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The Impact of the Haramain High-Speed Train on Land Prices and Urban Growth in the Neighborhoods of Tibah Municipality, Jeddah, Saudi Arabia

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Abstract

This applied study sought to measure the impact of the Haramain High-Speed Train (HHST) project on the neighborhoods of Tibah municipality by studying the impact of the train on land prices and urban growth in the years 2016, 2018, and 2021. Through the use of various statistical methods and a geographic information system (GIS) program, the study found that the average price of land near the train remained low, while the middle and far distant land prices experienced a gradual rise. The study also examined the rate of urban growth in the study area, demonstrating that the lands near the train were characterized by a high rate of growth, while the middle and far distant lands from the train line demonstrated a low level of urban growth. Further research should explore the economic effect of the train in Jeddah city in terms of employment and commercial investments as well as the economic impact of the railway system on the city's growth and expansion.

Keywords

Haramain High-Speed Train, Land Price, Urban Growth, GIS

1. Introduction

A transportation network represents an important part of a city's infrastructure, and it highlights the multiple uses of land within a specific area. The transportation network is the lifeline and beating heart of a city, saving people effort, time, and cost (Banister & Lichfield, 2003). High-speed rail (HSR) lines are frequently referred to as essential elements of global social and economic development, regional integration, and well-balanced societies. The world's growing environmental consciousness has encouraged the use of low-carbon transportation methods, such as high-speed trains, in place of other modes of transportation (Zhu et al., 2022). Nearly 3 billion people throughout the world now ride trains, demonstrating the tremendous growth in the number of trains in various nations and their increasing demand from long-distance passengers and short-distance city travelers (International Union of Railways, 2022).

Railway networks have contributed to economic growth in numerous countries, including the United States (Arzaghi & Henderson, 2008), Sweden (Sun et al., 2021), India, and China, enhancing national market integration (Donaldson, 2018). Transportation that is both efficient and accessible contributes to economic expansion and knowledge sharing. Yet, as seen with China's freeway networks (Zhou et al., 2017) and HSR improvements, and the infrastructure-led growth policies adopted by China and several other regions, unforeseen issues can arise (Guastella et al., 2017). A rail system has various impacts on adjacent areas, such as on the economy, land prices, urban growth, population density, and environmental pollution.

2. Literature Review

Several studies have addressed these impacts in detail using various methodologies. Despite the advantages of HSR for people's lives (e.g., mobility, products, services), some research on HSR has found evidence that the rate of employment mostly increases in areas far from the HSR, which reflects negatively on the economy (Li & Xu, 2018). Nonetheless, transportation generally plays an important role in economic development. Some studies using an economic perspective to assess markets and urban labor have found a positive impact of HSR on economic growth (Heuermann & Schmieder, 2014; Reggiani et al., 2011; Zou et al., 2021). One study examined 40 cities and found that the expansion of HSR between cities and regions led to improvements in both spatial accessibility and economic sustainability as well as economic development (Zhu, 2021). In addition, time savings, environmental advantages, and increased roadway safety have been identified as major factors in cost-benefit analyses. However, research has shown that the fiscal and social advantages of an HSR network only occur when the network reaches a certain size. When fiscal and social considerations are combined, it becomes clear that it is critical from a practical, legislative, and academic standpoint to identify and quantify the local economic impact of HSR service (de Rus Mendoza, 2012; Venables, 2007).

The majority of extant studies show that various kinds of intracity transportation facilities, such as metros, have an impact on land values and housing costs (Lee et al., 2018). Studies on conventional train systems typically show a positive effect on property and land values, (e.g., in China (He, 2020); Montreal, Canada; and Bangkok, Thailand (Dubé et al., 2013)). HSR is a land-based transport system that offers numerous advantages, including shorter journeys, increased output, and greater land and housing prices (Liu et al., 2021). HSR lines may indeed cause environmental problems, such as electromagnetic and carbon emissions, traffic congestion, and traffic noise, all of which affect property prices, living expenses, and crime rates (Geng et al., 2015). According to Chen (Chen, 2021), the Beijing-Shanghai HSR route has had a substantial effect on property values in medium- and small-sized towns (both locally and regionally). HSR may shift economic activity from the center of a city to the outskirts, raising land values in the area and impeding the influx of firms and workers (Wang et al., 2022). In such cases, the minor impact of transport on these outcome variables may suggest a significant advantage of transportation. Under conditions of spatial equilibrium, with the complete movement of labor and companies to the area, land values encompass all social returns generated by transportation connections (Arzaghi & Henderson, 2008).

Empirically, several previous studies have linked the impact of HSR to land prices. For example, when an HSR system is implemented, average land prices rise, with the effect varying due to land usage. One study determined that the prices of residential and commercial lands grew by 30% and 16%, respectively, while the price of industrial lands declined by 30%, assuming all other factors remained constant (Zhou et al., 2017). In a similar vein, Renzhi (Renzhi, 2018) noted that the value of the land around an HSR increased by 19.9% during the initial operating phase; therefore, the HSR had a favorable influence on local land prices. Another study surveyed a sample of 285 cities in China. The findings showed an increase in land prices by up to 10.3% on average, but prices differed depending on the location and type of house (Liu et al., 2021).

