A Longitudinal Study of Land Price Determinants

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Abstract
The market for land is inherently fluid and constantly changing; this necessitates a land tax assessment system that is amenable to continuous revision and capable of keeping pace with those changes. This study examines temporal changes in land price determinants from a property valuation perspective to enhance land tax policies. Using a mixed-effects model, land lots in Gangwon province, South Korea were longitudinally analyzed over a period of 20 years. The findings reveal increased demand for certain types of land lots, and stable or decreased demand for others. Prices for lots adjoining wide access roads, such as those with 25m and 18m widths, increased by approximately 200%. Similarly, prices for bag-shaped lots surged by roughly 250%. Demand for level and moderate-slope lots also grew stronger compared to steep-slope lots. Conversely, the preference for industrial-use lots decreased with prices declining by approximately 58%. Finally, the price gap between hilly land and forests became nearly negligible. One significant reason for an existing tax assessment system to become outdated is that the local authorities find it hard to identify and measure the gradual changes in land price determinants in the land market. The approach adopted in this study is expected to help local authorities enhance their land tax policies by updating their tax assessment systems in a timely manner, thereby improving horizontal equity in land taxation.
Keywords: horizontal equity, land price determinants, mixed-effects model, land tax policy, tax assessment system

Introduction

Property taxes play a multifaceted role in the national economy, which includes revenue generation and market regulation (Lin & Hsieh, 2021; Lin et al., 2023). However, their primary role is to generate revenue for local governments. The property tax is the most significant local tax in the South Korean tax system and accounts for approximately 15% of the total tax revenue (KOSIS, 2022). Local governments consider revenues from property taxation to be stable; due to the non-portable nature of its tax base (land and improvements), there is relatively low scope of property tax evasion (IAAO, 2017). However, in order to levy property taxes efficiently, local governments should establish a relevant tax assessment system.

Governments in many countries have attempted to design and maintain appropriate tax assessment systems to generate accurately assessed property values. In South Korea, several property valuation models have been created and operated according to property type: land, house, and commercial property valuation models (Ma, 2023). One of the problems with the present tax assessment system is that it has not been updated in a timely manner after its establishment. The problem of inconsistent and/or irregular updates is not limited to South Korea; many countries do not re-evaluate previously assessed property values promptly because of financial constraints, as seen in some US states and the UK (KROLL, 2022), or technical challenges, as seen in Japan (Iwasaki, 2021). However, over time, the nature of the property market inevitably changes, and the tax assessment system needs to be updated promptly to capture those changes. It is otherwise likely to produce assessed value that deviates immensely from current market value. This would eventually lead to taxpayers' appeals or allegations of unfairness and inequality.

In this study, the Korean tax assessment system for land is investigated. A study area is selected and the determinants of land prices and their changes over the past 20 years are examined. Through a longitudinal analysis of land price determinants, this study aims to identify temporal changes in price determinants, measure their impacts on assessed value, and ultimately provide an approach for the timely updating of assessment models that keep pace with land market dynamics.

Studies on land price determinants are abundant (Grimes & Liang, 2009; Gloudemans & Almy, 2011; Wen & Goodman, 2013; Capozza & Helsley, 2017). Factors like parcel size and accessibility, are well-known price determinants. However, research on temporal changes in land price determinants has rarely been conducted. Identifying and measuring trends in these determinants is crucial for the timely updating of tax assessment systems. This study tracks changes in land price determinants from a property valuation perspective. The findings are expected to help local governments identify and measure changes in valuation model components and enhance land tax policies.

Literature review

Horizontal equity in tax assessment system

Tax assessment system fairness is grounded in principles that ensure taxpayers are treated justly and that no group bears a disproportionate burden. Key principles include equitable valuation, appeal processes, and public participation (IAAO, 2017). Equitable valuation, the most critical principle, ensures that the assessed value of land accurately reflects its market value, so each landowner pays their fair share of taxes (Gilderbloom et al., 2012). This concept is further examined through horizontal and vertical equity.

Horizontal equity requires that land with similar characteristics and locations be taxed equally (Krupa, 2014). For example, two houses of similar size, condition, and neighborhood should have comparable assessed values. Achieving horizontal equity depends on accurately accounting for land price determinants, which vary by discipline. Economics emphasizes factors like population growth and per capita disposable income (Wen & Goodman, 2013), while property valuation focuses on physical elements such as parcel size, frontage, adjacent amenities (e.g., lakes, golf courses), views, traffic, and proximity to infrastructure like central business districts and rail stations (Gloudemans & Almy, 2011). Many valuation guidelines assume economic fundamentals like population growth remain constant (French, 2003; Tosh & Rayburn, 2004).

Vertical equity ensures that taxpayers with greater ability to pay contribute more, often through progressive tax rates. For instance, land valued under $100,000 might be taxed at 1%, while land over $1,000,000 could be taxed at 2%.

To maintain horizontal equity, local authorities must regularly reassess land values to reflect current market conditions. Outdated assessments can distort fairness—for example, irregularly shaped lots may gain value over time, but if reassessments are delayed, they remain under-taxed (Berry, 2021). Many countries struggle with this issue: Japan reassesses land every three years, yet policymakers worry about lagging market changes in urban areas (Iwasaki, 2021). California only reassesses land upon sale, creating disparities in tax burdens (Runner et al., 2016), while England's council tax bands, based on 1991 property values, are increasingly outdated and regressive (Adam et al., 2020). The IAAO recommends revaluation at least every six years to prevent such inequities (IAAO, 2017).

