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# Spatial Regression in the Presence of a Hierarchical Transportation Network: Application to Land Price Analysis

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Transportation networks have a hierarchical structure, and the spatial scale of their impact on urban growth differs depending on the hierarchy. However, in empirical analyses of the impacts that transportation has on land use and prices, such hierarchy is often examined using dummy variables, and the network dependence and heterogeneity of impacts are often ignored. Thus, this study develops a spatial regression method that considers not only spatial dependence, but also network dependence within a hierarchical transportation network. This method was developed by extending the random effects eigenvector spatial filtering approach. Subsequently, it was applied to a pre-existing analysis that focused on the impacts that high-speed rail (HSR) had on residential land prices in Japan over the last 30 years. The results of the analysis suggested that HSR lines had hierarchical effects on residential land prices. The results also provide interesting insight into the ongoing problem of Japanese urban hierarchy; that is, the excessive concentration of population and industry in the Tokyo metropolitan area.

**Keywords: high-speed rail, network dependence, spatial regression, Moran eigenvectors, land prices, urban form**



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## INTRODUCTION

Transportation networks are hierarchical. For example, a road network consists of expressways, national roads, prefectural roads, municipal roads, and others. The commuter rail network has major stations where rapid transit services are available and other stations where it is not. Such hierarchical transportation networks have heterogeneous impacts on urban structures, which is evidenced in the vast amounts of existing research regarding the interactions between land use and transportation (e.g., Newman and Kenworthy, 1996; Stanley, 2014).

High-speed rail (HSR) is one of the most influential transportation systems within urban structures in Japan (Takami and Hatoyama, 2008), China (Chen and Hall, 2011), and Europe (e.g., Garmendia et al., 2012). The presence of HSR causes a concentration of economic activities around stations and creates hierarchies within the urban network (Jiao et al., 2017). For example, Albalate and Bel (2012) suggested that Japanese HSR encouraged rapid growth in major cities, such as in Tokyo and Osaka, leading to a concentrated urban hierarchy. Similar results were obtained in Spain (Garmendia et al., 2012) and China (Jiao et al., 2017). Contrastingly, the HSR in France was found to encourage rapid growth in minor cities and create a dispersed hierarchy in the city network (Cervero and Bernick, 1996).

Moreover, HSR typically has rapid trains that only stop at major stations, and local trains that stop at every station. Such a hierarchy within the HSR network may create an urban hierarchy. However, in empirical analyses, such a hierarchy in transportation networks is often solely considered through the use of dummy variables that indicate differences in services, whilst ignoring network dependence.

To quantify the hierarchical impacts of HSR on urban growth, this study develops a spatial regression method that considers (i) network dependence, (ii) city-wise heterogeneity in each hierarchy, and (iii) spatial dependence (decaying with respect to Euclidean distance) by extending the random effects eigenvector spatial filtering (RE-ESF) approach (Griffith, 2003; Murakami and Griffith, 2015). Although it is typical to use spatial econometric models to consider spatial dependences (Anselin and Griffith, 1988; LeSage and Pace, 2009; Yamagata and Seya, 2019), the RE-ESF framework is flexible and can easily be applied to models for transportation research, as Yu et al. (2020) showed and as we will show later.

The number of studies considering network dependence is relatively limited. Cressie et al. (2006) and Garreta et al. (2010) considered network dependence on river networks, and Lu et al. (2017) and Ver Hoef (2018) considered dependence through road networks. Yet, these studies utilize either network dependence alone or compared Euclidean and network distances, then merely choosing the model with better accuracy. In the case of land prices, however, while there is spatial dependence, they may also be affected by network dependence and station-wise heterogeneity. Moreover, these variables can affect multiple hierarchies in the city network, as explained above. Based on our literature review, no regression studies simultaneously consider variables (i)–(iii).

This study analyzes the impact that HSR development has on land prices in Japan. Since 1964 when Japan's first HSR, the Shinkansen, first opened, major cities have been connected by the HSR network and urbanization has accelerated along rail lines. As discussed by Seya and Timmermans (2018), a properly executed transportation project may improve the land accessibility. An improvement in accessibility may be reflected in both the price of land and the concentration of development. Typically, the effect of transport on land use and development can take a relatively long time to observe, whereas the effect of transport on property values can occur sooner (Stokenberga, 2014). Existing studies have attempted to examine both the former and the latter. The results of the analysis, as explained below, indicate that both spatial dependence and HSR network dependence influence residential land prices. This suggests the importance of considering network dependence when analyzing interactions between land use and transport. We also observed a hierarchical pattern in which both major and minor cities were affected by network dependence. However, the former was further affected by another global network dependence.

The subsequent sections are organized as follows: Section methodology explains the method employed, section empirical analysis applies this method to an analysis that evaluates the influence that HSR has on urbanization in Japan, and section concluding remarks states the conclusions from this study.