The impact of HSR on property prices has been the subject of a number of studies, which have revealed both regional and local variations. Some academics have claimed that the effect varies according to factors like station type and position, railway type, economic development stage, housing market conditions, and land use (Blanquart & Koning, 2017; Perl et al., 2021). From a regional perspective, results may vary widely according to actual traveler volume and consumer profile (Ollivier et al., 2014; Varquez et al., 2020). According to Bowes and Ihlanfeldt (Bowes & Ihlanfeldt, 2001), home values can go up in the presence of a large selection of transportation options and the capacity to use multiple modes of transportation. In order to learn more about the connection between trains and rising home values, numerous speculative models have been proposed. Zheng and Kahn's (Zheng & Kahn, 2013) efficient market theory of asset pricing states that home values should reflect the present discounted value of future rentals. According to the theory, large-scale investments in infrastructure should lead to shifts in the behavior of metropolitan real estate markets.

In addition, markets influence land prices, since variations in construction costs reflect the values of inhabitants' physical attributes, accessibility, infrastructure, and services provided to dwellings (Debrezion et al., 2005). One study applied the sectional pleasure pricing model; it discovered that stations with regular train service have flexibility near 0.03 for residences up to 2 km away (Debrezion et al., 2005). Moreover, HSR affects the distribution of urban agglomeration and land prices (Okamoto & Sato, 2021). Independent mathematical models have been widely used to analyze this type of data. One such study examined the impact of HSR on urban dynamics and property pricing by using an ANOVA analysis and dummy variable regression to explore practical variables. The findings showed effects on regional accessibility, city planning processes, and land pricing (Rungskunroch et al., 2020).

On the other hand, regarding the impact of HSR on urban growth, one study found that HSR has two such effects at the regional, local, and national levels. Ureña (Ureña et al., 2009) analyzed the influence of HSR from two perspectives: the station site creates a new subarea, and the new area creates relationships based on the enhancement of connections. Wang (Wang, 2015) argued that HSR has an influence on urban growth because it generally improves accessibility in the region, with the land near an HSR station enjoying higher accessibility than land outside the HSR station area. Frequent and simple movement fosters regional integration; HSR can improve the central placement of a regional center while also providing more equitable opportunities for everyone. The implementation of HSR involves gaining a development area, which often becomes a growth region (Wang, 2015), but it also has a negative impact due to the increased population in the area (Wang, 2015).

Changing urban land use structure, local government interference in the land market, and alterations in urban economic development variables (such as urbanization, employment transfer, and public investment) have all been shown to significantly impact urban land use efficiency (ULUE). As an example, Luo (Luo & Li, 2019) argued that a rise in ULUE in Chinese cities could result from economic development, a considerable degree of opening up, and increased investment in fixed assets. (Guastella et al., 2017) claimed that ULUE is proportional to the size of the metropolis. Thus, according to traditional location theory, proximity to public transportation is a robust indicator of land use. China's massive investment in HSR has led to a dramatic rise in intercity travel, which has altered the nature and purpose of metropolitan land use and impacted the flow of people and goods between cities. Since then, researchers have been paying more attention to the impact of transit infrastructure, especially HSR, on ULUE (Qiao & Huang, 2021).

Some scholars have debated the scale of a train's influence in metropolitan areas. In this context, researchers often refer to three train projects that were implemented in the United Kingdom, Japan, and Germany (Blanquart & Koning, 2017). The United Kingdom employed the equilibrium model during their HSR project to analyze the advantages and costs of the railway, Japan used the fundamental model of supply and demand to examine the impact of the train on tourism and jobs, and Germany measured the influence of the train on the country's economy. One study discovered no connection between trains and urbanization (Ollivier et al., 2014), while a different study found that the trains contributed to accessibility and provided a link between regions. One researcher explored railway-induced urban growth by employing a GIS-based SLEUTH model to study slope, land use, exclusion, urban transportation, and hill-shade; the results showed that, when population in urban regions increased, urban cover expanded and spatial growth occurred (Varquez et al., 2020). GIS may play a vital role in measuring urban growth, along with remote sensing, and researchers consider it an important method for measuring and mapping urban growth patterns. This method uses the measure of urban sprawl patterns to evaluate trends in urban upgrading (Bhatta, 2009; Sudhira et al., 2004). Moreover, using social data, such as population, improves understandings of the phenomenon of urban sprawl and the relationship between cause and effect. Also, an identification of the social factors represented by population growth contributes to assessing the impact of the patterns of change in urban land use experienced by a city (Suribabu et al., 2012). In contrast to the literature review above, heterogeneity is found when measuring the impact of trains on urban development, urban agglomeration, and the growth of real estate prices. For example, the parts of cities far from trains have been found to be characterized by low urban growth and low land prices compared to the land near the trains (e.g. Hensher et al., 2012; Lu & Zeng, 2022).