Although studies on land price determinants are abundant, research on the dynamics of these determinants is relatively scarce. A few studies have examined changes in the price factors of land over time, but these were undertaken mainly from a financial perspective. Their main concern was the impact of interest rates on property prices over time (Jordà et al., 2015; Leamer, 2015; Piazzesi & Schneider, 2016; Sutton et al., 2017). Specifically, creating monetary policies such as increasing and decreasing interest rates, and identifying their impact on real estate prices were popular topics of the studies (Glaeser et al., 2012; Lim & Tsiaplias, 2018; Chong, 2020).

However, studies on the dynamics of land price determinants from a property valuation perspective have been scarce; this lack of interest has led to static assessment systems in many countries, including South Korea. Thus, a significant gap between the assessed and current market values is revealed, indicating the existence of an outdated assessment system. This study attempts to bridge this gap by investigating temporal changes in land price determinants from a tax assessment view.

Longitudinal analysis using a mixed-effects model

The mixed-effects model is an improved version of the ordinary regression model. The formal development of this model is credited to Raudenbush and Bryk (2002), who applied it in educational research. It is different from the ordinary regression model, in that it can deal with both fixed and random effects (hence, its name). Fixed and random effects are variables that respectively have constant and varying effects on a target variable. By considering random and fixed effects, the mixed-effects model incorporates variations at multiple levels in the data (Zuur et al., 2009). Therefore, the mixed-effects model is effective when the data to be analyzed have hierarchical structures: for example, students in classrooms and patients in hospitals.

A hierarchical data structure can also be identified from a temporal perspective. When cases are measured repeatedly for a certain period, the data are referred to as data with a temporally nested structure. For example, when land prices in a fixed sample are surveyed repeatedly over several years, the data are considered to have a temporal hierarchy. Because annually measured land prices on the same lot are more similar than prices on different lots, the mixed-effects model is well suited for analyzing longitudinal data by employing land lots as a group-level variable and yearly land prices as an individual-level variable. By contrast, an ordinary regression model cannot appropriately account for this nested structure and may lead to biased or inefficient estimates when applied to such data (McElreath, 2020).

Several studies have frequently used the mixed-effects model. Student performance such as exam scores are highly dependent on class-level environments, like the education style of teachers. In this case, a mixed-effects model is ideal because the group-level effect, that is, the classroom effect is essential for understanding student performance (Belloc et al., 2011; Pellagatti et al., 2021; Masci et al., 2022). Another popular use case of a mixed-effects model is in studying the performance of doctors; doctors’ performance depends heavily on hospital environments, and thus, their performance should be evaluated by considering the factors of the hospitals to which they belong (Burford & Rosenthal-Stott, 2017; Abel & Elliott, 2019; Cochrane et al., 2021). Similarly, repeatedly measured data, that is, longitudinal data have been frequently investigated through a mixed-effects modeling approach (Wu & Zhang, 2006; Cunnings & Finlayson, 2015; Mandel et al., 2023). In this study, land prices on the same benchmark lots were surveyed repeatedly for 20 years; thus, a mixed-effects model was adopted to analyze this longitudinal data.

Methods and Materials

Dataset and study area

Benchmark lot data were collected from a government site[1] and used for the analysis. This dataset includes not only land characteristics, such as site area and zoning, but also price information surveyed by valuation experts. The government introduced the Benchmark Lot Announcement System in 1989 (Lee, 2022); the information on benchmark lots is used in various domains, including the determination of compensation for land acquired through eminent domains, valuation for collateral loans, and reference prices for property transactions in the market.

In South Korea, the price of a benchmark lot is not an assessed or estimated value determined solely by appraisers. Instead, it is derived from directly transaction prices—specifically, it is calculated by averaging the actual transaction prices of land lots in the immediate vicinity of the benchmark lot. These prices are then reviewed by a panel of local experts, including real estate brokers, consultants, and property appraisers. If the average price is deemed irrelevant, the land lot is excluded from the benchmark lot list. As a pseudo-transaction price, it is widely used beyond property assessment—for eminent domain compensation, collateral loan valuation, and market reference prices—unlike assessment systems in other countries, where values are typically limited to taxation.[2]

In this study, benchmark lots in Gangwon province were examined. Gangwon province is located in the eastern part of the Korean Peninsula, containing both urban and rural counties. Its population in 2022 was 1.5 million (KOSIS, 2023). This study selected Gangwon province to track the dynamics of price determinants of both urban and rural land over 20 years.

The dataset used in this study covers a 20-year duration between 2004 and 2023. More specifically, 15,387 benchmark lots were surveyed repeatedly for 20 years, forming a temporally nested dataset. Thus, the actual number of observations in this dataset is 307,740 (15,387 lots × 20 years). The summary statistics of these benchmark lots are presented in Table 1. The study area and distribution of the benchmark lots are presented in Figure 1. A typical median site is 1,546 m^2 with a price of 23,000 KRW/m^2. The unit price shows a wide distribution ranging from 90 KRW/m^2 to 11,400,000 KRW/m^2: low prices generally correspond to land for rural usage such as forest and hilly land, while high prices are usually commanded by land for urban usage such as those for commercial buildings and single-detached houses.

