

Article

Spatial Patterns of Bridge Deterioration and Municipal Maintenance Potential for Municipality-Managed Bridges in the Chubu Region of Japan

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Abstract

Aging bridge infrastructure poses a growing challenge for Japanese municipalities under population decline, fiscal constraints, and shortages of technical personnel. This study analyzes municipality-managed bridges in the Chubu region of Japan by integrating bridge inspection records with demographic, fiscal, technical staffing, and regional-condition indicators. Bridge deterioration severity for 237 municipalities was evaluated, and its spatial structure was examined using Global Moran's I and local indicators of spatial association (LISA), which respectively indicate whether similar deterioration levels are regionally clustered across the study area and where local clusters or spatial outliers occur. The results showed significant positive spatial autocorrelation, indicating that deterioration is spatially clustered and locally heterogeneous. Municipal maintenance potential was then represented through principal component analysis and classified by cluster analysis, identifying seven municipal types characterized by different combinations of depopulation, wide-area management burden, land-use conditions, and fiscal constraints. By integrating deterioration severity, LISA composition, and maintenance-potential typologies, the study distinguished municipalities where low deterioration is spatially stable, municipalities where highly deteriorated areas are locally concentrated, and municipalities where deterioration is high but spatially dispersed. These findings provide a basis for targeted support and strategic bridge management.

Keywords: bridge deterioration; municipal bridge management; spatial autocorrelation; LISA; principal component analysis; cluster analysis; maintenance potential; local governments



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1. Introduction

Aging infrastructure has become a major societal challenge in many developed countries. In Japan, this challenge is particularly serious, as local governments are responsible for maintaining large infrastructure stocks under conditions of population decline, fiscal constraints, and shortages of technical personnel. Among infrastructure assets, road bridges are especially important because their deterioration directly affects safety, mobility, regional connectivity, and the continuity of local socio-economic activities. This point has also been emphasized in previous bridge infrastructure studies, which argue that bridge management should be considered not only in terms of structural condition but also in relation to hazard exposure and the functional role of the road network at the regional scale [1]. At the same time, some municipalities are finding it increasingly difficult to sustain bridge maintenance

at conventional service levels, particularly in rural areas and regions with significant geographic constraints. In addition, recent evidence from Japan suggests that urban shrinkage substantially reduces local fiscal revenues, implying that population decline may directly weaken the fiscal basis required for infrastructure maintenance [2].

Previous studies on bridge management have mainly focused on engineering-oriented issues, including deterioration prediction, inspection methods, life-cycle cost analysis, maintenance optimization, and budget allocation [3–6]. These studies have contributed to asset-level bridge management by improving diagnosis, prediction, maintenance prioritization, and decision-making methods. In addition, recent empirical evidence suggests that bridge deterioration is influenced not only by bridge specifications, such as structural material, bridge length, and construction year, but also by environmental conditions, including coastal distance, deicing salts, traffic volume, rainfall, snowfall, temperature, and elevation [7].

Recent studies have also applied data-driven and portfolio-level approaches to bridge inspection and maintenance data. For example, Chuang et al. analyzed bridge management database records in Taiwan using clustering and association algorithms to identify deterioration-prone bridge configurations and components [8]. Saler et al. proposed a portfolio-level classification and prioritization method for municipal bridge stocks by considering typological, geometric, structural, deterioration, and seismic vulnerability factors [9].

However, the implementation of bridge maintenance at the municipal level is also constrained by non-engineering factors. Studies on local governments have shown that maintenance spending and public investment are affected by fiscal capacity, expected population change, and political or administrative decision-making structures [10,11]. These findings suggest that bridge deterioration should be interpreted not only in relation to structural and environmental conditions, but also in relation to the demographic, fiscal, technical staffing, geographic, and administrative conditions of the municipalities responsible for managing bridge assets.

Therefore, a remaining research gap is the limited integration of inspection-based bridge deterioration data, municipality-level maintenance potential, and spatial autocorrelation at the municipal scale. To address this gap, this study examines how bridge deterioration severity is associated with municipal maintenance potential and spatial clustering patterns. A further limitation of the existing literature is that spatial heterogeneity in bridge deterioration has often been treated descriptively rather than analytically. Even when regional differences are visually apparent, it is not always clear whether these patterns reflect statistically meaningful spatial clustering or merely scattered local variation. This distinction is particularly important for municipality-managed bridge stocks because neighboring municipalities may share similar topographic, climatic, and socio-economic constraints while still exhibiting different deterioration outcomes depending on their management capacity and organizational conditions. It is therefore necessary to examine not only the severity of bridge deterioration but also its spatial structure. In this regard, local indicators of spatial association (LISA) provide an established framework for identifying statistically meaningful local spatial clusters and outliers [12]. In this study, Local Moran's I is used as a local indicator of spatial association. To avoid terminological confusion, the method is hereafter referred to as LISA, except where the Local Moran's I statistic itself is introduced.

Against this background, this study focuses on municipality-managed road bridges in the Chubu region of Japan. Using bridge inspection records, demographic and fiscal indicators, technical staffing data, and regional condition variables, this study analyzes bridge deterioration from two complementary perspectives. First, it identifies the spatial

structure of bridge deterioration severity using Global Moran's I and local indicators of spatial association (LISA). Second, it develops a multidimensional representation of municipal maintenance potential through principal component analysis (PCA) and classifies municipalities using cluster analysis. By integrating these two perspectives, this study constructs a municipal typology that captures not only the severity of observed bridge deterioration but also the administrative, social, and geographic conditions under which such deterioration tends to occur.

The scientific significance of this study lies in linking inspection-based bridge deterioration with municipal-level maintenance capacity and spatial dependence. This approach extends bridge deterioration analysis from an asset-level engineering perspective to a regional infrastructure governance perspective.

This study makes three main contributions. First, it demonstrates that bridge deterioration severity is not randomly distributed across municipalities, but exhibits spatial clustering and local heterogeneity. Second, it shows that municipal maintenance potential can be represented as a multidimensional structure shaped by vulnerability, spatial management burden, land-use conditions, and fiscal constraints, rather than by a single variable such as fiscal capacity alone. Third, by combining deterioration levels, spatial clustering patterns, and maintenance-potential typologies, this study provides an integrated analytical framework for identifying municipalities that may require different policy responses, such as preventive maintenance support, targeted technical assistance, inter-municipal collaboration, or strategic network prioritization.

The practical significance of this study lies in its relevance to evidence-based infrastructure policy. As it becomes increasingly unrealistic to maintain all bridge assets according to uniform standards, local governments need analytical tools that can distinguish among municipalities with high deterioration and clear spatial concentration, those with high deterioration but dispersed patterns, and those that maintain relatively low deterioration despite structurally unfavorable conditions. Such distinctions are important for prioritizing infrastructure maintenance works and public support, as well as for identifying management practices that may be transferable to other municipalities. In this sense, this study contributes not only to bridge management research but also to broader discussions on infrastructure governance under demographic and fiscal decline.