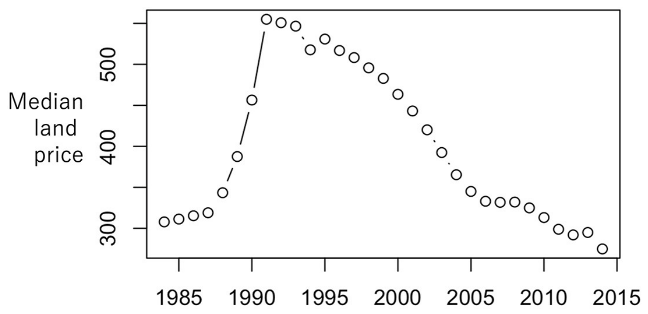


**FIGURE 1 |** Median residential land price per area (1976–2014).

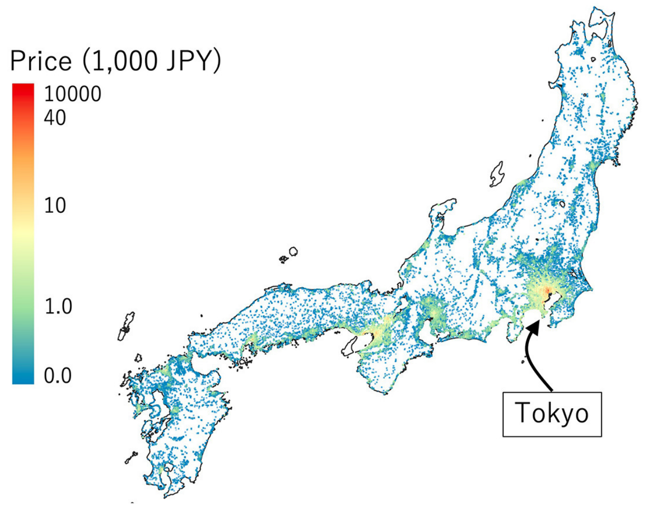


**FIGURE 2 |** Spatial distribution of the residential land price per area (2000).

## METHODOLOGY

### Data Model

This study assumes the following model for the land price $y_i$ at the $i$-th location:

$$\log\left(y_i\right) = \sum_{k=1}^{K} x_{i,k}\beta_k + s_i + \sum_{m=1}^{M} z_{i,m} + \varepsilon_i, \qquad \varepsilon_i \sim N\left(0, \sigma^2\right), \quad (1)$$

where $x_{i,k}$ denotes the $k$-th explanatory variable, $\beta_k$ is the regression coefficient, $s_i$ denotes (iii) spatially dependent process, and $z_{i,m}$ denotes influence from the $m$-th HSR network characterized by (i) and (ii). $\varepsilon_i$ represents data noise with variance $\sigma^2$. Following land price modeling studies (e.g., Tsutsumi and Seya, 2009; Kunimi and Seya, 2021), land price has been log-transformed.

This study considers $M$ transportation networks, each of which has the same network structure but different set of stations/nodes; the $m$-th network has the stations/nodes that the

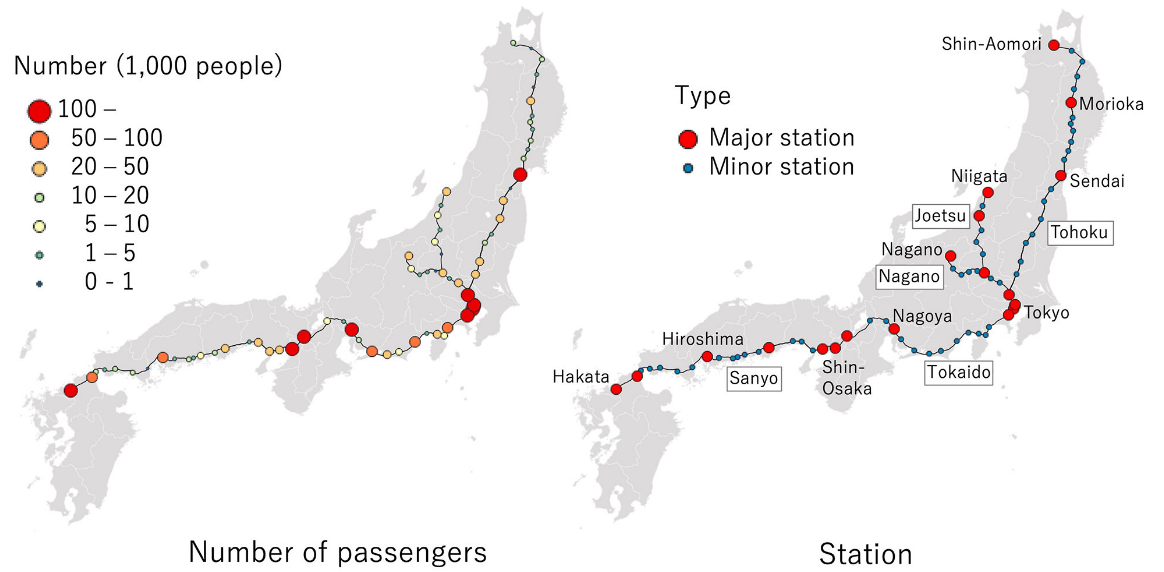


**FIGURE 3 |** Study area and the high-speed rail network. The major stations and other stations are shown in the right panel while the number of passengers is shown in the left. In the right panel, route names are surrounded by black border while station names are not. The major stations are considered as the nodes of the global network while all the stations are considered as the nodes of the local network.

**TABLE 1 |** Summary of the high-speed rail lines.

| Name | Line | Year of opening | Daily mean number of passengers (2000)[a] |
|---|---|---|---|
| Tokaido-Sanyo Shinkansen | Tokyo-Hakata | 1964 (Tokyo-Osaka)<br>1972 (Osaka-Hakata) | 617,745 |
| Tohohoku Shinkansen | Tokyo-Aomori | 1982 (Tokyo-Morioka)<br>2002 (Morioka-Hachinohe)<br>2010 (Hachinohe-Aomori) | 237,792 |
| Joetsu Shinkansen | Tokyo-Niigata | 1982 | 107,386 |
| Hokuriku Shinkansen | Tokyo-Nagano | 1997 | 32,931 |

*Although Hokuriku and Tokaido Shinkansen lines are extended after 2015, they are not shown here because our target period is until 2014.*
[a]*Transport Policy Research Organization, Japan (2020).*