In Saudi Arabia, the government has allocated $7 billion for railway construction projects to ensure secure, effective, and long-lasting train service (Dornier Group, 2023). One such transportation project is the Haramain High-Speed Train (HHST), a project within the Kingdom's Vision 2030. The HHST provides one form of urban transport in Jeddah City, and it required both good infrastructure and substantial funding to build. The HHST has impacted Jeddah's population since people take the train rather than drive to Makkah City to perform umrah or pray in the Al-Haram Mosque or the Prophet's Mosque in Medina City. Using the HHST reduces the cost and travel time between cities. However, in Jeddah, the HHST tracks run along the median strip of the Al-Haramain Expressway (HE), where it passes through some of the municipalities of Jeddah city, whereas in Tibah, the HHST track shifts away from the median strip of the HE into Tibah municipality, which has led to the expropriation of properties situated on the HHST track. Furthermore, in recent years, Tibah municipality has seen rapid urbanization and population growth as a result of Jeddah's project for developing and restoring slum neighborhoods based on modern, civilized visions, which has resulted in some population movement from slum neighborhoods to Taiba neighborhoods. Due to these factors, this area was selected for this study. The study's significance stems from the scarcity of studies on railway-related topics in Saudi Arabia; moreover, researchers have yet to provide a logical explanation for the impact of the HHST on land prices or urban growth because the train is relatively new to Jeddah. Hence, this study is the only one exploring the impact of the HHST on land prices and urban growth in Saudi Arabia, reflecting the deep research gap on this issue. Therefore, this study aims to provide a comprehensive understanding of the effects of the HHST on land prices and urban growth in the neighborhoods of Tibah Municipality in Jeddah City between 2016 and 2021. It addresses two questions: To what extent has the HHST affected land prices (commercial and residential) in the neighborhoods of Tibah Municipality in Jeddah City, particularly in terms of land near of far from the train? How has urban growth changed over time, specifically during the periods before and after the HHST was established?

The remainder of this paper can be outlined as follows: Section 2 presents the study area; Section 3 describes the data collection process and methodology; Section 4 presents the results; Section 5 discusses the findings; and the final section offers a conclusion.

3. Study Area

The location of this study is Jeddah, the second largest city in Saudi Arabia. The study focuses on the neighborhoods of the Tibah municipality, which is located in the northeastern part of Jeddah. Geographically, Tibah municipality is located between 21˚43˚30˚N longitude and 39˚24˚0˚E latitude (**Figure 1(a)**). Taiba municipality covers approximately 443 km^2 of Jeddah and is one of the largest municipalities in Jeddah, comprising 17 neighborhoods (**Figure 1(b)**). Some of the neighborhoods are strategically located near the HHST, while other neighborhoods are characterized by a large urban agglomeration and are far from the HHST. This municipality is remarkable for a number of tourist attractions planned for the near future and its existing development projects, such as the HHST project. Furthermore, its large land area has contributed to the desire of a significant number of investors to construct commercial real estate projects here.

4. Data Collection and Methodology

The data used in this study come from two different resources: one set was obtained from the Saudi Ministry of Justice and the second from the United States Geographical Survey (USGS) Earth Explorer. The data from the ministry describes annual land prices for commercial and residential land in each neighborhood within the study area for the years 2016, 2018, and 2021 (**Table 1**). The USGS provided satellite images that were used to determine urban growth in the years 2016, 2018, and 2021. The year 2016 was specifically chosen to determine the status of the region before the train began operating, whereas 2018 marked the opening of the HHST in Jeddah. The year 2021 was chosen to determine the effects and changes which occurred in the region after the HHST began operating in Jeddah. **Appendix A** shows the distribution of the study sample between residential areas and commercial areas. **Figure 2** shows that the 73 residential areas make up 50.3% of the sample, while the 71 commercial areas make up 49.3%. It also shows the distribution of the sample according to its proximity or distance from the train, with 33.3% of areas located near the train track, 41.7% of areas far from the track, and the remaining 25% of areas between these.