The remainder of this paper is organized as follows. Section 2 examines the spatial distribution and spatial autocorrelation of bridge deterioration severity in the Chubu region. Section 3 develops indicators of municipal maintenance potential, applies PCA and cluster analysis, and identifies municipal typologies based on maintenance-related conditions. Section 4 integrates deterioration severity, LISA results, and maintenance-potential typologies to derive an interpretable municipal classification. Section 5 discusses the policy implications for bridge management and municipal support, and Section 6 concludes the paper.

2. Bridge Deterioration in the Chubu Region

2.1. Bridge Deterioration Index and Municipal Distribution

Bridge data were obtained from the Nationwide Road Facility Inspection Database for municipality-managed bridges in Nagano, Shizuoka, Aichi, Gifu, and Mie prefectures. The dataset was downloaded in October 2025. Bridges with recorded upper-level condition ratings were included in the analysis. A total of 237 municipalities in the Chubu region were analyzed. The bridge deterioration index was calculated using the deterioration assessment method proposed by the Japan Society of Civil Engineers [13]. The bridge deterioration index, D_t , is defined by Equation (1).

$$D_t = p_t^{(I)} \cdot 0 + p_t^{(II)} \cdot 0.125 + p_t^{(III+IV)} \cdot 0.875 \quad (1)$$

where $p_t^{(I)}$, $p_t^{(II)}$, and $p_t^{(III+IV)}$ denote the proportions of bridges classified into inspection condition categories I, II, and III/IV, respectively, among all inspected bridges. Table 1 shows the categories of integrity diagnosis [14]. The integrity diagnosis consists of four categories: Category I represents a sound condition, whereas Category IV indicates an emergency action stage requiring urgent intervention. Categories II and III correspond to intermediate stages, namely the preventive maintenance stage and the early action stage, respectively. The weights of 0, 0.125, and 0.875 were adopted from the deterioration assessment method proposed by the Japan Society of Civil Engineers [13]. In this weighting scheme, Category I bridges are assigned a weight of 0 because they are classified as sound. Category II bridges are assigned a smaller weight because they correspond to the preventive maintenance stage, whereas Categories III and IV are assigned a larger weight because they correspond to the early-action or emergency-action stages. Thus, higher category numbers indicate more serious bridge conditions and a greater need for maintenance or corrective action. A larger value of D_t indicates a greater share of deteriorated bridges and thus a lower overall condition level within a municipality. The bridge deterioration index used in this study is not intended to represent a mechanistic deterioration model of individual bridges. Rather, it is a weighted aggregation index based on inspection condition ratings, designed to summarize the relative severity of bridge deterioration at the municipal level.

Table 1. Categories of integrity diagnosis [14].

Category	Diagnosis	Condition
I	Sound	The structure has no functional impairment.
II	Preventive maintenance stage	The structure has no functional impairment, but preventive maintenance is desirable.
III	Early action stage	There is a possibility of functional impairment, and corrective action should be taken at an early stage.
IV	Emergency action stage	The structure is functionally impaired, or there is a high possibility of functional impairment; urgent action is required.

Figure 1 shows the municipal distribution of bridge deterioration severity. The deterioration index is visualized as a continuous contour surface: darker areas indicate municipalities with higher bridge deterioration severity and a relatively larger share of deteriorated bridges, whereas lighter areas indicate municipalities with lower deterioration severity and a relatively larger share of sound bridges. This enables a visual assessment of spatial unevenness in bridge deterioration across municipalities.

Municipalities with relatively high bridge deterioration severity were concentrated mainly in inland areas, particularly in Nagano and Gifu prefectures, whereas municipalities with relatively low deterioration severity were more common in southern Aichi and western Shizuoka. Thus, bridge deterioration severity was not uniformly distributed within the Chubu region but exhibited clear regional variation. These findings suggest that bridge deterioration is associated not only with the management conditions of individual municipalities but also with broader regional factors such as topography, climate, bridge stock accumulation, traffic conditions, and differences in maintenance systems.

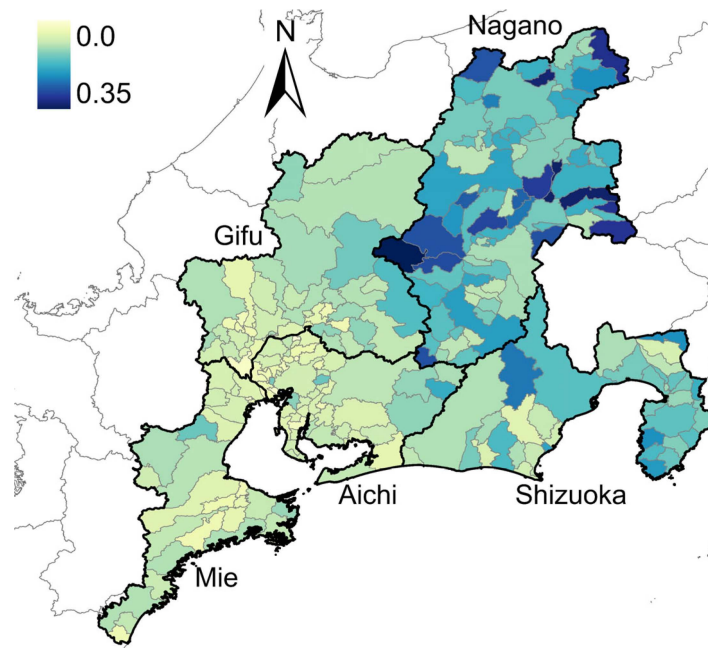


Figure 1. Municipal distribution of bridge deterioration severity.

2.2. Spatial Autocorrelation of Bridge Deterioration

The spatial pattern shown in Figure 1 does not by itself indicate whether the observed distribution is merely coincidental or reflects meaningful spatial clustering. In this study, spatial correlation does not refer to temporal correlation in the deterioration process of the same bridge. Instead, it refers to the geographical dependence of bridge deterioration levels among neighboring municipalities. The purpose of applying spatial autocorrelation analysis is to examine whether municipalities with similar deterioration levels are spatially clustered. To examine this issue, spatial autocorrelation in bridge deterioration severity was analyzed using Global Moran's I. Global Moran's I was calculated according to Equation (2) to examine whether bridge deterioration severity exhibits overall spatial autocorrelation [15].

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (2)$$

where N is the number of spatial units, x_i and x_j are the observed values for municipalities i and j , $\bar{x}$ is the mean value, and w_{ij} is the spatial weight between municipalities i and j . In this study, the spatial weight matrix was constructed using first-order rook contiguity, whereby municipalities sharing a common administrative boundary were defined as neighbors. The weights were row-standardized to account for differences in the number of neighboring municipalities. Municipalities with no adjacent municipalities, such as island municipalities, were treated as non-neighbor units.

The calculated Global Moran's I was 0.48418, with a z-score of 11.361378 and a p -value below 0.001, indicating a statistically significant positive spatial autocorrelation in bridge deterioration severity. In other words, municipalities with similar levels of deterioration severity tended to be located near each other rather than being randomly distributed. To identify local spatial clusters, LISA was calculated using the Local Moran's I statistic according to Equation (3) [12].