$m$-th class train stops[1]. Later, we analyze the impact of the rapid and local HSR networks on urban hierarchy, assuming $M = 2$. The influence from the $m$-th network $z_{i,m}$ is modeled as follows:

$$z_{i,m}=w_{i,I(m)}\left(b_m + n_{I(m)}+n^*_{I(m)}\right). \tag{2}$$

The nearest station from the $i$-th location in the $m$-th network is indexed by $I(m)$. $n_{I(m)}$ models (i) the dependence through the $m$-th network, and $n^*_{I(m)}$ models (ii) the station-wise heterogeneity. While $n_{I(m)}$ and $n^*_{I(m)}$ are stochastic processes defined by the network, they are assumed to influence the land price nearby the $I(m)$-th station (i.e., spill-over from the station). While the expectations of these processes are assumed to be zero, the $b_m$ parameter estimates the mean increase of the logged land price at each station owing the $m$-th transport network. $w_{i,I}$ determines the strength of the influence that the $i$-th location receives from the nearest station $I(m)$. It is specified as follows:

$$w_{i,I(m)} = \exp\left(-\frac{d_{i,I(m)}}{R_{I(m)}}\right), \tag{3}$$

where $d_{i,I(m)}$ is the Euclidian distance between the $i$-th location and the $I(m)$-th station. $R_{I(m)}$ represents the distance that the spatial spillover extends from the $I(m)$-th station. This study parameterizes it as $R_{I(m)} = R_m A_{I(m)}$ where $R_m$ is a range parameter and $A_{I(m)}$ is a multiplier adjusting the range according to the scale of the $I(m)$-th station. Later, it is given by the square root of the number of passengers at the station.

In short, Equation (1) models logged land price using explanatory variables $\{x_{i,1},\ldots,x_{i,K}\}$, (iii) spatial dependent effects $s_i$, (i) dependent and (ii) heterogenous effects induced by the $M$ transportation networks $\{n_{I(1)},\ldots,n_{I(M)},n^*_{I(1)},\ldots,n^*_{I(M)}\}$, and noise $\varepsilon_i$. Since $s_i$, $n_{I(m)}$, and $n^*_{I(m)}$ can be collinear each other, these effects must be identified and analyzed carefully.

[1]The $M$ networks can also be defined by different transportation networks (e.g., bus and railway networks).

**TABLE 2 |** Summary of models.

| Name | Description | Spatial dependence ($s_i$) | Global-level effects ($z_{i,1}$) | Local-level effects ($z_{i,2}$) |
|---|---|---|---|---|
| LM | Basic log-linear regression model | | | |
| SM | Spatial regression model (RE-ESF) | × | | |
| SM_G | SM + Global-level effects | × | × | |
| SM_L | SM + Local-level effects | × | | × |
| SM_GL | SM + Global and local-level effects | × | × | × |

*SM is a standard spatial regression model while SM_G, SM_L, and SM_GL are spatial regression models considering network effects. "×" is used to indicate the models considering each property.*

## Process Model

### Spatially Dependent Process $s_i$

Moran coefficient (MC; Griffith, 2000) is a diagnostic statistic of spatial dependence. The MC value for a vector $\mathbf{y}$ is defined as follows:

$$MC\left[\mathbf{y}\right]=\frac{N}{\mathbf{1}'\mathbf{C1}}\frac{\mathbf{y}'\mathbf{MCMy}}{\mathbf{y}'\mathbf{My}}, \tag{4}$$

where $\mathbf{C}$ is a symmetric spatial proximity matrix with zero diagonals. $\mathbf{M} = \mathbf{I} - \mathbf{11}'/N$ is a centering matrix where $\mathbf{I}$ is an identity matrix $\mathbf{1}$ is a vector of ones. In the absence of spatial dependence in $\mathbf{y}$, the expectation of $MC\left[\mathbf{y}\right]$ equals $-\frac{1}{N-1} \approx 0$. If $N$ is sufficiently large, $MC\left[\mathbf{y}\right] > 0$ if $\mathbf{y}$ is positively dependent while $MC\left[\mathbf{y}\right] < 0$ if it is negatively dependent.

It is known that the MC of the $p$-th eigenvector $\mathbf{e}_p$ of the $\mathbf{MCM}$ matrix yields (Griffith, 2003).

$$MC\left[\mathbf{e}_p\right]=\frac{N}{\mathbf{1}'\mathbf{C1}}\lambda_p. \tag{5}$$

Equation (5) suggests that $\mathbf{e}_p$ has a positively dependent map pattern if $\lambda_p > 0$ while the opposite is true if $\lambda_p < 0$. In other words, the $P$ eigenvectors $\mathbf{e}_1, \ldots, \mathbf{e}_P$ corresponding positive eigenvalues $\{\lambda_1, \ldots, \lambda_P\}$ explains positive spatial dependence. Thus, the $P$ eigenvectors are sufficient for modeling positively dependent spatial processes, which is predominant in most real-world cases.

Using the $P$ eigenvectors, RE-ESF models positively dependent spatial process as follows:

$$s_i=\sum_{p=1}^{P} e_{i,p}\gamma_p, \quad \gamma_p \sim N\left(0, \tau^2\lambda_p^{\alpha}\right), \tag{6}$$

where $e_{i,p}$ is the $i$-th element of $\mathbf{e}_p$ and $\tau^2$ denotes the variance of the process (e.g., $\tau^2 = 0$ means no spatially dependent variation). The $\alpha$ parameter determines the scale or the MC value of the process. Specifically, the expectation of $I\left[\mathbf{s}\right]$ where $\mathbf{s} = [s_1, \ldots, s_N]'$ approaches the theoretical maxima, which implies the largest-scale map pattern, as $\alpha \to \infty$, while the expectation approaches zero, which implies the smallest-scale map pattern, as $\alpha \to -\infty$. Thus, Equation (6) attempts to estimate the structure of the underlying process through the $\tau^2$ and $\alpha$ parameters (see Murakami and Griffith, 2021).