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[1] The Ministry of Land, Infrastructure and Transport provides the public with this dataset on the web, https://www.data.go.kr/data/15052273/fileData.do.

[2] Additionally, non-benchmark lots—which comprise the majority of land lots in South Korea—are assessed based on appraiser-derived opinions of value. Consequently, its use is legally restricted to taxation, excluding applications like eminent domain or collateral loans..

Table 1. Summary statistics for 15,387 benchmark lots

Variable	Min.	Median	Mean	Max
Unit price (KRW/m²)	90	23,000	163,300	11,400,000
Site area (m²)	11.2	1,546.0	5,189.7	412,066.0
Use	Dry field 4,330 (28.1%), Single-detached house 3,983 (25.9%), Paddy field 2,334 (15.2%), Forest 1,986 (12.9%), Commerce 1,648 (10.7%), Mix of commerce and residence 741 (4.8%), Hilly land 166 (1.1%), Industry 96 (0.6%), Orchard 83 (0.5%), Miscellaneous 20 (0.1%)			

Figure 2 shows the first 100 samples of the benchmark lots used in this study. The vertical line indicates the range of prices surveyed for each lot over 20 years and the dot denotes the mean of the measured prices. Figure 2 shows that within the same land lot, yearly land prices tend to be similar to each other, but across land lots, the variation is far greater. Thus, Figure 2 effectively shows the necessity that the 20-times repeatedly measured prices should be modeled by considering a land lot to which yearly land prices belong, supporting the use of a mixed-effects model.

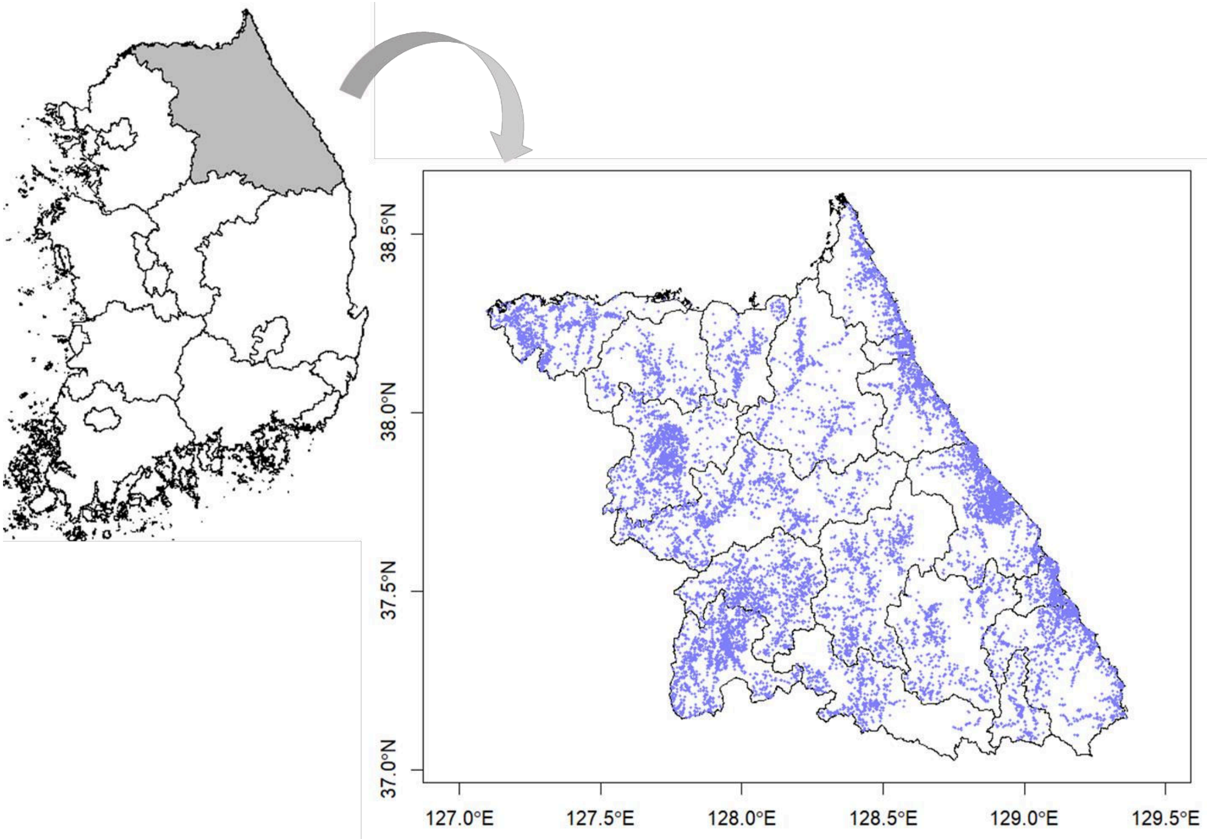

Fig 1. Study area and distribution of benchmark lots
Note: The dots represent 15,387 benchmark lots.