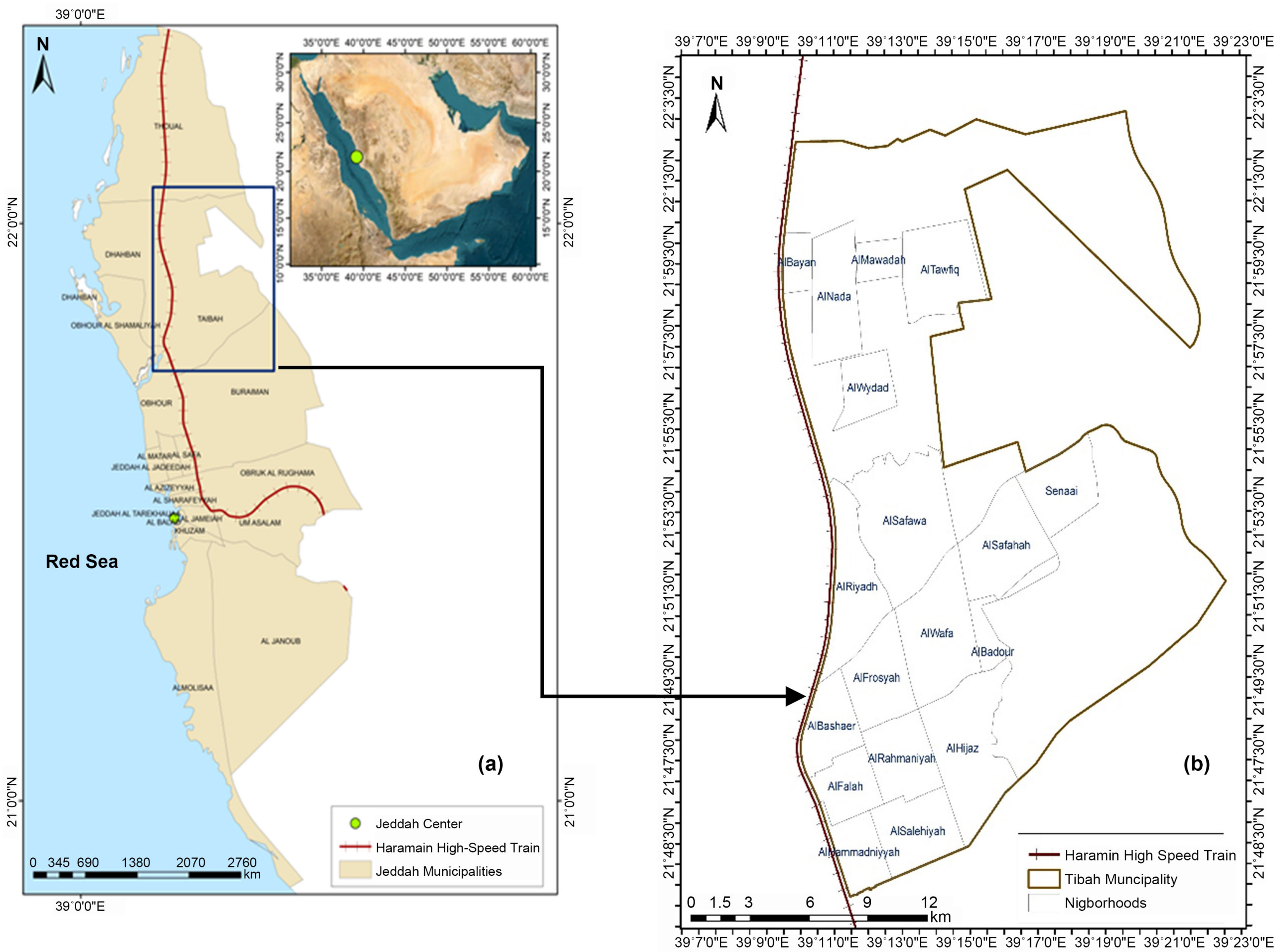
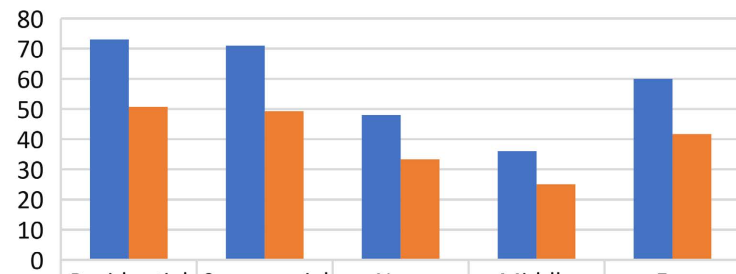


Figure 1. (a) Jeddah municipality location; (b) Study area location.



	Residential	Commercial	Near	Middle	Far
Frequency	73	71	48	36	60
Percent	50.7	49.3	33.3	25	41.7

Figure 2. Data frequency.

4.1. Hypothesis and Independent Mathematical Model

This aspect of the study involves one dependent variable (average price per square meter) and several independent variables (distance from the train track, land use, and year). Based on the first research question, the study hypothesizes that the existence of the HHST and its passage near various neighborhoods led

Table 1. Average price[1] of real estate in the neighborhoods of Tibah Municipality[2].

Year		2016		2017		2018		2019		2020		2021	
		Type											
Neighborhoods	**Distance from HHST**	R	C	R	C	R	C	R	C	R	C	R	C
AlHammadniyyah	Near	2477	2311	1577	2826	2175	2173	2005	2745	1858	2745	1754	1718
AL Falah	Near	2495	2234	2447	833	2161	1255	1897	991	1335	991	1648	1722
AlBashaer	Near	954	1010	736	1727	814	278	902	1074	998	1074	845	813
AlRiyadh	Near	610	560	548	487	495	610	517	502	516	502	820	701
AlFrosyah	Middle	860	690	728	856	708	759	884	734	1023	734	906	1348
AlSalehiyah	Middle	1037	1565	937	1354	1006	1401	1061	1213	1229	1213	1394	1299
AlSafawa	Middle	202	250	230	280	133	215	150	230	102	190	454	500
AlWydad	Far	105	177	200	210	150	280	170	300	190	280	209	320
AlNada	Far	125	145	110	130	180	250	150	160	110	130	246	350
AlWafa	Far	510	1164	405	646	407	652	493	742	578	742	786	947
AlTawfiq	Far	180	700	203	855	140	149	484	420	1413	888	2289	2308
AlRahmaniyah	Far	524	756	684	803	805	1223	1343	1400	1707	1400	1226	2242

to a change in land prices. Due to the variation in the prices of residential land versus commercial land, the study proposes the following hypotheses:

H1: The average price per m^2 for residential areas does not differ greatly from the average price per m^2 for commercial areas in each region.

H2: No difference in average prices exists between neighborhoods. In other words, all regions have the same average price per m^2.

H3: The passage of the train through the area led to changes in land prices from one region to another.

4.2. Data Analysis

A paired two-sample t-test was used to verify the hypotheses. This statistical method allows for a comparison between two groups of cases or between the values of a single group investigated at two separate times (Ross & Willson, 2017). The researchers also used the Student's t-test to determine whether or not the results were replicable. The average prices for residential land were compared with those for commercial land using a paired two-sample t-test between (Anr, Anc), (Amr, Amc) and (Afr, Afc), as defined in (Table 2). A correlation coefficient matrix, expressed using correlation coefficient heat maps, was used to show the correlation between real estate prices for each type of property in different regions. One color was used for a positive correlation and another for a

[1] All prices shown in Saudi Arabian Riyal (SAR) per m2, where 1 US Dollar equals 3.75 SAR.