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_j w_{ij} (x_j - \bar{x}) \quad (3)$$

where x_i is the value for municipality i , $\bar{x}$ is the mean value, w_{ij} is the spatial weight between municipalities i and j , and S^2 is the variance term. Based on whether each municipality's deterioration value and its spatial lag were above or below their respective mean values, municipalities were classified into four local spatial association categories: high-high (HH), low-low (LL), high-low (HL), and low-high (LH). In the LISA classification, HH indicates a municipality with a high deterioration value surrounded by municipalities with high values, whereas LL indicates a municipality with a low deterioration value surrounded by municipalities with low values. HL indicates a high-value municipality surrounded by low-value municipalities, and LH indicates a low-value municipality surrounded by high-value municipalities. High and low values were determined relative to the mean of the bridge deterioration index and its spatial lag. The statistical significance of local spatial association was evaluated at the 5% level, and only statistically significant local spatial associations were classified into these four categories. Municipalities without statistically significant local spatial association were classified as N.S. In Figure 2, N.N. denotes municipalities without neighboring municipalities under the first-order rook contiguity definition. Figure 2 presents the LISA results. HH clusters were observed mainly in northern and central Nagano, while LL clusters were found around the border area of Aichi, Gifu, and Mie prefectures and in the Kii Peninsula. In addition, some HL and LH municipalities were identified, indicating local outliers whose deterioration tendencies differed from those of surrounding municipalities. These results suggest that the distribution of bridge deterioration severity is characterized not only by local clustering but also by local heterogeneity.

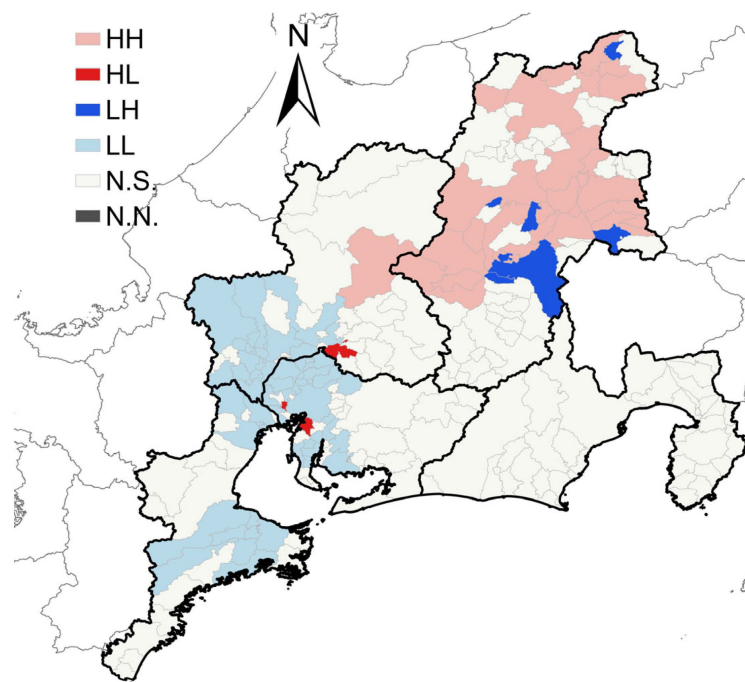


Figure 2. LISA results.

Overall, the results indicate that bridge deterioration severity is not randomly distributed across municipalities but exhibits both spatial clustering and local heterogeneity associated with regional conditions. This implies that bridge deterioration should not be treated solely as an issue of individual municipalities, but rather as a phenomenon that must be understood in relation to wider regional and spatial contexts.

3. Municipal Maintenance Potential and Typology

3.1. Indicators of Municipal Maintenance Potential

The non-engineering and managerial indicators were selected according to four criteria: relevance to municipal bridge maintenance burden or capacity, availability and comparability across all municipalities, consistency with policy-relevant dimensions of local infrastructure management, and suitability for aggregation at the municipal level. To capture municipal maintenance potential in a multidimensional manner, the indicators were organized into five perspectives: maintenance burden, administrative and technical capacity, fiscal capacity, regional baseline conditions, and regional constraint conditions. The primary outcome indicator of this study is the bridge deterioration index. In this study, bridge maintenance performance is not measured as the operational performance of individual maintenance actions, but is represented by the municipality-level bridge deterioration index. The non-engineering indicators are used to characterize the conditions under which municipalities manage their bridge stocks.

The other indicators are not proposed as additional structural deterioration indicators, but are used as explanatory indicators representing municipal maintenance potential, including maintenance burden, technical capacity, fiscal capacity, and regional constraints. Because this study aims to explore the multidimensional structure of municipal maintenance potential, no theoretically predetermined weights were assigned to these explanatory indicators. Instead, the indicators were standardized and analyzed using PCA to identify the major dimensions underlying municipal maintenance potential.

Population and the elderly population were obtained from the 2020 Population Census of Japan [16]. General administrative staff and civil engineers were obtained from the FY2024 Survey on Personnel Management in Local Public Entities [17]. The fiscal capacity index, current account balance ratio, and real debt service ratio were obtained from the FY2024 List of Key Financial Indicators of Local Public Entities [18]. Land area and habitable land area were obtained from the national municipal land area statistics [19]. Total expenditures and civil engineering expenditures were obtained from the FY2024 Survey of Municipal Settlement Conditions [20]. Bridge-related data were taken from the Nationwide Road Facility Inspection Database downloaded in October 2025 [21].

Several variables were constructed specifically for this study. The aging rate was calculated as the proportion of the population aged 65 years and above. The habitable land ratio was calculated as habitable land area divided by total land area. The civil engineer ratio was defined as the number of civil engineers divided by the number of general administrative staff. Bridge density was calculated as the number of bridges per total land area, and bridges per capita as the number of bridges per total population.

In addition to continuous indicators, qualitative variables representing institutional and geographic conditions were also introduced. These variables were converted into dummy variables through one-hot encoding for principal component analysis. Heavy snowfall areas were classified into three categories: none, heavy snowfall area, and special heavy snowfall area [22]. Depopulation status was classified into none, partially depopulated, and fully depopulated [23]. Agricultural area type was classified into urban, flat agricultural, intermediate agricultural, and mountainous agricultural areas [24].

3.2. Principal Component Analysis Using 11 Continuous Indicators

First, principal component analysis (PCA) was conducted using only continuous variables to identify the basic structure of municipal maintenance potential. Eleven variables were used: population, land area, aging rate, fiscal capacity index, current account balance ratio, real debt service ratio, civil engineering expenditure ratio, habitable land ratio, civil engineer ratio, bridge density, and bridges per capita. Since these variables were measured

on different scales, they were standardized to a mean of zero and a standard deviation of one prior to PCA. The principal components were interpreted using eigenvalues, contribution ratios, cumulative contribution ratios, and signed loadings obtained by multiplying eigenvectors by the square root of the corresponding eigenvalues.