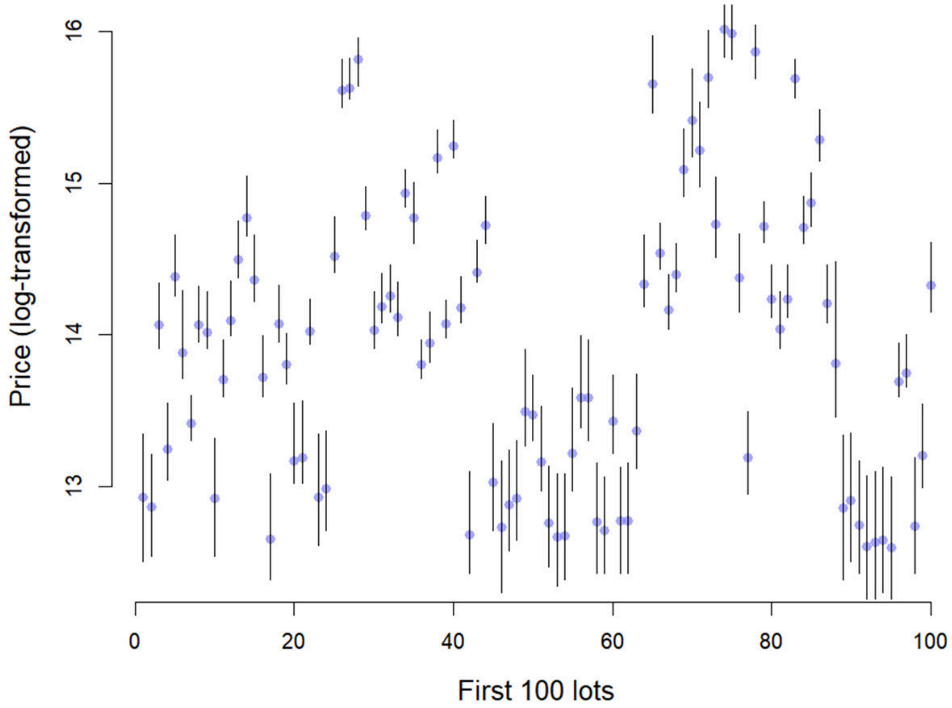

Fig 2. Land price distribution for the first 100 land lots
Note: The vertical line indicates the range of prices measured over 20 years, and the dot denotes the mean of the measured prices.

Model specification
The model used in this study can be represented as follows:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{Zu} + \boldsymbol{\varepsilon} \quad (1)$$

where y is a 307,740 (15,387 lots × 20 years) × 1 column vector (log-transformed land prices) and X is a matrix consisting of 14 explanatory variables. The 14 variables are divided into ten main and four interaction terms. The ten main terms include a fixed intercept, year, the square of the year, county (18 levels), site classification (11 levels), zone (8 levels), use (10 levels), slope (3 levels), lot shape (3 levels), and width of the road on which a lot abuts (7 levels). To capture the varying relationship between land prices and the explanatory variables over time, four interaction terms with the year were created for the following variables: use, slope, lot shape, and road width. Interaction terms for other variables such as site classification and zone were not employed because their coefficients were not significant, and the improvement in the model selection criteria (Akaike Information Criterion, Bayesian Information Criterion, and log-likelihood) was negligible. [3] The vector β describes the fixed-effects coefficients corresponding to the 14 explanatory variables.

While $\boldsymbol{X\beta}$ represents the fixed effects, $\boldsymbol{Zu}$ explains the random effects. Z is a 307,740 × 30,774 matrix for the two random effects (a random intercept and a coefficient of year) and the 15,387

[3] The model used in this study yielded an AIC of -229,827, BIC of -229,093, and log-likelihood of 114,982. In comparison, a model with additional interaction terms for county, site classification, and zone produced an AIC of -222,327, BIC of -221,742, and log-likelihood of 111,219. These results indicate that the model used in this study provides a superior fit to the data compared to the alternative model with additional interaction terms.

lots in Gangwon province, and thus, 30,774 columns (2 random effects × 15,387 lots); u indicates a 30,774 × 1 vector depicting the two random effects (the random complement to the fixed β) for the 15,387 lots; and the 307,740 × 1 column vector $\boldsymbol{\varepsilon}$ represents the residuals.[4]

The fixed effects $\boldsymbol{X\beta}$ can be represented as below:

$$Land\ prices_{it} = \text{Intercept} + Year_{it} + Year_{it}^2 + County_{it} + Site\ Classification_{it} + Zone_{it} + Use_{it} + Slope_{it} + Shape_{it} + Road\ width_{it} + Use_{it} \times Year_{it} + Slope_{it} \times Year_{it} + Shape_{it} \times Year_{it} + Road\ width_{it} \times Year_{it} + \varepsilon_{it},$$
$$\varepsilon_{it} \sim N(0, \sigma_{it}^2) \quad (2)$$

where i and t represent the land lot and time period, respectively. In the equation, year, squared year, and interaction terms with the year were utilized to capture the nonlinear effects of time on land prices.

For the random effects, the intercepts for the 15,387 land lots and by-lot random slopes for the effect of year were examined. Thus, the error term variance can be expressed as:

$$\boldsymbol{\alpha}_{land\ lot} \sim N(0, \Sigma_{2\times 2}) \quad (3)$$

In this study, the model specified through Equations (1) and (3) was determined as the final model based on the likelihood ratio tests that assessed the full model with the effects shown in Equations (1)–(3) against the reduced models without the effects in question.[5] The parameters of the final model were estimated using the Restricted Maximum Likelihood method because it can provide unbiased estimates of both fixed and random effects, thus addressing some of the limitations of the standard Maximum Likelihood estimation. (Pinheiro & Bates, 2000).