### Network Dependent Process $n_{I(m)}$

Equation (6) is readily extended to model dependence among stations through the $m$-th network as follows:

$$n_{I(m)}=\sum_{q_m=1}^{Q_m} e_{I(m),q_m}\gamma_{q_m}, \quad \gamma_{q_m} \sim N\left(0, \tau_m^2\lambda_{q_m}^{\alpha_m}\right), \tag{7}$$

where $\mathbf{e}_{I(m)} = [e_{I(m),1}, \ldots, e_{I(m),Q_m}]'$, and $\lambda_{q_m}$ are the $q_m$-th eigen-pair corresponding positive eigenvalue extracted from a doubly centered proximity matrix $\mathbf{M}_m\mathbf{C}_m\mathbf{M}_m$ on the $m$-th network. The $(I(m), J(m))$-th element of the $\mathbf{C}_m$ matrix may be defined by a function decaying with respect to the shortest-path distance, travel time, or other distances between the stations $I(m)$ and $J(m)$. The parameters $\tau_m^2$ and $\alpha_m$ estimate the variance and scale of the dependent process upon the network. While Equation (7) models a dependence on the $m$-th network, it influences on the land prices nearby the $I(m)$-th station though a spillover, that decays with respect to $w_{i,I(m)}$, as previously explained.

### Station-Wise Heterogenous Process $n^*_{I(m)}$

The following station-wise random intercept is assumed for $n^*_{I(m)}$:

$$n^*_{I(m)}\sim N\left(0, \nu_m^2\right), \tag{8}$$

where $\nu_m^2$ is a variance parameter. The random intercepts take uniformly zero values when $\nu_m^2 = 0$, while the intercepts have large variation across stations when $\nu_m^2$ is large. In general, consideration of such a group effect is crucial to avoid estimation bias attributed to the heterogeneity by groups (ecological fallacy; see Piantadosi et al., 1988).

## Summary

By substituting the process models (6–8) into Equation (1), our model is written as follows:

$$\begin{aligned}
\log\left(y_i\right) &= \sum_{k=1}^{K} x_{i,k}\beta_k + \sum_{p=1}^{P} e_{i,p}\gamma_p + w_{i,I(m)}b_m \\
&+ \sum_{m=1}^{M}\sum_{q_m=1}^{Q_m}\left(w_{i,I(m)}e_{I(m),q_m}\right)\gamma_{q_m} + \sum_{m=1}^{M} w_{i,I}n^*_{I(m)} + \varepsilon_i, \\
&\varepsilon_i \sim N\left(0, \sigma^2\right) \\
&\gamma_p \sim N\left(0, \tau^2\lambda_p^{\alpha}\right), \quad \gamma_{q_m} \sim N\left(0, \tau_m^2\lambda_{q_m}^{\alpha_m}\right), \\
&n^*_{I(m)}\sim N\left(0, \nu_m^2\right).
\end{aligned} \tag{9}$$

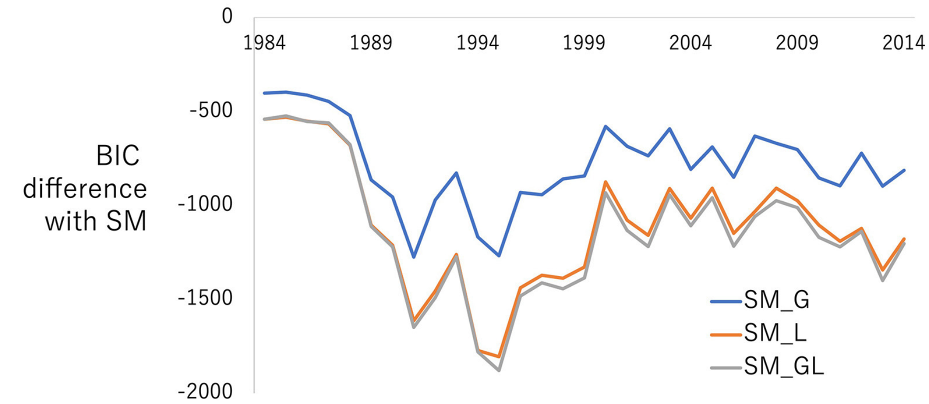


**FIGURE 4 |** BIC differences between SM and {SM_G, SM_L, SM_GL}. A larger negative value means better model accuracy relative to SM.

Equation (9) is a mixed effects model with random coefficients $\{\gamma_p, \gamma_{q_m}, n_I^*\}$ regularized by the variance parameters $\{\tau^2, \alpha, \tau_1^2, \ldots, \tau_M^2, \alpha_1, \ldots, \alpha_M, \nu_1^2, \ldots,, \nu_M^2\}$. While the model estimation can be slow for large samples because of the need to optimize the $2 + 3M$ variance parameters, Murakami and Griffith (2019) developed a fast restricted maximum likelihood (REML) method to estimate a spatial mixed effects model (see Murakami et al., 2020) including Equation (9). The model is estimated using the REML. Since the original fast REML does not assume the $R_m$ parameter in $w_{i,I(m)}$, it is optimized though a grid search (grid size: 1 km) in the subsequent empirical part. Therefore, the fast REML is iterated while varying the $r$ value, and the value maximizing the restricted likelihood is adopted.

## EMPIRICAL ANALYSIS

### Outline

This section applies the developed model to the HSR to examine the HSR's effects on urbanization between 1984 and 2014 through land price analysis. The study area included the main island of Japan (Honshu) and the Kyushu region where the HSR runs. The explained variable is the logged officially assessed residential land price per area [JPY/m$^2$] (source: National Land Numerical Information download service (NLNI); https://nlftp.mlit.go.jp/ksj/). The yearly sample size ranged between 26,264 (1984) and 45,008 (1998). In this study, the static model is estimated on an annual basis (i.e., for each cross-section).