Table 2 presents the component loadings, eigenvalues, and cumulative contribution ratios for the 11 continuous indicators. The first principal component showed large positive loadings for the aging rate and bridges per capita, and large negative loadings for the fiscal capacity index, habitable land ratio, and civil engineer ratio. This component, therefore, represents municipalities with high aging rates and relatively large bridge burdens per resident but comparatively weak fiscal and technical bases, and was interpreted as a vulnerability axis. The second principal component showed large positive loadings for land area, population, and the civil engineer ratio, and was interpreted as representing scale and wide-area management burden. The third principal component showed large positive loadings for the current account balance ratio and real debt service ratio, and a large negative loading for the civil engineering expenditure ratio; it was therefore interpreted as representing fiscal rigidity and room for civil engineering investment.

Table 2. Component loadings, eigenvalues, and cumulative contribution ratios for the 11 continuous indicators.

Evaluation Indicator	PC1	PC2	PC3	PC4	PC5
Population	−0.42	0.58	−0.02	−0.21	0.40
Area (km ²)	0.11	0.80	−0.11	−0.13	0.04
Aging rate (%)	0.88	0.07	0.14	−0.19	0.03
Fiscal capacity index	−0.87	−0.01	−0.24	0.00	−0.14
Current balance ratio (%)	−0.36	0.35	0.70	0.16	0.02
Real debt service ratio (%)	0.48	0.08	0.57	0.47	0.22
Civil engineering expenditure ratio (%)	0.12	0.12	−0.65	0.58	0.39
Habitable area ratio (%)	−0.85	−0.39	0.07	0.00	0.14
Civil engineer ratio (%)	−0.58	0.56	−0.01	−0.09	−0.02
Bridge density (bridges/km ²)	−0.55	−0.44	0.25	−0.17	0.51
Bridges per capita (bridges/person)	0.70	−0.13	−0.11	−0.41	0.37
Eigenvalue	3.94	1.79	1.41	0.90	0.80
Cumulative contribution rate (%)	35.6	51.9	64.7	72.8	80.0

Overall, the analysis based only on continuous variables suggested that municipal maintenance potential is structured mainly by three dimensions: vulnerability, scale and wide-area management burden, and fiscal operation. However, this analysis did not sufficiently capture regional conditions such as depopulation, heavy snowfall, and agricultural area type. Therefore, these categorical variables were added in the next step to reorganize municipal characteristics in a way that more fully reflects regional conditions.

3.3. Principal Component Analysis Using 21 Indicators Including Regional Conditions

Next, PCA was conducted using 21 indicators by adding 10 one-hot-encoded categorical variables related to regional conditions to the 11 continuous variables. The additional variables were urban area, flat agricultural area, intermediate agricultural area, mountainous agricultural area, no depopulation, partially depopulated, fully depopulated, no heavy snowfall, heavy snowfall area, and special heavy snowfall area. Table 3 presents the component loadings, eigenvalues, and cumulative contribution ratios for the 21 indicators. Princi-

pal components with eigenvalues greater than 1.0 were retained, resulting in six principal components with a cumulative contribution ratio of 72.4%.

Table 3. Component loadings, eigenvalues, and cumulative contribution ratios for the 21 indicators.

Evaluation Indicator	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Population	−0.33	0.44	−0.28	−0.10	0.08	0.09	0.50
Area (km ²)	0.23	0.74	−0.07	−0.07	0.04	−0.14	0.32
Aging rate (%)	0.87	−0.15	−0.11	−0.17	0.04	0.08	0.05
Fiscal capacity index	−0.84	0.13	−0.09	0.18	0.05	−0.12	0.03
Current balance ratio (%)	−0.30	0.31	0.00	−0.57	−0.07	0.50	−0.06
Real debt service ratio (%)	0.46	0.00	0.33	−0.23	−0.24	0.54	0.02
Civil engineering expenditure ratio (%)	0.15	0.21	−0.05	0.72	−0.01	−0.06	−0.06
Habitable area ratio (%)	−0.86	−0.17	0.00	0.01	−0.29	−0.01	−0.13
Civil engineer ratio (%)	−0.50	0.51	−0.24	−0.13	0.24	0.09	0.10
Bridge density (bridges/km ²)	−0.56	−0.21	−0.03	−0.16	−0.39	−0.02	−0.29
Bridges per capita (bridges/person)	0.66	−0.29	−0.27	−0.09	−0.02	−0.27	0.01
Urban area	−0.78	0.26	−0.42	−0.02	−0.02	0.05	−0.26
Flat agricultural area	−0.11	−0.32	0.43	−0.11	−0.55	−0.27	0.45
Intermediate agricultural area	0.19	−0.01	0.64	0.17	0.61	0.22	−0.05
Mountainous agricultural area	0.78	−0.06	−0.44	−0.06	−0.16	−0.08	0.02
Non-depopulated municipality	−0.82	−0.20	0.12	0.20	−0.03	0.14	0.18
Partially depopulated municipality	0.13	0.47	0.31	−0.31	0.05	−0.50	−0.12
Fully depopulated municipality	0.81	−0.07	−0.32	−0.02	0.00	0.15	−0.12
Non-snowy area	−0.37	−0.73	−0.18	−0.23	0.38	−0.06	0.15
Heavy snowfall area	0.17	0.66	0.28	−0.14	−0.14	−0.24	−0.27
Special heavy snowfall area	0.35	0.32	−0.05	0.49	−0.40	0.35	0.08
Eigenvalue	6.59	2.86	1.63	1.53	1.40	1.27	0.92
Cumulative contribution rate (%)	31.3	44.8	52.5	59.8	66.4	72.4	76.8

The first principal component showed large positive loadings for the aging rate and fully depopulated status, and large negative loadings for the habitable land ratio, fiscal capacity index, and no-depopulation status. This component was interpreted as representing depopulation, aging, and structural disadvantage. The second principal component showed large positive loadings for land area, heavy snowfall area, and the civil engineer ratio, and was interpreted as representing spatial management burden associated with scale and heavy snowfall conditions. The third principal component was mainly associated with intermediate agricultural area, flat agricultural area, mountainous agricultural area, and urban area, and was interpreted as representing differences in land use and regional structure. The fourth principal component showed a large positive loading for the civil engineering expenditure ratio and a large negative loading for the current account balance ratio, together with a contribution from special heavy snowfall area; it was interpreted as representing civil engineering expenditure and fiscal operating flexibility. The fifth principal component was mainly composed of intermediate agricultural area, flat agricultural area, bridge density, and heavy snowfall conditions, and was interpreted as representing agricultural regional structure and bridge stock distribution. The sixth principal component showed positive contributions from the real debt service ratio, current account balance ratio, and special heavy snowfall area, and negative contributions from

partially depopulated status and bridges per capita; it was interpreted as representing a composite dimension of fiscal burden and structural disadvantage.

3.4. Cluster Analysis Based on Principal Component Scores

Cluster analysis was then conducted using the scores of the first to sixth principal components derived from the 21-indicator PCA, with the aim of classifying municipalities according to maintenance potential. The k-means method was employed. Candidate numbers of clusters ranging from $k = 2$ to 8 were compared using the within-cluster sum of squares and the silhouette coefficient. Figure 3 shows the elbow curve for k-means clustering, and Figure 4 shows the silhouette coefficients for the candidate numbers of clusters. The elbow curve showed that the reduction in within-cluster sum of squares became moderate after $k = 4$ and further diminished after $k = 6$, whereas the silhouette coefficient reached its maximum at $k = 7$. Considering both statistical validity and interpretability, $k = 7$ was adopted. To reduce dependence on initial values, 100 random initializations were used, the maximum number of iterations was set to 300, and a fixed random seed was employed to ensure reproducibility. The overall tendencies were also confirmed to remain stable under alternative random seeds.