[4] The notations of Winter (2018) are adopted in this study.
[5] In the literature, this model is generally referred to as the *random slope model* (Heisig & Schaeffer, 2019; Khoda Bakhshi & Ahmed, 2023).

Results and implications for land tax policy

Results

The model specified in Equations (1)–(3) was fitted to the land price data. Table 2 shows the results. According to the Random effects panel in the table, the intraclass correlation coefficient (ICC) is approximately 0.957 [calculated as 0.4014 ÷ (0.4014 + 0.0180)]. This suggests that 95.7% of the total variance in land prices arises from differences between individual lots, reinforcing the appropriateness of a mixed-effects modeling approach.

Table 2. Results of a mixed-effects model

Fixed effects (n = 307,740)			
	Estimate	Standard error	t-value
Intercept	11.3077	0.0231	489.9
Year	0.0954	0.0006	171.0
Year^2	-0.0017	0.0000	-210.1
County_2	-0.3360	0.0190	-17.7
County_3	-0.6522	0.0284	-22.9
County_4	-0.8368	0.0260	-32.2
County_5	-1.1678	0.0219	-53.3
County_6	-0.1704	0.0283	-6.0
County_7	-0.9913	0.0326	-30.4
County_8	-0.3704	0.0258	-14.4
County_9	-1.0053	0.0277	-36.3
County_10	0.1760	0.0200	8.8
County_11	-0.8530	0.0266	-32.0
County_12	-0.9928	0.0259	-38.3
County_13	-0.6954	0.0234	-29.7
County_14	-0.9883	0.0349	-28.3
County_15	-0.4538	0.0243	-18.7
County_16	-0.2847	0.0222	-12.8
County_17	-0.9546	0.0315	-30.3
County_18	-0.3940	0.0229	-17.2
(Remaining variables not shown for readability)			
Random effects (group = 15,387)			
Land lot level		Variance	Standard deviation
	Intercept	0.4014	0.6336
	Year	0.0005	0.0213
Yearly price level		0.0180	0.1341
R^2			
Marginal R^2: 0.922		Conditional R^2: 0.996	

In the table, the fixed effects alone account for 92.2% of the variance in the data, while the full model—incorporating both fixed and random effects—explains 99.6% of the variance. For the fixed effects, the coefficients of year and squared year are significant, as shown in the t-value column in Table 2. This indicates that land prices have changed nonlinearly over the past 20 years. Most coefficients of the other variables are also significant, and their signs (positive or negative) are generally reasonable. For example, the county comprises 18 levels, and most coefficients are negative, except for County_10, as shown in the table. The reference level in the county is Chuncheon-si (County_1), where the provincial government office is located; thus, Chuncheon-si generally commands a higher land price than other counties. This led to negative coefficients in most counties in Gangwon province. One exception is Wonju-si (County_10), the most populous city in Gangwon province, where the land price level is known to be higher than that in Chuncheon-si.

For the random effects, the standard deviation at the land lot level indicates how much variability in land prices is explained by the lot to which the yearly prices belong. As indicated in Table 2, the intercept and Year show standard deviations of 0.6336 and 0.0213, respectively. Thus, Equation (3) can be represented as follows:

$$\boldsymbol{\alpha}_{land\ lot} \sim N(0, \begin{bmatrix} 0.6336^2 & -0.0070 \\ -0.0070 & 0.0213^2 \end{bmatrix}) \quad (4)$$

The standard deviation at the yearly price level is 0.1341 which corresponds to σ in Equation (2). This represents the remaining variability after the land lot level variability is explained. Because the total amount of the standard deviation is 0.7890 (0.6336+0.0213+0.1341), the yearly price only accounts for 17% (0.1341/0.7890) of the total variability of land prices, leaving 83% variability at the land lot level. The fact that the land lot level is responsible for 83% of the price variability warrants the use of a mixed-effects model for the longitudinal analysis of land prices. A single-level ordinary regression model is likely to be severely inefficient in capturing land price variability over the course of time examined in this study.

The goodness-of-fit of the model adopted for this study is shown in Figure 3. Land prices predicted by the model appear to follow the observed land prices closely. Thus, it can be concluded that the results in Table 2 can be safely used for subsequent analyses.