**Figures 1**, **2** display the temporal and spatial distributions of the land prices. As shown in **Figure 1**, the median land price peaked in 1991 when Japan was in a bubble economy, which lasted from 1986 until 1991. After that, the economy stagnated and land price began a gradual decline. This was especially true around major urban areas, including the Tokyo metropolitan area (see **Figure 2**).

As shown in **Figure 3**, the HSR stretches outwards from Tokyo in every direction. Among the HSR lines summarized in **Table 1**, the Tokaido-Sanyo Shiknansen, which connects Tokyo and Hakata through Nagoya, Kyoto, and Osaka with the maximum speed of 275–300 km/h, is the busiest line. This line is thought to have had a huge impact on urban growth. The other lines which connect Tokyo to other major cities have maximum speeds between 240 and 320 km/h.[2]

Each of these lines have rapid trains that only stop at major stations. This is indicated by red circles in **Figure 3** (left). However, local trains stop at every station. In other words, Japanese HSR has a global-level HSR network, whose proximity matrix $\mathbf{C}_1$ is defined by the distance among the major stations that the rapid trains stop, and a local-level network with proximity matrix $\mathbf{C}_2$ being defined by the network distance among all the HSR stations. The $(I(m), J(m))$-th element of the $\mathbf{C}_m$ matrix is given by $\exp\left(-\frac{d_{I(m),J(m)}}{r_m}\right)$ where the distance $d_{I(m),J(m)}$ between stations is given using the shortest travel time, which is defined as (network distance) $\times$ (the maximum speed). The $r_m$ value is given by the longest distance between two adjacent stations/nodes in the $M$-th network[3]. The $r_m$ value acts as a prior for the scale of the network dependence, and the scale is adjusted to fit the data by estimating the $\alpha_m$ parameter as explained in section summary.

Regarding $A_{I(m)}$, to determine the range of the spillover from the $I(m)$-th station (see Equation 3), the square-root of the average number of daily passengers in 2013 (source: NLNI) is used[4]. The resulting range is $R_{I(m)} = R_m A_{I(m)}$, wherein the spillover becomes larger for stations with more passengers. The $R_m$ parameter is estimated by maximizing the restricted likelihood.

The explanatory variables considered as are follows: Euclidean distance to the nearest railway station among stations including

[2]Mini-Shinkansen that goes through conventional railway is not considered in this study because their maximum speed is 130 km/h, which is considerably slower than our targets and impacts may be different.

[3]It is an analog of relevant studies (e.g., Murakami and Griffith, 2015) that gave the same range parameter by the longest distance between two adjacent nodes in a network connecting all sample sites for modeling spatial dependence.

[4]Area in the $R_m$ distance radius equals $\pi R_m^2$. Therefore, it is reasonable assume that population in the radius is proportion to $R_m^2$. In other words, $R_m^2 \propto$ *population*, or equivalently, $R_m \propto \sqrt{population}$. Given that, we assume the square-root of the number of passengers as the adjustment factor $A_{I(m)}$ for the distance range parameter $R_m$.

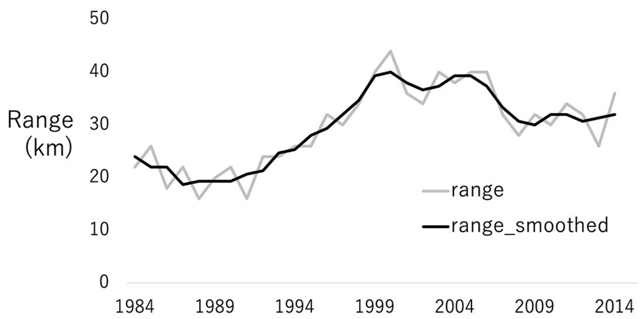


**FIGURE 5 |** Estimated range of the spatial spill-over from the Tokyo station. The gray line represents the raw estimates, and the black line represents the smoothed estimates, which are used in the subsequent analysis.

those for non-high-speed rail lines (Sta_dist [km]), bus stop (Bus_dist [km]), airport (Air_dist [km]), and prefectural government official (Gov_dist [km]); and dummy variables for residential land (Res), commercial land (Com), and industrial land (Ind). All these variables were acquired from NLNI.

The objective of this empirical analysis is to examine if the HSR network has hierarchical effects influencing the major cities though the global-level network and the major and local cities through the local-level network. Section accuracy comparison result verifies the existence of global and local effects through accuracy comparison. Section estimation results visualized the estimated effects.

## Accuracy Comparison Result

The accuracy of the models summarized in **Table 2** were compared using Bayesian Information Criterion (BIC). The BIC values of all the spatial models are considerably smaller, and therefore better, than LM, suggesting the presence of the conventional spatial dependence ($s_i$). **Figure 4** plots the differences in the BIC values between SM and {SM_G, SM_L, SM_GL}. Based on this figure, consideration of both the global and local networks can improve the BIC. In particular, throughout the target period, the best accuracy was achieved by SM_L and SM_GL which consider the local-level effects. The local network dependence appears more influential on land price than the global network dependence is. Based on that result, land prices near minor stations may be strongly influenced by network dependence from Tokyo, for example. From 1984 to 1988, SM_L achieved the best, or smallest, BIC values in 4 or 5 years. After 1989, SM_GL achieved the best BIC values out of all of the years that were analyzed. Both the HSR's global and local networks may affect land prices. Based on this result, we report an estimated result of SM_GL in the subsequent sections.