[2] Taiba municipality has 17 neighborhoods; however, the study only focused on 12 neighborhoods because data for the remaining neighborhoods (e.g., AlMawadah, AlBayan, Senaai, AlBadour, and AlHijaz) were not available from the Ministry of Justice.

Table 2. Symbols and abbreviations used in the study.

Symbol	Meaning
An	An area near the train track
Af	An area far from the train track
Am	An area a middle distance from the train track
Anr	Residential area near the train track
Afr	Residential area far from the train track
Amr	Residential middle distance from the train
Anc	Commercial area near the train track
Afc	Commercial area far from the train track
Amc	Commercial area a middle distance from the train track
R	Residential
C	Commercial

negative correlation to describe the correlations between different features/variables (Zheng & Wu, 2019). A regression line demonstrates the relationship between one or more independent variables and a dependent variable. The study used an analysis of variance (ANOVA) test to confirm the outcomes of the previous steps. This test is used to resolve testing errors or errors of alpha level inflation (Kim, 2017). **Figure 3** shows the data analysis methodology.

4.3. Image Processing and Classification

Three Landsat satellite images were obtained from USGS Earth Explorer to study the Landsat 8 OLI/TIRS area (path 170, row 45). The images were taken on January 6, 2016, January 7, 2018, and May 11, 2021, as noted in (**Table 3**). The Landsat satellite images selected were already rectified and georeferenced to a projection system with WGS 1984 Zone 37N for the study area, and all data used in the study were carried out using the Universal Transverse Mercator (UTM) projection. In the end, subgroup settings were used with all images, including all urban growth borders throughout the study area (with urban growth in this study referring to land use associated with settlement areas and a built-up residential or commercial area). ArcGIS 10.8 software was used to process the images. The imagery was geometrically corrected during the process using pre-processing calibration, which included topographic and atmospheric corrections. A supervised classification method of maximum likelihood, based on field knowledge of the study area, was adopted to classify the pre-processed images. The images were classified using a training feature to retrieve set signatures selected to be used in the classification process. The training data then offers a guide, using the software to provide the kind of pixel selected for certain types of land use within the study area (**Figure 4**). The advantages of using the supervised classification method of maximum likelihood include the following: 1) effective maximum likelihood estimator yields accurate values in larger groups; 2) information class generator; 3) site-based self-assessment; and 4) reusable training areas (Sathya & Deepa, 2017).