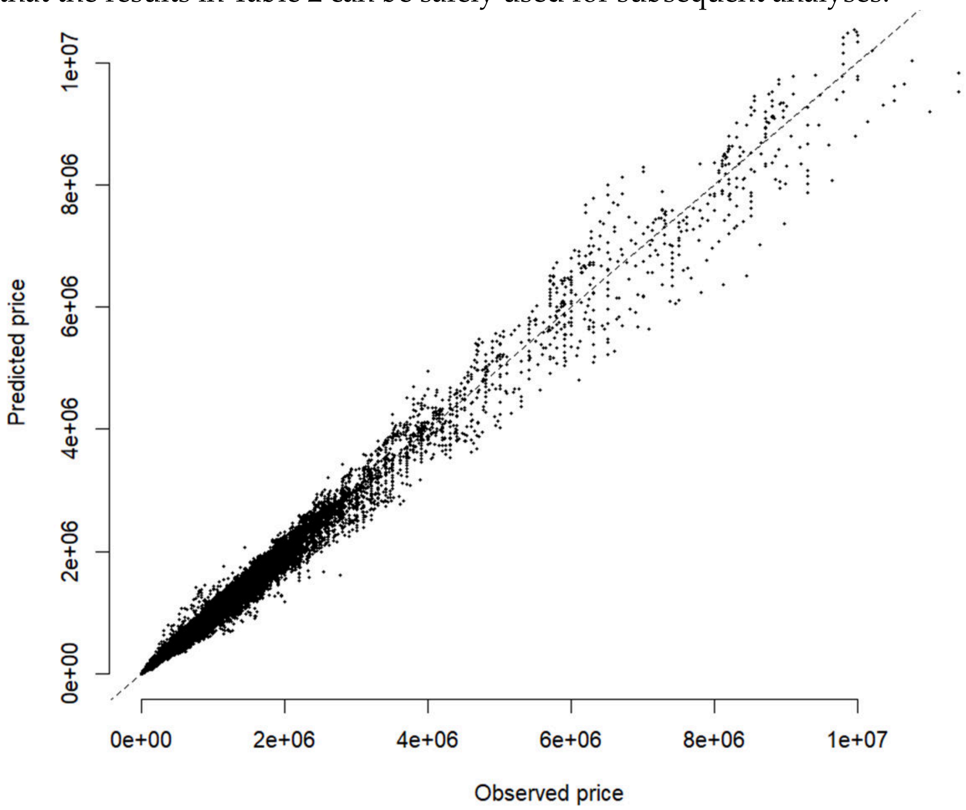

Fig. 3. Goodness-of-fit of the model
Note: The horizontal axis indicates the observed (measured) price and the vertical axis denotes the price predicted by the model adopted in this study. The diagonal dotted line indicates the 45-degree line.

Changes in land price determinants
Four interaction terms with the year were utilized to capture the varying relationship between land prices and their determinants. First, Figure 4 shows the impact of road width on land prices. The figure was created by fixing the road width category to a particular level (for example, a 25m wide level) and varying the variable year from 2004 to 2023. Other variables were held constant by replacing their values with the corresponding mean (in the case of continuous variables) or mode (in the case of categorical variables).[6] Over time, land prices in all road width categories show an increasing trend. However, the rate of increase is much higher in wider categories such as 25m and 18m, where prices have been risen by approximately 200%. This indicates that the preference for a land lot with a wide road became stronger than in the past. This increased preference for lots conveniently accessible by vehicle should be reflected in the tax assessment system. Buyers sometimes avoid wider roads because of noise pollution and community severance[7] (Lee and Park, 2014). However, in this study, the market participants welcomed the wider roads.

Figure 5 presents the effect of lot shape on land prices. Land lots with a regular shape show a higher price level than those with other shapes (the irregular and bag-shaped lot). Bag-shaped lots have an extremely narrow entrance and were the least preferred in the market in 2004. However, its demand is now significantly strong and appears to have nearly the same preference as a regular lot in 2023, reflecting a price increase of roughly 250%. This occurrence is counterintuitive, because bag-shaped lots significantly reduce the effective site area available for construction (Asami & Niwa, 2008). However, this study found that market participants showed no preference for bag-shaped or regularly shaped lots. If the tax assessment system were not updated in a timely manner to reflect this change in preference in the market, it would yield an assessed value that deviates from current market value.

Figure 6 shows the impact of slope on land prices. Prices of flat land lots (the category level) are highest, followed by land lots with moderate slope, and then steep-slope lots. This order of price is understandable because it becomes more difficult to develop and construct buildings on land with steeper slopes. Difficulty in improving a land lot means an increase in construction cost, which decreases sales prices in the market. However, a noticeable change in the market over the past two decades is that the preference for level- and moderate-slope lots grew stronger than that for steep-slope lots. This trend was unexpected because advancements in construction techniques have made it relatively easier to develop steep-sloped lots compared to the past. This change should also be incorporated into the design of the tax assessment system.

[6] Figures 5–7 were also created in a similar manner.
[7] Community severance is used to describe the situation where a road acts as a barrier, separating residents on one side from those on the other.

Finally, Figure 7 demonstrates the influence of land use on land prices. Panel (a) in the figure shows all ten categories in land use: each land use category follows its own price movement trajectory. Panel (b) presents land lots with relatively high price levels, that is, those used for commerce, and those for a mix of commerce and residence. Preference, or the price premium for land lots in these categories appears to rise as time goes by. Panel (c) shows land lots with mid-ranged price levels. A noticeable category is industry: the preference for industrial land lots has steadily decreased, with prices declining by approximately 58% over the past 20 years. Panel (d) presents land lots with low price levels, that is, those used for hilly land and forests: the price gap between the two categories appears to reduce gradually and becomes nearly negligible in 2023.