## Estimation Results

**Figure 5** plots the estimated range $r_{I(m)}$ of the spillover effects from the Tokyo station. The range, which ∼20 km in the 80s and gradually increased during 90s, became ∼40 km in 2000. The HSR may have encouraged urban development and, therefore, urban sprawl (Bagan and Yamagata, 2012) in this period. Contrastingly, the range gradually declined after 2000. Note that this pattern is similar to the net population inflow to the Tokyo metropolitan area (Ministry of Land Infrastructure Transport and Tourism (MLIT), 2014, p. 3), which increased from just after the end of the bubble in 1991 until the 2008 financial crisis, although it peaked a slightly earlier. As the optimized range values are a bit noisy as shown in the gray line in **Figure 5**, we smoothed the value as shown in the black line and used in the subsequent SM_GL model estimation.

**Figure 6** plots the regression coefficients estimated in each year. Sta_dist, Bus_dist, Gov_dist, which are accessibility measures, are negatively significant within certain periods. The coefficients on Sta_dist is smaller than Bus_dist, meaning that railway station has a long-range effect whereas the bus stop has a short-range effect. The result is reasonable given that buses are typically responsible for local transportation. The coefficients for Gov_dist are smaller than those for Sta_dist and Bus_dist, indicating longer-range effects. Again, this is reasonable given that only 41 prefectural offices cover the entire study area. The coefficients on Air_dist had values near zero and tended to be statistically insignificant.

Res, Com, and Ind were all positively significant. Among the three, Com was the largest and Ind was the smallest coefficient. Commercial land, which has many urban facilities, was found to be the most popular area. Meanwhile, industrial land, which may suffer from air pollution and noise, was the cheapest area of the three land types.

Based on the fact that the coefficients for Sta_dist, Res, Com, and Ind all declined over the study period, a decline in land prices during a stagnate economy appeared to be especially severe in urban areas, specifically those that were near railway stations.

The left panel in **Figure 7** plots the estimated spatially dependent process ($s_i$). The process identified two hotspots around Tokyo and Osaka, which are two major urban areas. However, Osaka's hotspot gradually diminished, whereas Tokyo is still the dominant hotspot as of 2014. This result suggests that there has been a popular residential area concentrated around Tokyo for years.

The middle panel of **Figure 7** maps the effects of the global-level network dependence ($w_{i,I(1)}(b_1 + n_{I(1)})$). The dependence was estimated to increase the land price around the major stations, including the Nagoya and Hakata stations in Tokaido-Sanyo Shinkansen. The increase was substantial in Osaka and Kyoto. Because these cities dramatically improved their accessibility to Tokyo through the HSR, the increase in land price was reasonable. Similar increases in land price were also found around major stations outside Tokyo, likely due to the accessibility to Tokyo and other major cities caused by the HSR. Contrastingly, the global-level network dependence did not increase land prices in Tokyo after 2005. In short, the global-level network dependence is especially beneficial for major cities outside Tokyo.

Based on the right panels in **Figure 7** showing the global-level station-wise effects ($w_{i,I(1)}(b_1 + n^*_{I(1)})$), land price along Tokaido-Sanyo Shinkansen increased not only dependently through the network but also heterogeneously/independently within each major city. Given that Tokaido-Sanyo Shinkansen runs along