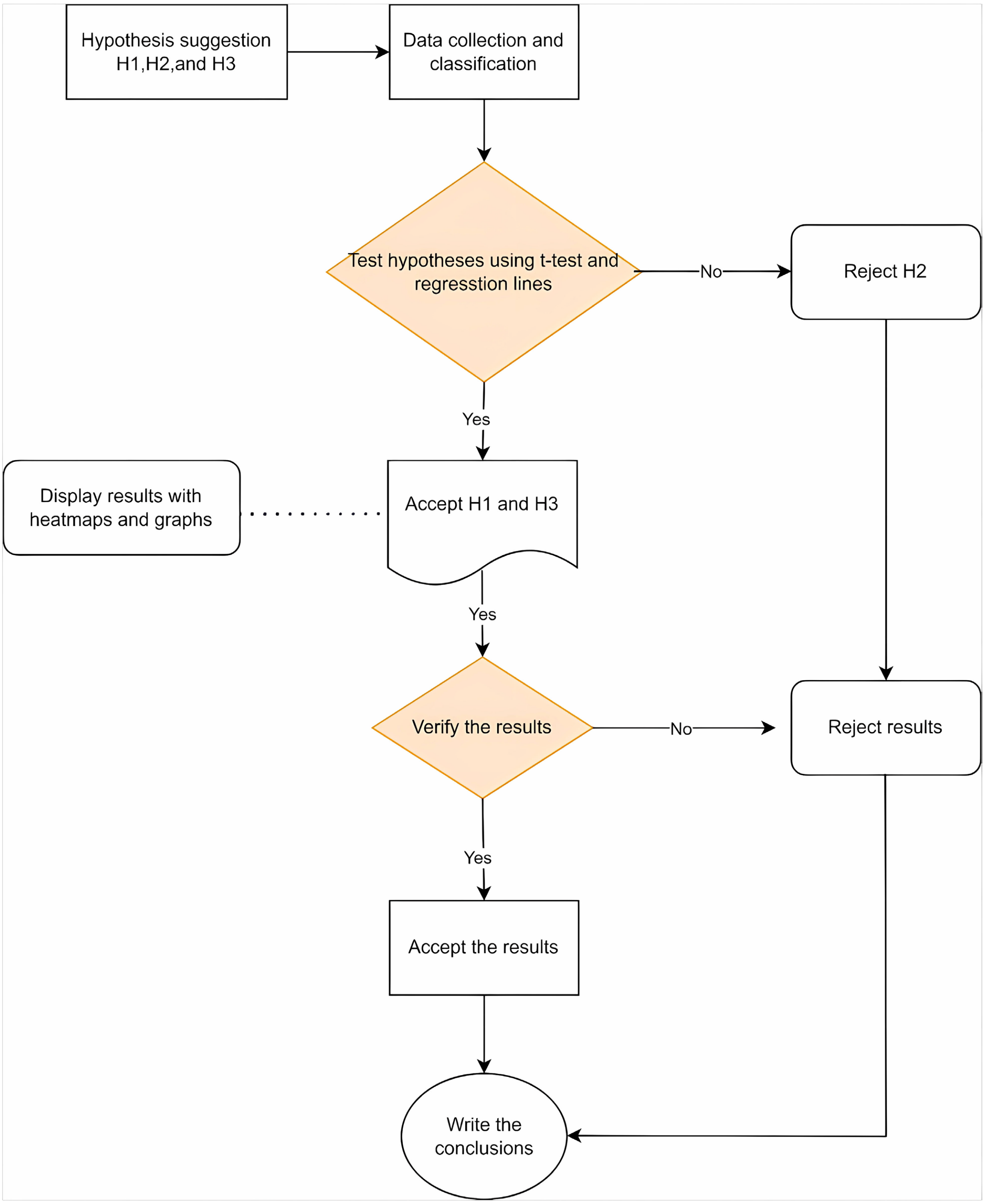


Figure 3. A flowchart showing the methodology for analyzing the data in this section.

Table 3. Information on Landsat data used in this research.

Satellite	Sensor	Path/row	Date of acquisition	Grid cell size (m)
LANDSAT 8	OLI TIRS	170/45	January 6, 2016	30
LANDSAT 8	OLI TIRS	170/45	January 7, 2018	30
LANDSAT 8	OLI TIRS	170/45	May 11, 2021	30

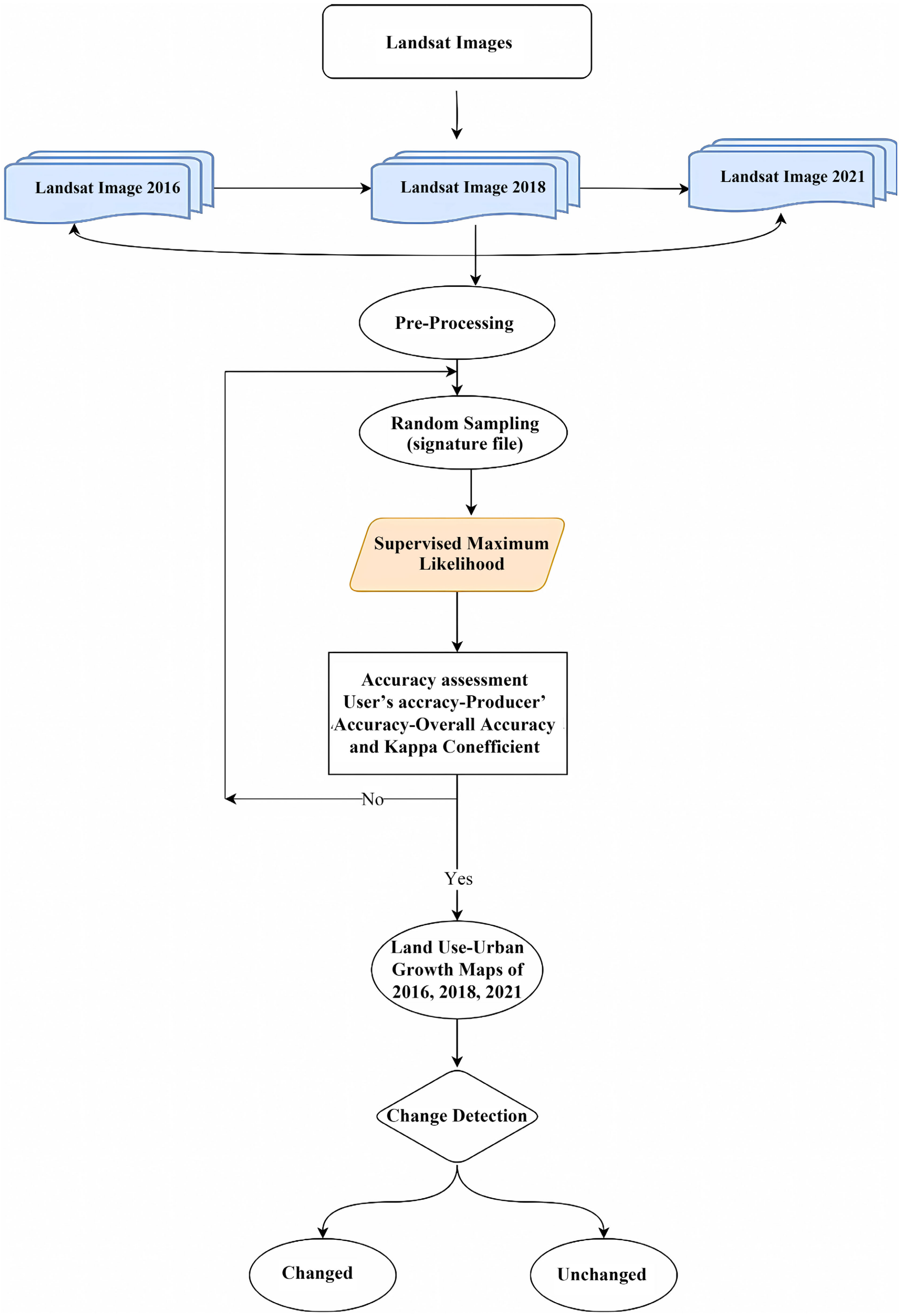


Figure 4. Flowchart of the research methodology.