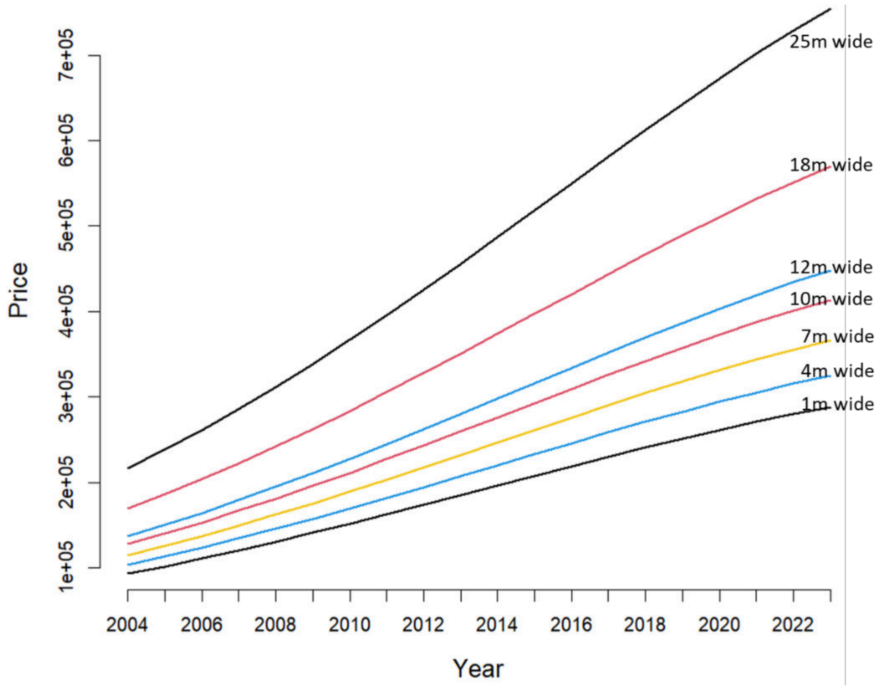

Fig. 4. Impact of road width on land price
Note: The horizontal axis indicates the years 2004–2023, and the vertical axis denotes the prices predicted by the model.

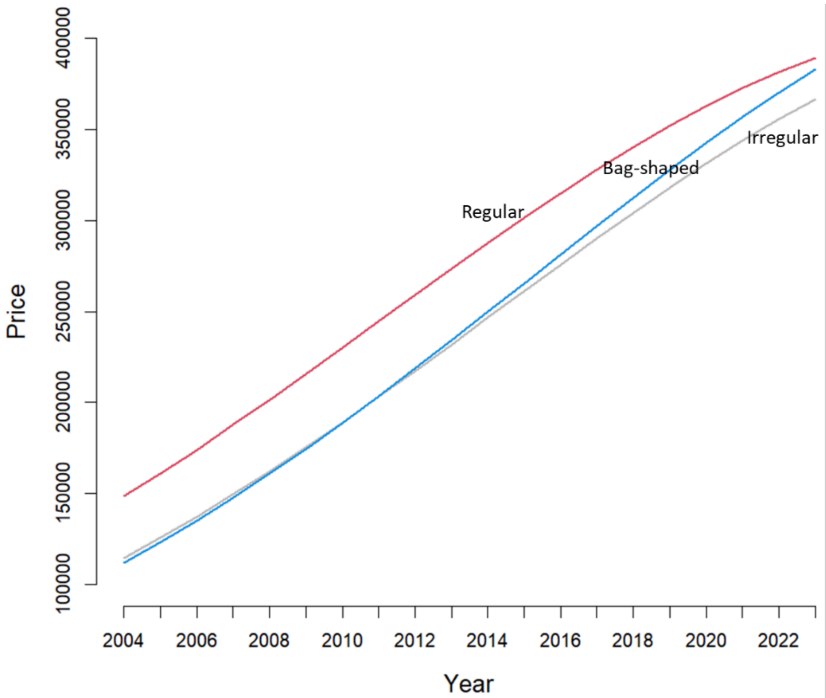

Fig. 5. Impact of lot shape on land price
Note: The horizontal axis indicates the years 2004–2023, and the vertical axis denotes the price predicted by the model.

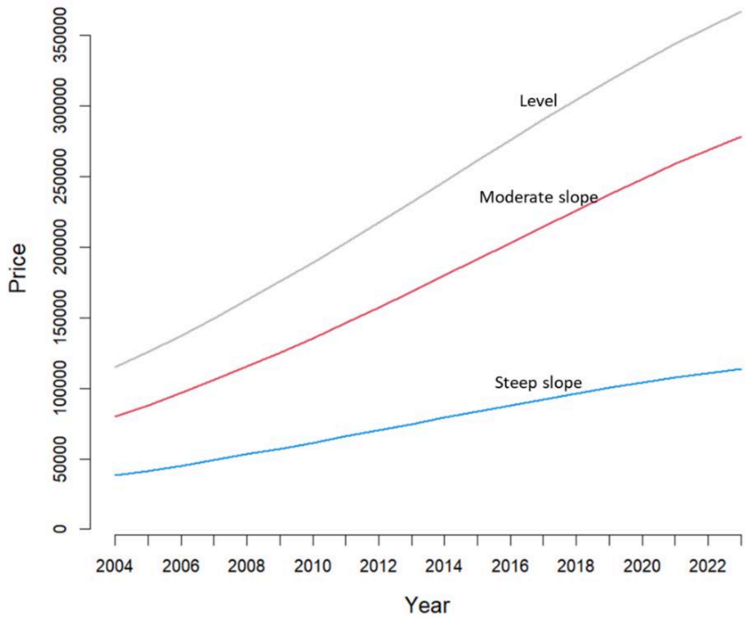

Fig. 6. Impact of slope on land price
Note: The horizontal axis indicates the years 2004–2023, and the vertical axis denotes the price predicted by the model.

