrants between 2017 and 2050. In the case of Scenario A4 (increasing by 40% from 2026 to 2050), the current population in City L (275,000 people) could be maintained in 2050.

Figure 12 shows the relationship between the increase rate of total population and the increase rate of in-migrants. We obtained the result that total population increased by 1.8% by increasing in-migrants by 10%.

It was suggested that in-migrants were important causal indicators from the viewpoint of population growth in the future, and the measure for in-migrants could be effective in increasing total population.

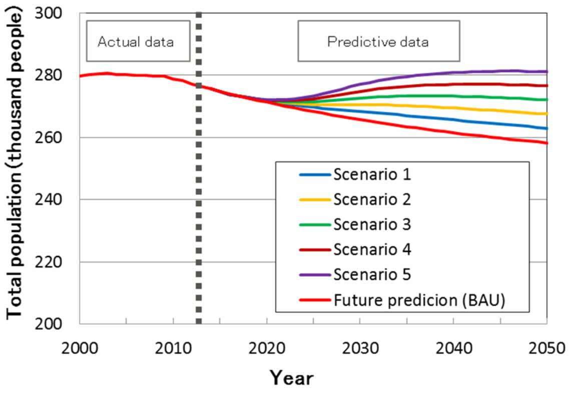


Figure 11: Simulation result for total population in 5 scenarios by introducing measure for in-migrants in City L.

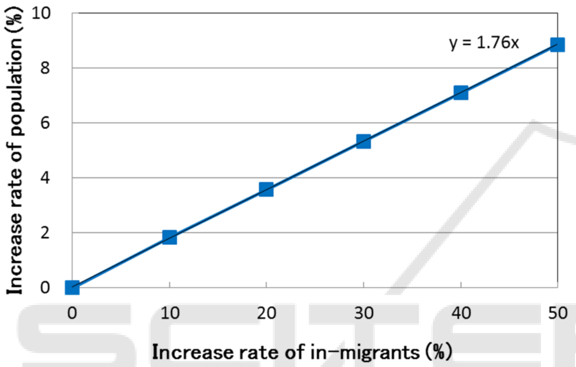


Figure 12: Relationship between increase rate of total population and increase rate of in-migrants in City L.

5 CONCLUSIONS

We proposed a method for selecting indicators that have a causal relation with social issues based on a causal inference. If there was a causal relation between two sets of time-series data, the slope of the approximation line of the time-shifted correlation coefficients at the base time returned a negative value. The causal inference was verified by using the samples of time-series data and we constructed a network of the causal indicators. In addition, we also achieved future predictions via the vector autoregressive model using the causal indicators. The model was verified using the actual time-series data of the 87 regional cities. As a result, it was possible to simulate future predictions by introducing the practical and effective measures (for in-migrants) that originated from the social issue (with a total population decrease).

It was easily possible to determine the causal indicators and to quantify the effect of introducing the measures via the model using the causal indicators in this study. For future work, we will be able to apply this method to a number of issues by including more indicators related to economic factors and the environment in the network, and expanding it to various fields. Moreover, it is necessary to verify the effects of introducing measures considering regional characteristics based on actual case studies.

In terms of establishing a sustainable society, we consider that regional cities can decide on appropriate measures related to indicators that have a causal relation with the social issues, and execute future predictions easily if these measures are introduced.

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