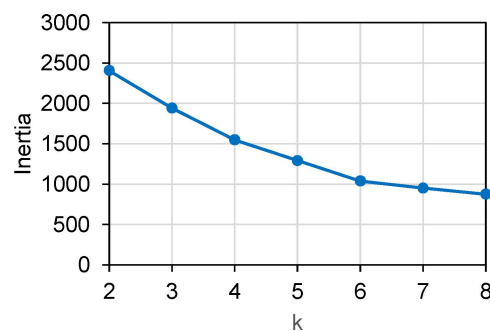


Figure 3. Elbow curve for k-means clustering.

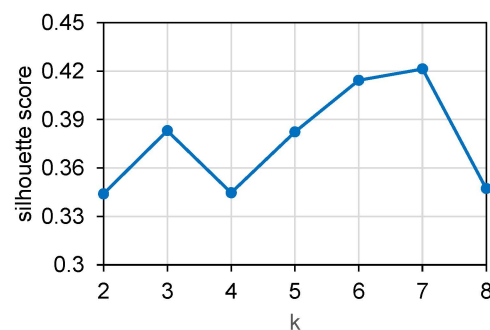


Figure 4. Silhouette coefficients for candidate numbers of clusters.

The decision to adopt seven clusters was based not only on statistical criteria but also on interpretability. With $k = 6$, municipalities with different levels of depopulation, heavy snowfall exposure, fiscal conditions, and management burden tended to be grouped together, making the resulting types less distinguishable. By contrast, $k = 7$ produced clearer separation among municipalities with different maintenance-related conditions and yielded more policy-relevant interpretations.

Figure 5 presents a heatmap of the cluster-level scores for the first six principal components. Red indicates larger positive values and blue indicates larger negative values, allowing the principal components that most strongly characterize each cluster to be identified visually. The values shown in the heatmap represent cluster-level principal

component scores, whereas the explanatory importance of each component should be assessed separately through its contribution ratio.

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
PC1	1.51	2.51	4.01	0.73	3.61	−0.98	−1.79
PC2	3.05	0.03	1.59	−0.80	−1.09	−1.77	5.52
PC3	1.47	−0.69	−0.19	1.10	−1.40	1.48	−1.21
PC4	−0.94	0.08	2.43	0.51	−0.79	−0.39	−0.25
PC5	0.12	0.01	−1.93	1.35	0.21	−1.90	−0.20
PC6	−1.18	0.16	1.61	0.44	−0.32	−0.75	0.48

Figure 5. Heatmap of cluster-level scores for the first six principal components.

Cluster 3 showed strongly positive scores on the first, fourth, and sixth principal components, with values of 4.01 on PC1, 2.43 on PC4, and 1.61 on PC6, indicating overlapping disadvantages related to depopulation, aging, complex fiscal burden, and structural disadvantage. Cluster 5 also exhibited a high PC1 score of 3.61, suggesting a strong influence of depopulation and aging, whereas its negative scores on PC2 and PC3 implied a different pattern from Cluster 3 in terms of wide-area burden and regional structure. Cluster 2 had a strongly negative PC1 score of −2.51, indicating relatively low levels of depopulation, aging, and fiscal weakness. Cluster 6 showed a negative score on PC2 (−1.77) and a positive score on PC3 (1.48), suggesting relatively weak influence from scale and heavy snowfall but relatively strong regional structural characteristics. Cluster 7 had the highest positive score on PC2 (5.52), indicating a particularly strong spatial management burden associated with scale and heavy snowfall. Cluster 1 also showed a high PC2 score (3.05), together with positive values on PC1 and PC3, indicating both management burden and some degree of structural disadvantage. Cluster 4 was characterized by relatively high scores on PC3 (1.10) and PC5 (1.35), indicating strong land-use and agricultural regional characteristics.

Overall, the seven clusters were not defined by a single principal component, but rather by different combinations of the first to sixth components. This indicates that differences in municipal maintenance potential are shaped by multiple dimensions, including depopulation and aging, wide-area burden and heavy snowfall, land-use conditions, bridge stock distribution, civil engineering expenditure, and fiscal burden. Figure 6 shows the spatial distribution of the municipal typology. Each cluster exhibited distinct characteristics in terms of maintenance management potential, based on differences in principal component scores.

The resulting municipal clusters can be summarized as follows.

Cluster 1 was characterized by high values on the second principal component and positive values on the first and third principal components, indicating a relatively high spatial management burden associated with wide-area and heavy-snow conditions. Cluster 2 showed a strongly negative value on the first principal component, indicating relatively low levels of depopulation, aging, and fiscal weakness. Cluster 3 showed high values on the first, second, fourth, and sixth principal components, suggesting the coexistence of multiple unfavorable conditions. Cluster 4 was characterized by high values on the third and fifth principal components and thus reflected differences in agricultural area type and land-use conditions. Cluster 5 showed a high value on the first principal component and low values on the second and third, indicating a strong influence of depopulation and aging. Cluster 6 showed a low value on the second principal component and a high value on the third, indicating relatively weak effects of wide-area and heavy-snow conditions but relatively strong land-use and regional structural characteristics. Cluster 7 showed a particularly high value on the second principal component and a negative value on the first, indicating relatively limited depopulation pressure but pronounced spatial management burden.

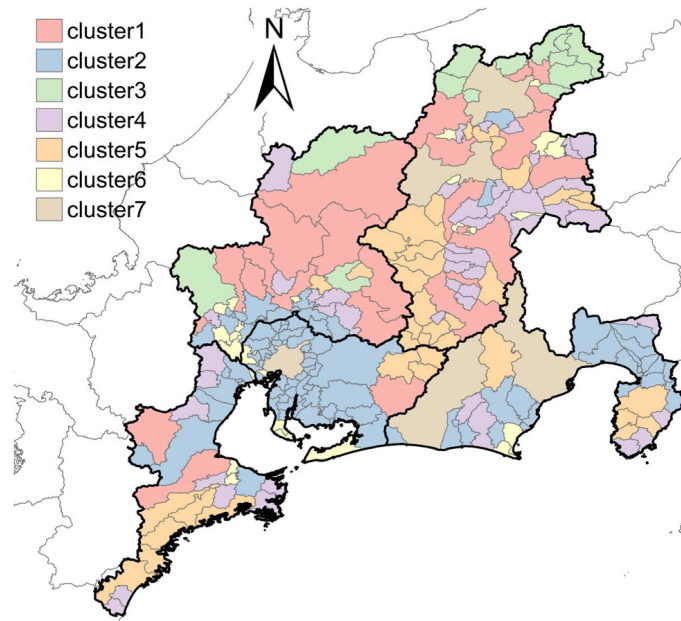


Figure 6. Spatial distribution of the municipal typology.