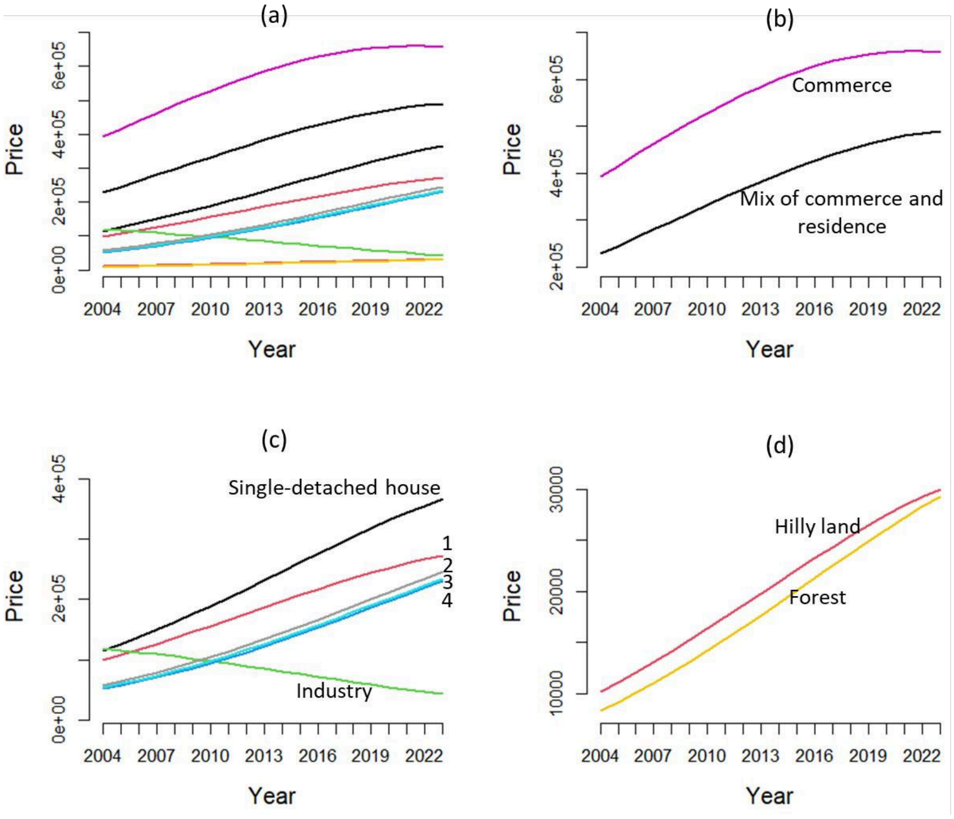

Fig. 7. Impact of land use on land price

Note: The horizontal axis indicates the years 2004–2023, and the vertical axis denotes the price predicted by the model. Panel (c): 1 – Miscellaneous land, 2 – Dry field, 3 – Paddy field, 4 – Orchard.

Implications for tax assessment policy

Figures 4–7 reveal dynamic shifts in land lot preferences over the past 20 years, with demand rising for some types while declining or stagnating for others. These changes—some expected, others requiring further investigation—must be reflected in tax assessment updates to maintain horizontal equity.

However, many countries face challenges in implementing regular reassessments. Financial limitations, as seen in parts of the US and the UK, often hinder timely updates (KROLL, 2022). Even in regions where funding is less of an issue, the absence of effective tools to identify and quantify changes in land price determinants poses a significant barrier. While geographic information systems (GIS) are widely used for spatial analysis, they are less effective in tracking temporal variations in these determinants (Hughes et al., 2020).

In this context, the data-driven approach employed in this study—utilizing mixed-effects models and interaction terms—offers a robust solution. By efficiently capturing temporal changes in price determinants, this methodology provides a scalable framework for tax administrations.

Rather than mandating annual updates, assessments should be revised whenever substantial shifts in land price determinants are detected. The approach outlined in this study enables precise identification and measurement of these changes, ensuring that tax assessments remain both equitable and responsive to market conditions.

Conclusion

This study collected benchmark lot data in Gangwon province and investigated the determinants of land prices. To identify the temporal change of land price determinants, the study undertook a longitudinal analysis of the land prices over 20 years. The results revealed that many price determinants experienced an increase or decrease in preference for the past 20 years: the preference for land lots adjoining wide roads, bag-shaped lots, level lots, and moderately sloped lots increased, while the preference for land for specific uses like industry experienced a decline.

The tax assessment system should be updated timely to keep pace with these changes in the market. If the system is not updated promptly, the assessed value would deviate from market value, leading to taxpayers' complaints and appeals. One of the reasons for the lag in system updates is that it is hard to identify the changes in price determinants and measure their influence on land prices. Using a mixed-effects model and interaction terms, the longitudinal analysis showed how temporal changes in price determinants can be identified and measured. Thus, the approach used in this study is expected to be adopted conveniently by local authorities, thereby enhancing their land tax policies.

This study examined the land market in Gangwon Province, South Korea. However, real estate market is well known for its locality. Land markets in other regions are likely to exhibit significant heterogeneity in terms of landscape, property types, buyer and seller characteristics, and government regulations. While this study focused on physical land characteristics, potential omitted variables—such as socioeconomic factors or market sentiment—may further influence land assessment. Thus, future research should apply the approach adopted in this study to diverse geographical settings to enhance the generalizability of these findings.

Compliance with Ethical Standards
The author declares that there is no conflict of interest.
The author received no specific funding for this research.
Dataset used in this study are publicly available at https://www.data.go.kr/data/15052273/fileData.do.

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