4.4. Accuracy Assessment

The accuracy assessment is an important step in remote sensing and GIS data processing. This process determines the information value of the generated data to a user. The evaluated image's overall accuracy is determined by comparing each pixel as identified against specified land cover conditions derived from the relevant ground truth data. The accuracy of the producer is a measure of omission errors, that is, a measure of the accuracy of land cover categories in the actual world. The accuracy of the user is measured based on commission errors (Campbell & Wynne, 2011; Congalton, 1991; Jensen, 1996; Rwanga & Ndambuki, 2017). The values obtained using GIS help to measure and detect the rate of change in urban growth (Aburas et al., 2017). One of the major tools for measuring changes in land use and determining urban growth patterns involves change detection between aerial photographs (Hardin et al., 2007). Furthermore, GIS, through aerial picture analysis, can help to illustrate shifts in urban expansion over time (Hamdy et al., 2017). Numerous methodologies have been employed to detect urban change, but researchers have not yet agreed on the best strategy for detecting changes in urban land use. The Kappa coefficient (K) is one method for determining the accuracy of GIS software in detecting urban land change (Liu et al., 2004; Wang et al., 2011). In this study, the accuracy assessment—the most significant final step in the classification process—was carried out using a stratified random sampling method to create a reference point for each Landsat image from 2016, 2018, and 2021. An aggregate of 100 sampled points was created from the classified satellite images of the study area. Furthermore, a confusion matrix was calculated between two kinds of classified images and their truth points, then created based on the same satellite images using "visual explanation." The accuracy assessment was calculated for urban and non-urban areas. Overall accuracy was calculated using Equation (1) (Alkaradaghi et al., 2018), and a kappa coefficient (K) was calculated using Equation (2) (Congalton & Green, 2019; Gashaw et al., 2017; Zhu & Liu, 2014).

$$OA = \left(C/A\right) * 100 \tag{1}$$

where

OA: *classification accuracy in general.*

C: *number of accurate points.*

A: *number of points of references overall.*

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_i + * x + 1\right)}{N^2 - \sum_{i=1}^{r}\left(x_i + * x + 1\right)} \tag{2}$$

where

r: *number of classes.*

N: *total of points.*

x_{ii}: *points in row i and column i being observed.*

x_{i+}: *row i's marginal total.*

x_{+i}: *column i's marginal total.*

The kappa equation is used to measure the agreement between the expected and observed ratings of a data set during correction for agreement that occurs by change (Landis & Koch, 1977).

4.5. Change Detection

Generally, change detection is a significant aspect of the technique commonly used to assess land change and urban growth using Landsat images or land use maps that have the same spatial resolution as ArcGIS software (Alkan et al., 2013; Kilic et al., 2006; Suribabu et al., 2012; Tan et al., 2010). This research used Landsat Thematic Mapper data from 2016, 2018, and 2021 to observe the changes in urban land use that occurred during the selected years. Categories of land use, including urban and non-urban land, were assigned by extracting each pixel based on supervised classification to analyze the change detection for different classes of land use.

5. Results

5.1. Hypothesis and Independent Mathematics Model

The patterns of inequality in average price per m^2 vary over time with the location of the plots and their proximity to the train track. Figure 5 shows that the disparity in the behavior of the average price per m^2 in each region, according to its proximity to the train, began in 2016. Especially in regions close to the train (Anr, Anc), the price per m^2 deteriorated year after year, while the average price per m^2 rose rapidly in regions far from the tracks (Afr, Afc). Particularly from late 2017 onwards, the increase in price inequality became more widespread, while the middle areas remained at a steady, slow rate of increase (Amr, Amc). The gap between prices had disappeared by late 2021 in areas both near and far from the train (Anr, Afc), shifting from a large gap at the beginning of 2016. Figure 5 also shows that no significant difference could be found between the price of commercial areas and the price of residential areas in each distinct area (An, Am, Af). In the years 2017 and 2018, a major recession began in the real estate market. However, the market rebounded and flourished at the end of 2021. Accordingly, the patterns of inequality in average price per m^2 vary over time with the location of the plots and their proximity to the train track.

Table 4 presents the comparison of (t Stat) and (t Critical) for all regions. Since

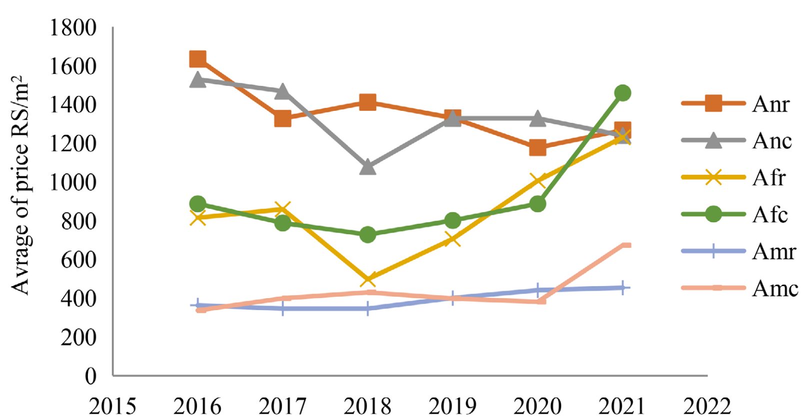


Figure 5. Changes in average price per m^2 over time for each region.