Taken together, these seven clusters represent different combinations of depopulation and aging, wide-area burden and heavy snowfall, land-use conditions, bridge stock distribution, civil engineering expenditure, and fiscal burden, and thus constitute a typology of municipal maintenance potential.

4. Integration of Deterioration and Municipal Typologies

4.1. Mean Deterioration Severity and Standard Deviation by Cluster

Next, the relationship between the cluster typology and bridge deterioration severity was examined. In assessing the characteristics of bridge deterioration by cluster, it is not sufficient to consider only the mean deterioration level, because the mean value indicates the overall deterioration level of municipalities belonging to a cluster but does not reveal whether such deterioration is spatially concentrated or spatially dispersed. Conversely, LISA analysis captures local spatial concentration but does not directly indicate the magnitude of deterioration severity itself. Therefore, this study examined both deterioration level and spatial aggregation in combination.

To evaluate deterioration severity by cluster, the mean and standard deviation of the bridge deterioration index were calculated for each of the seven clusters identified in Section 3.4. Table 4 presents the mean bridge deterioration severity and standard deviation for each cluster. Clusters 3 and 5 exhibited relatively high mean deterioration values, 0.176 and 0.164, respectively, whereas Clusters 2 and 6 showed relatively low values, 0.082 and 0.083, respectively. These results indicate that the clusters differ clearly in terms of deterioration severity.

Table 4. Mean bridge deterioration severity and standard deviation by cluster.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Number of municipalities	23	88	13	46	37	25	5
Mean value	0.132	0.082	0.176	0.150	0.164	0.083	0.134
Standard deviation	0.059	0.037	0.070	0.078	0.074	0.048	0.047
Type	Medium deterioration	Low deterioration	High deterioration	Medium deterioration	High deterioration	Low deterioration	Medium deterioration

The cluster means were then ranked in ascending order and grouped into three relative categories based on a tercile-based interpretation: high-deterioration clusters, medium-deterioration clusters, and low-deterioration clusters. As a result, Clusters 3 and 5 were classified as high-deterioration clusters; Clusters 1, 4, and 7 as medium-deterioration clusters; and Clusters 2 and 6 as low-deterioration clusters. This made it possible to position each cluster relative to the others in terms of deterioration severity level.

In addition, the high-deterioration clusters tended to show relatively large standard deviations, suggesting a certain degree of internal heterogeneity. By contrast, the low-deterioration clusters, especially Clusters 2 and 6, showed relatively small standard deviations, indicating that deterioration severity remained comparatively stable at a low level. Thus, comparison of mean deterioration severity provides a useful first step for distinguishing whether a cluster lies on the high-deterioration side or the low-deterioration side.

4.2. LISA Composition by Cluster

Next, the composition of LISA categories within each cluster was compared in order to examine the spatial aggregation characteristics of deterioration. Table 5 presents the proportions of the LISA categories for each cluster. Clear differences in LISA composition were observed among clusters. In particular, Clusters 2 and 6 had relatively high proportions of LL municipalities, while Clusters 3 and 7 showed relatively high proportions of HH municipalities. By contrast, Clusters 4 and 5 had relatively high proportions of NS municipalities, indicating that local spatial concentration was not especially clear in these clusters.

Table 5. Composition of LISA categories by cluster.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
HH	21.7	0.0	38.5	13.0	24.3	8.0	40.0
HL	0.0	3.4	0.0	0.0	0.0	0.0	0.0
LH	4.3	1.1	7.7	4.3	0.0	4.0	0.0
LL	13.0	40.9	7.7	6.5	5.4	40.0	20.0
NS	60.9	54.5	46.2	76.1	70.3	48.0	40.0
Type	Dispersed type	Dispersed type	High-deterioration concentrated type	Dispersed type	Dispersed type	Low-deterioration concentrated type	High-deterioration concentrated type

Based on the composition of LISA categories, spatial aggregation tendencies were further classified. First, attention was paid to the proportion of statistically non-significant municipalities (NS). Clusters in which NS accounted for 50% or more were interpreted as having weak or unclear local spatial concentration and were categorized as dispersed type.

For clusters in which NS accounted for less than 50%, local spatial concentration was regarded as relatively clear. These clusters were then further classified according to the composition of significant LISA categories after excluding NS. Specifically, if LL accounted for 50% or more of the significant cases, the cluster was classified as a low-deterioration aggregation type. If HH accounted for 50% or more, the cluster was classified as a high-deterioration aggregation type. In this way, the analysis first judged the clarity of spatial concentration through the proportion of NS and then distinguished the direction of spatial concentration through the relative dominance of HH or LL.

4.3. Relationship Between Mean Deterioration Severity and LISA Aggregation Index

The mean bridge deterioration value represents the deterioration level of each cluster, whereas the LISA composition indicates whether that deterioration tends to be geographically concentrated or spatially diffuse. By considering both indicators together, it becomes possible to distinguish, for example, between a cluster with high mean deterioration but

weak spatial concentration and a cluster with high mean deterioration and a clear local concentration of highly deteriorated municipalities. In addition, even clusters with similar mean deterioration levels can be differentiated by their LISA composition, allowing the analysis to determine whether low deterioration is stably distributed or whether some degree of high-deterioration concentration is embedded within the cluster. The significance of this two-dimensional approach lies in its ability to separate deterioration magnitude from its spatial manifestation and thereby examine the association between deterioration patterns and municipal maintenance-potential typologies in a more integrated manner.

Figure 7 shows the relationship between mean bridge deterioration severity and the LISA aggregation index for each cluster. The horizontal axis represents the mean bridge deterioration severity of each cluster, while the vertical axis represents the difference between the HH proportion and the LL proportion. Larger positive values indicate stronger local concentration of highly deteriorated municipalities, whereas larger negative values indicate stronger local concentration of low-deterioration municipalities. Bubble size represents the number of municipalities included in each cluster.

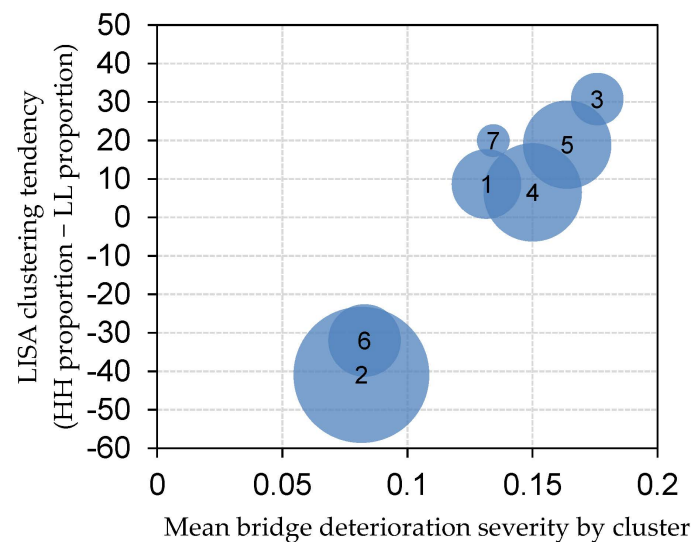


Figure 7. Relationship between mean bridge deterioration severity and the LISA aggregation index by cluster.