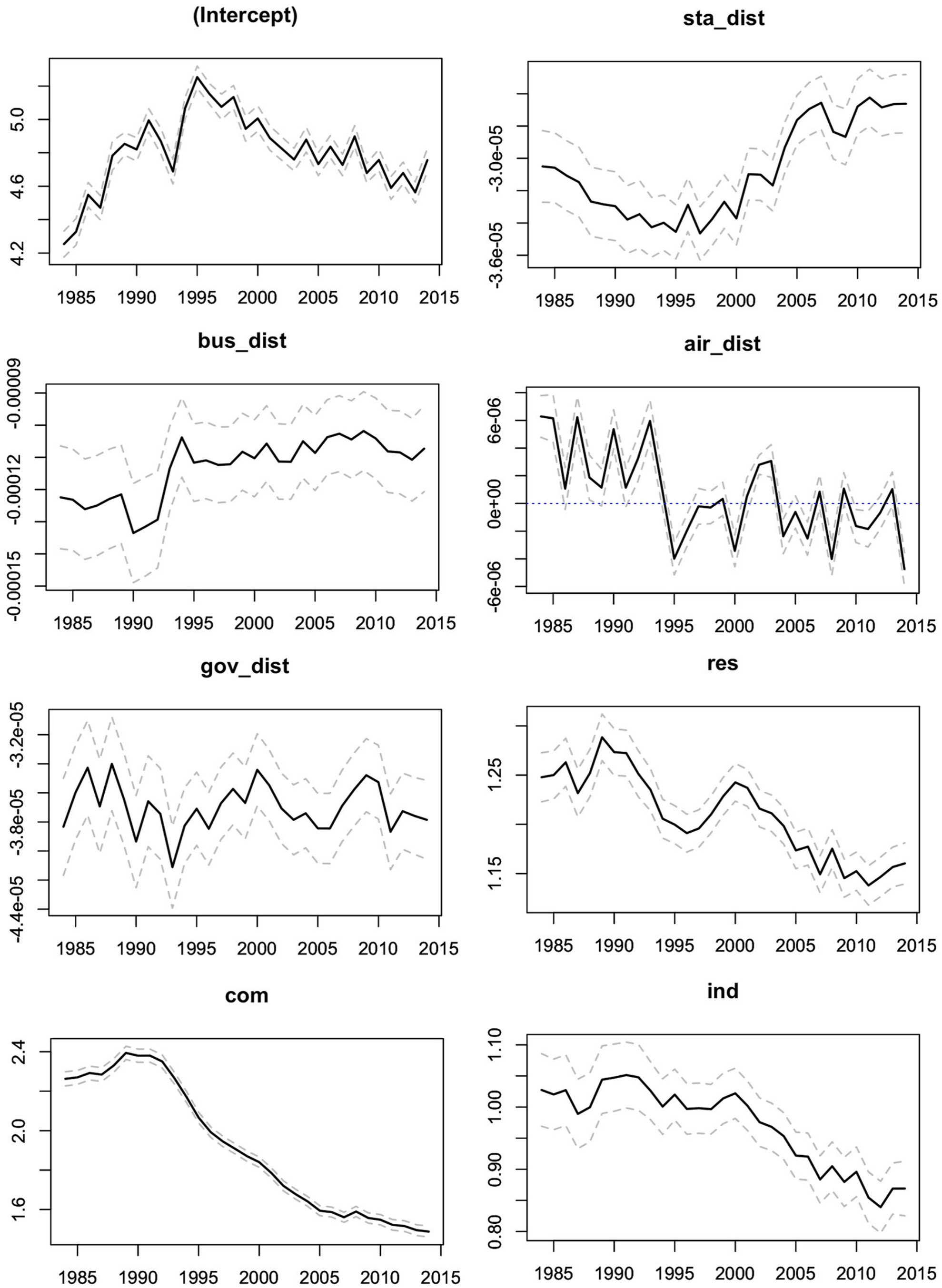


**FIGURE 6 |** Coefficients estimated from SM_GL. Solid line represents the coefficient estimates and dashed lines represent the upper and lower limits of the 95 percent confidence intervals.

Taiheiyo Belt, which covers a concentration of various industries, this heterogeneity is attributable to differences in industrial structure in each major city. Unlike the global-level network dependence (middle column of **Figure 7**), the station-wise effect increases land prices in the Tokyo metropolitan area. The land price patterns in Tokyo are estimated to be highly heterogeneous, relative to other major cities.

**Figure 8** plots the estimated local-level effects. The local-level network dependence strongly increases land prices between Tokyo and Sendai, along the Tohoku Shinkansen. The increase in land price is substantial in the city of Utsunomiya, which has a minor station. This result is intuitively consistent given that the HSR allowed Utsunomiya to become a commuter town for Tokyo. It follows that the section of the Tohoku Shinkansen near

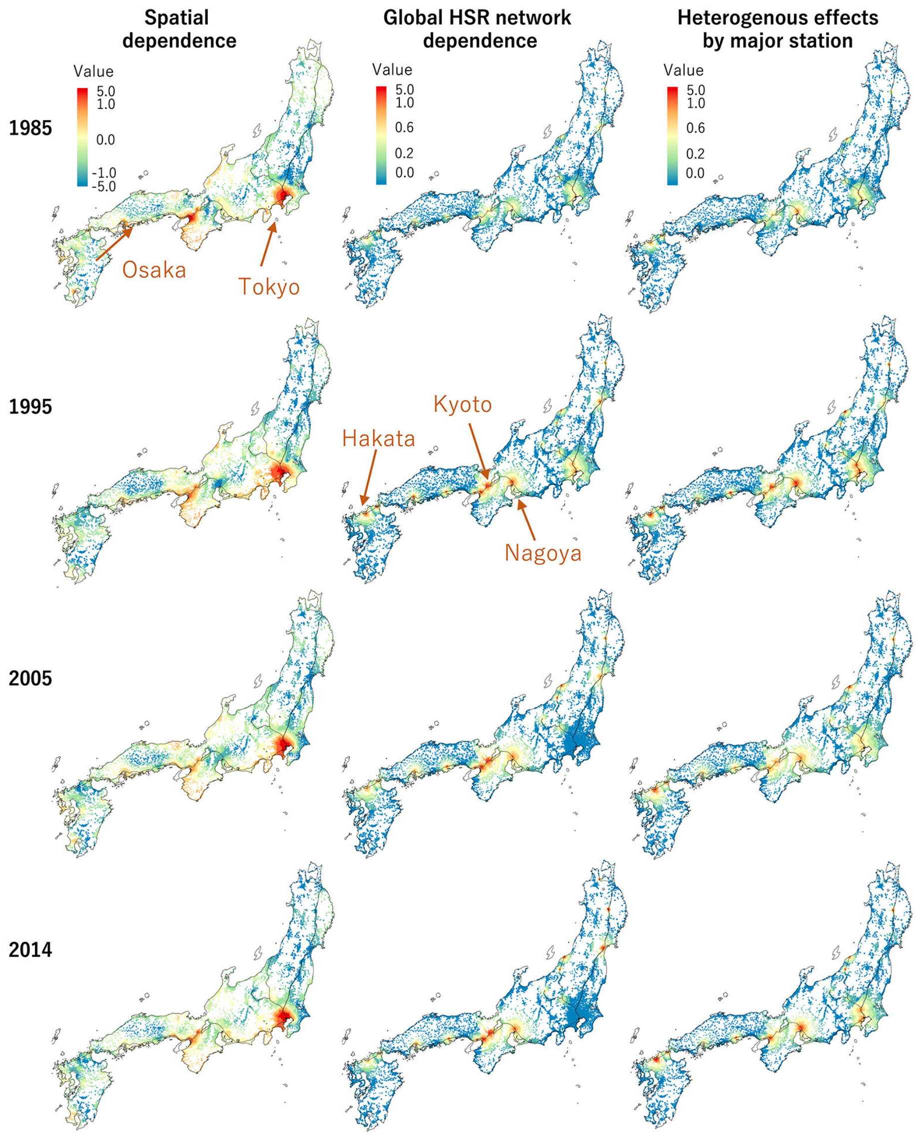


**FIGURE 7 |** Estimated spatial dependent effects and spill-over effects from the global network dependence through the HSR (1985, 1995, 2005, 2014). For comparison, the same color scale is assumed for all the panels in this figure and **Figure 8** except for the left four panels in this figure.

Tokyo benefitted strongly from aspects of the local-level HSR network.