Clusters 2 and 6 were located in the low-deterioration and LL-dominant area, indicating that they are characterized by local concentration of municipalities with low deterioration severity. By contrast, Cluster 3 showed both the highest mean deterioration severity and a positive HH-dominant position, indicating that highly deteriorated municipalities are locally concentrated in this cluster. Cluster 5 also showed a high mean deterioration level and a tendency toward the HH side, but because its NS proportion remained relatively high, its local spatial concentration was less distinct than that of Cluster 3. Meanwhile, Clusters 1, 4, and 7 were positioned at intermediate deterioration levels, but their spatial aggregation tendencies differed, indicating that clusters with similar deterioration levels do not necessarily share the same spatial structure.

Overall, these results indicate that the clusters based on maintenance potential exhibit different characteristics not only in deterioration severity level but also in spatial aggregation pattern. Therefore, the interpretation and naming of the clusters should take into account not only the maintenance-potential profile of each cluster but also the level of deterioration severity and the way in which deterioration is spatially manifested.

4.4. Integrated Municipal Typology Based on Maintenance Potential and Spatial Deterioration Structure

Based on the integrated interpretation of maintenance potential, bridge deterioration severity, and spatial aggregation patterns, the seven clusters were named as follows. Cluster 1 was designated the Wide-area Heavy-Snow/Moderate-Deterioration Type because it is characterized by management burden associated with wide-area and heavy-snow conditions while its deterioration level remains moderate. Cluster 2 was designated the Urban-Infrastructure Stable/Low-Deterioration Type because it has a relatively stable fiscal and human-resource base and a low mean deterioration level. Cluster 3 was designated the Compound-Difficulty/High-Deterioration Aggregation Type because it combines multiple unfavorable conditions—such as depopulation, aging, wide-area management burden, and fiscal pressure—with the highest mean deterioration level and a clear concentration of highly deteriorated municipalities. Cluster 4 was designated the Agricultural Regional Characteristic/Moderate-Deterioration Type because agricultural area type and land-use conditions are strongly reflected while the deterioration level remains moderate. Cluster 5 was designated the Depopulation-Aging Advanced/High-Deterioration Type because it is strongly influenced by depopulation and aging and has a high mean deterioration level, although its spatial concentration is not especially clear. Cluster 6 was designated the Regional Characteristic/Low-Deterioration Aggregation Type because the effects of wide-area and heavy-snow conditions are relatively limited while regional structural conditions are pronounced and low-deterioration municipalities are locally concentrated. Cluster 7 was designated as the Large-Scale Wide-Area/High-Deterioration Aggregation Type because, despite its moderate mean bridge deterioration level, it was characterized by a large wide-area management burden and a relatively strong spatial concentration of highly deteriorated municipalities.

Taken together, these seven types integrate differences in maintenance potential—such as depopulation and aging, wide-area burden and heavy snowfall, land-use structure, and fiscal burden—with differences in deterioration level and spatial aggregation pattern. They therefore provide an interpretable typology for understanding municipal bridge-management challenges from multiple perspectives.

5. Discussion

5.1. Implications of the Integrated Municipal Typology for Bridge Management

Finally, the policy implications of the municipal typology derived in this study are discussed. In this study, bridge deterioration severity was treated as an indicator of the current state of deterioration, whereas the cluster typology based on municipal maintenance potential was treated as an indicator of the administrative, social, and geographic conditions under which deterioration is likely to emerge. In addition, LISA analysis was used to identify whether deterioration tends to be locally concentrated or whether its spatial pattern is relatively weak or dispersed. By combining these three dimensions, municipalities can be evaluated not simply by the magnitude of deterioration, but in an integrated way that also considers how deterioration is spatially manifested and under what structural conditions it occurs.

From this perspective, the Urban-Infrastructure Stable/Low-Deterioration Type and the Regional Characteristic/Low-Deterioration Aggregation Type can be understood as types with relatively favorable deterioration conditions, in which low-deterioration municipalities are also locally concentrated. In these clusters, severe deterioration concentration is not currently evident, suggesting that maintenance systems are functioning to a certain extent. For such municipalities, an appropriate policy approach would be to maintain the current management level while continuing to strengthen preventive maintenance and improve the efficiency of inspection and repair planning.

5.2. High-Deterioration Clustered and Dispersed Municipalities

By contrast, the Compound-Difficulty/High-Deterioration Aggregation Type represents municipalities facing multiple disadvantages, including depopulation, aging, wide-area management burden, and fiscal pressure, while also exhibiting high mean bridge deterioration severity and a local concentration of highly deteriorated municipalities. These municipalities may be regarded as priority targets for support, since both their current deterioration level and their future maintenance risk are high. In particular, the challenges they face may exceed the capacity of individual municipalities, making external interventions—such as support for securing technical personnel, inter-municipal cooperation, and more targeted subsidy schemes—especially important.

The Depopulation-Aging Advanced/High-Deterioration Type also showed high mean deterioration severity, but its spatial concentration was not especially clear. This suggests that although these municipalities contain highly deteriorated bridges, deterioration is not concentrated in a strongly clustered manner but is more unevenly distributed within or across municipalities. Therefore, a uniform support approach may be less effective than a strategy that prioritizes interventions according to the distribution of bridge stocks and the importance of individual structures within the local network.

A particularly important finding of this study is that unfavorable maintenance potential does not necessarily lead directly to a high-deterioration concentration pattern. For example, Cluster 5 was characterized by strong depopulation and aging effects and can therefore be regarded as structurally disadvantageous in terms of maintenance potential. However, its LISA results showed a high proportion of non-significant municipalities ($NS = 70.3\%$), indicating a spatial pattern different from that of Cluster 3, where high-deterioration municipalities were clearly concentrated. In other words, even among municipalities facing strong structural disadvantages, deterioration does not always appear in the form of highly concentrated local clusters.

Similarly, Cluster 1 also carried a relatively high management burden associated with wide-area and heavy-snow conditions, but its mean deterioration level remained moderate and its spatial concentration was comparatively dispersed. This indicates that even when municipalities face unfavorable maintenance conditions, the way deterioration appears may differ. Such differences suggest that deterioration patterns cannot be explained solely by fiscal conditions, demographic structure, or geography, but may also reflect variations in internal management systems, decision-making processes, and the prioritization of inspection and repair.

5.3. Policy Implications for Targeted Support and Network Prioritization

This point is particularly important from the perspective of evidence-based policymaking. The typology proposed in this study makes it possible not only to identify municipalities requiring priority support, but also to compare municipalities operating under similar structural conditions yet exhibiting different deterioration outcomes. Such comparisons can provide clues for identifying management practices that contribute to the suppression of deterioration. In particular, municipalities that face relatively unfavorable conditions but do not exhibit strong deterioration clustering appear to be promising cases for future detailed case studies. Through such comparative investigation, it may become possible to identify transferable practices related to the roles of technical staff, maintenance decision-making, public consensus building, outsourcing, and inter-municipal collaboration.

In addition, under long-term population decline in Japan, maintaining all bridge assets at uniform service levels is becoming increasingly unrealistic. Future infrastructure management will therefore require not only the continuation of existing maintenance systems but also strategic decisions regarding prioritization, concentration of resources,

reorganization of bridge networks, and in some cases planned downsizing. In this context, a typology that integrates deterioration severity, spatial concentration, and municipal maintenance potential can provide a useful basis for determining which bridge groups should be prioritized and where wide-area cooperation should be strengthened.

Overall, the municipal types identified in this study can serve not only as a tool for understanding the present condition of bridge deterioration, but also as a basis for identifying municipalities that require priority support, comparing management practices in structurally disadvantaged areas, and informing future policy discussions on infrastructure restructuring and strategic adaptation under demographic decline.

5.4. Limitations and Future Research

Several limitations of this study should be noted. First, this study did not explicitly incorporate detailed bridge-level engineering attributes, such as structural type, bridge length, bridge size, material, construction year, and repair history. These factors can influence deterioration mechanisms and maintenance requirements. For example, small underpass-type bridges may show different deterioration and maintenance patterns from larger bridges or bridges with different structural systems. Therefore, future research should integrate municipal-level administrative indicators with bridge-level structural attributes and should examine additional indices representing the structural typology and average size of bridges managed by each municipality. Second, the analysis was conducted at the municipal level and therefore captures aggregate maintenance conditions rather than the detailed operational processes of individual municipalities. As a result, factors such as organizational decision-making, prioritization of interventions, and informal coordination practices could not be directly observed. Third, although the study integrated bridge condition data with demographic, fiscal, and regional indicators, it did not directly evaluate how specific maintenance actions or institutional arrangements affect deterioration outcomes over time. Fourth, this study did not assign theoretical or policy-based weights to the indicators of municipal maintenance potential. The indicators were treated as exploratory variables and analyzed using PCA after standardization. Future research should examine weighting schemes that reflect the relative importance of fiscal capacity, technical staffing, maintenance burden, and regional constraints, based on expert judgment, policy priorities, or empirical validation using longitudinal maintenance and deterioration data. Fifth, this study did not directly incorporate bridge maintenance expenditure. Although road and bridge expenditure would appear to be a relevant indicator, publicly available municipal financial statistics do not consistently distinguish bridge inspection, repair, rehabilitation, replacement, and maintenance activities from road construction, improvement, and other road-related expenditures. In particular, road and bridge expenditure may include a substantial amount of spending for new road construction and improvement, rather than maintenance of existing bridges. Therefore, using this expenditure category as a direct proxy for bridge maintenance expenditure could obscure the specific relationship between maintenance investment and bridge deterioration. Future research should incorporate more detailed expenditure data, such as bridge inspection costs, repair costs, rehabilitation costs, and replacement costs, when such data are available. Overall, the results of this study should be interpreted as an exploratory screening framework rather than as a definitive basis for establishing causal relationships between bridge deterioration and municipal managerial or social conditions. In Japan, local governments are increasingly responsible for maintaining aging infrastructure under demographic, fiscal, and technical constraints. Therefore, a framework that makes otherwise less-visible municipal maintenance conditions quantitatively interpretable can support evidence-based discussions on the sustainability of infrastructure maintenance. However, more detailed analysis is needed

to interpret the mechanisms behind the observed clustering and statistical associations, including the incorporation of bridge-specific indicators, detailed maintenance expenditure data, and policy or management-related information.

Future research should therefore extend this typology through detailed qualitative and comparative case studies of selected municipalities. In particular, municipalities operating under structurally unfavorable conditions but showing relatively restrained deterioration clustering may provide useful insights into effective management practices. Such work would help clarify the roles of technical staff, repair decision-making, public consensus building, outsourcing arrangements, and inter-municipal coordination, thereby contributing to a more comprehensive policy design that integrates engineering rationality with social and institutional rationality in bridge management.

6. Conclusions

This study analyzed 237 municipalities in the Chubu region of Japan by integrating bridge inspection data from the Nationwide Road Facility Inspection Database with demographic, fiscal, geographic, and regional condition indicators. The aim was to examine the association between the spatial structure of bridge deterioration and municipal maintenance potential.

First, the municipal distribution of bridge deterioration severity showed clear regional unevenness. Relatively high deterioration levels were observed mainly in inland areas, particularly in Nagano and Gifu prefectures, whereas relatively low deterioration levels were more common in southern Aichi and western Shizuoka. Global Moran's I and LISA analysis further demonstrated that bridge deterioration severity exhibits significant positive spatial autocorrelation, with both local clusters and local outliers present within the study region. These findings indicate that bridge deterioration is not randomly distributed, but rather has a distinct spatial structure associated with regional conditions.

Second, principal component analysis showed that municipal maintenance potential is structured by multiple dimensions rather than by any single factor. The analysis using continuous variables indicated that vulnerability, scale and wide-area management burden, and fiscal operation constitute the basic structure of maintenance potential. The analysis using 21 indicators further incorporated regional conditions and enabled municipal characteristics to be organized into six principal components. Based on these component scores, cluster analysis classified municipalities into seven types with different combinations of depopulation and aging, wide-area burden and heavy snowfall, land-use structure, bridge stock distribution, civil engineering expenditure, and fiscal burden.

Third, by integrating cluster results with the mean bridge deterioration index and the composition of LISA categories, this study identified multiple patterns linking maintenance potential and spatial deterioration structure. These included clusters characterized by low deterioration and local concentration of low-deterioration municipalities, clusters characterized by high deterioration and local concentration of highly deteriorated municipalities, and clusters with high deterioration but comparatively weak spatial concentration. This integrated approach made it possible to distinguish not only where deterioration is severe, but also how deterioration is spatially manifested and under what municipal conditions such patterns tend to occur.

The scientific significance of this study lies in linking inspection-based bridge deterioration with municipal-level maintenance capacity and spatial dependence. This approach extends bridge deterioration analysis from an asset-level engineering perspective to a regional infrastructure governance perspective. In particular, by integrating maintenance-potential typologies with the spatial structure of deterioration, this study provides a framework for identifying municipalities in which deterioration tends to cluster, as well

as municipalities in which deterioration clustering remains limited despite structurally unfavorable conditions.

These findings should be interpreted as exploratory statistical trends rather than as definitive evidence of causal relationships between bridge deterioration and municipal managerial or social conditions.

The proposed framework can be applied to other countries and regions where bridge inspection data, local administrative statistics, and spatial boundary data are available. Although the specific indicators and administrative units should be adapted to each country's institutional context, the basic framework—integrating inspection-based deterioration, spatial autocorrelation, and local maintenance capacity—is transferable.

These findings provide a basis for future bridge management policy, including the identification of municipalities requiring priority support, comparative analysis of management practices in structurally disadvantaged areas, the strengthening of inter-municipal cooperation and technical assistance, and long-term infrastructure strategies involving network prioritization and reorganization. Future research should build on this typology through detailed qualitative case studies of individual municipalities, focusing on the roles of technical staff, maintenance decision-making, public consensus building, outsourcing, and inter-municipal coordination. Such work would contribute to a more comprehensive bridge management policy that integrates engineering rationality with social and institutional rationality.

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