This study verified the existence of hierarchical effects that influence major cities along the HSR lines due to the global-level network, and minor cities due to the local-level network. Further, the effects of HSR are heterogenous in different spaces. Regarding trends over time, the Tokyo metropolitan area's role as the largest metropolitan area in Japan has not changed during the studied period. However, its contents have changed. When compared to the 1980s, the influence that spatial dependence had has gradually strengthened and that of HSR networks has weakened since the 2000s. That is, the spillover effect that the Tokyo metropolitan area experiences from other metropolitan areas is weakening. This is a phenomenon that can only be understood when both spatial and network dependences are considered.

## CONCLUDING REMARKS

Transportation networks encourage a hierarchy within urban growth. However, in extant literature, these hierarchies are usually examined by simply using dummy variables, and the network dependence within the impacts is often ignored. Using the example of HSR in Japan, this study proposed a regression method for the simultaneous estimation of spatial dependence, network dependence among stations, and station-specific heterogeneity. The empirical results verified that there are hierarchical effects along HSR lines. The findings provide an interesting insight into an ongoing problem within the Japanese urban hierarchy; that is, the fact that the spillover effect that the Tokyo metropolitan area experiences from other metropolitan areas is weakening.

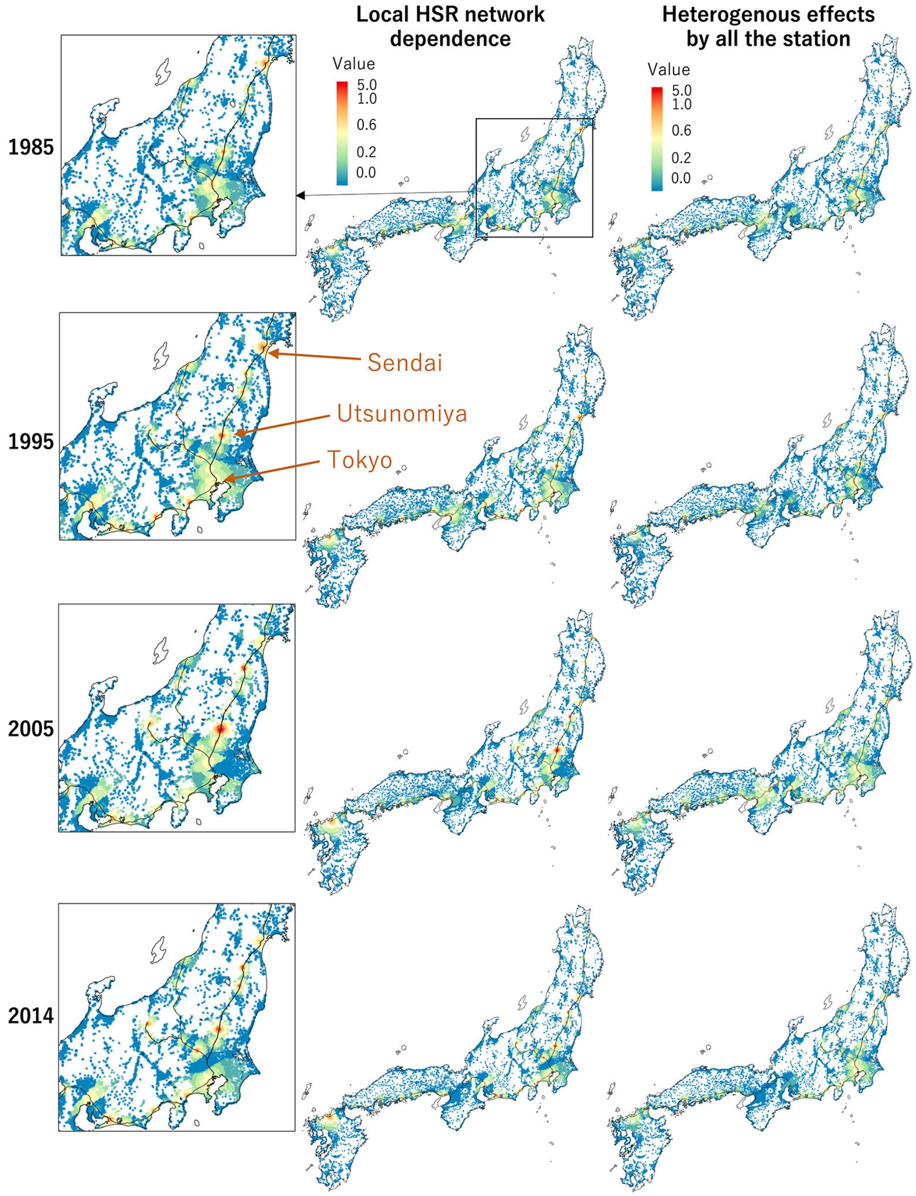


**FIGURE 8 |** Estimated spatial dependent effects and spill-over effects from the local network dependence through the HSR (1985, 1995, 2005, 2014). The former around Tokyo is zoomed. See **Figure 7** for the color scale.

The proposed method allows for modeling dependencies on multiple networks simultaneously and can achieve efficient computation through an extension of the RE-ESF approach. However, several issues remain to be examined in future studies. For example, although this study focused on railway networks, the proposed modeling method can be applied to other transportation networks, including airports and ports. Additionally, this model can be expanded into a spatiotemporal model that allows for the consideration of dynamic processes that underly urbanization. Therefore, it may also be pivotal to consider a network's direction (e.g., Tokyo strongly influences Osaka, but the opposite might be less remarkable). Similarly, although this study considered only two levels with HSR lines, there are more levels to be examined in future research.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

DM developed the model and applied the model to land price analysis. HS created the land price dataset and provided ideas for model development. DM and HS contributed in writing the manuscript. Both authors contributed to the article and approved the submitted version.

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