Table 4. Paired two-sample t-test for means (Anr, Anc), (Amr, Amc), and (Afr, Afc).

	Anr	Anc	Amr	Amc	Afr	Afc
Mean	1357.67	1328.42	391.89	436.28	852.23	924.90
Variance	24384.02	25996.17	2268.92	14322.42	62852.81	72270.38
Observations	6	6	6	6	6	6
Pearson correlation	0.37		0.58		0.84	
df	5		5		5	
t Stat	0.40		−1.09		−1.22	
sig-t two-tail	0.71		0.33		0.28	
t Critical two-tail	2.57		2.57		2.57	

sig-t (0.33) > α (0.05) for the mean between (Anr, Anc), sig-t (0.28) > α (0.05) for the mean between (Amr, Amc), and sig-t (0.71) > α (0.05) for the mean between (Afr and Afc), hypothesis H1can be accepted. Accordingly, no significant difference was found in the average price per m^2 for the residential and commercial areas in each region at the 95% confidence interval. Therefore, they can be treated as if they are the same type in the same region.

Table 5 shows the difference in prices between regions and has been compared using a paired two-sample t-test for the means between (Anr, Afr), (Anr, Amr) and (Amr, Afr). Since sig-t (0.016) < α (0.05) for the mean between (Anr, Afr), sig-t (0.000) < α (0.05) for the mean between (Anr, Amr) and sig-t (0.003) < α (0.05) for the mean between (Amr and Afr), hypothesis H2 can be rejected. Based on the results, a significant difference exists in the average price per m2 from one region to another at the 95% confidence interval. Thus, the study found that the average residential and commercial prices are similar within the same region, but the prices differ from one region to another.

Correlation coefficient heatmaps were used to measure the extent of the impact of the HHST on land prices in the neighborhoods of study. Heatmaps are colored illustrations of data tables in which data are represented visually, with individual values represented by color in a matrix. Multiple responses and predictor variables can be combined into one figure to help identify patterns in a data set by highlighting similarities and/or differences among them. In addition to being visually appealing, heatmaps are easier to analyze quickly than standard analytic reports. These heatmaps use color to represent the strength of the correlation between two variables, with dark green indicating a strong negative correlation and dark red indicating a strong positive correlation. This can be especially beneficial when dealing with large datasets.

Table 6 below presents a heatmap for this study that shows the correlation between real estate prices in different neighborhoods for each type of property. While the negative correlation coefficients (green color) are shown between the neighborhoods near and far from the train, the positive correlation coefficients (red color) are shown between the neighborhoods far and at a middle distance from the train track.

Table 5. Paired two-sample t-test for means (Anr, Afr), (Anr, Amr) and (Amr, Afr).

	Anr	Afr	Anr	Amr	Amr	Afr
Mean	1357.667	852.2333	1357.667	391.8889	391.8333	852.3333
Variance	24384.02	62852.81	24384.02	2268.919	2279.767	62929.87
Observations	6	6	6	6	6	6
Pearson correlation	−0.44792		−0.63734		0.779838	
df	5		5		5	
t Stat	3.540077		12.44497		−5.22934	
sig-t two-tail	0.016561		5.94E−05		0.003384	
t Critical two-tail	2.570582		2.570582		2.570582	

Table 6. Heatmap of the correlation between real estate prices in different neigh-borhoods for each type of property.

	Anr	Anc	Afr	Afc	Amr	Amc
Anr	1.00					
Anc	0.37	1.00				
Afr	−0.45	0.24	1.00			
Afc	−0.26	−0.12	0.84	1.00		
Amr	−0.64	−0.16	0.78	0.73	1.00	
Amc	−0.40	−0.46	0.61	0.89	0.58	1.00

The most common statistical method is a regression analysis (linear or logistic). A regression line represents the behavior of a set of data and can be used for forecasting purposes. It describes the connection between one or more independent variables (x) and a dependent variable (y). For continuous data, a normal distribution can be assumed; this approach can be used to find patterns in huge datasets. For example, it can be used to figure out how a particular element, such the year x, affects the movement of an asset. A regression analysis predicts a number, called the y variable or the response variable. In linear regression, one independent variable is utilized to explain and/or forecast the result of y. A linear regression line can be found using an equation of the form $y = a + bx$, where the constants a and b can be calculated as follows (Crawford, 2006; Hazra & Gogtay, 2016):

$$a = \underline{y} - b\underline{x},\quad b = \frac{SS_{xy}}{SS_x}, \tag{3}$$

$$SS_{xy} = \sum\left(x - \underline{x}\right)\left(y - \underline{y}\right), \tag{4}$$

$$SS_x = \sum\left(x - \underline{x}\right)^2 \tag{5}$$

In the last column of (**Table 7**), the slope of the first line is negative (−57.014), which indicates that the price of land in the area surrounding the train has been

Table 7. Regression lines.

Region	Regression lines	R^2	Slope of line
Area close to the train track	$y_1 = -57.014x + 116426$	$R^2 = 0.6618$	−57.014
Area far from the train track	$y_2 = 85.086x - 170857$	$R^2 = 0.4074$	85.086
Middle distance from the train	$y_3 = 34.071x - 68359$	$R^2 = 0.702$	34.071

decreasing steadily. The other two lines demonstrate a positive slope, meaning that the price of land in areas far from the train and at a middle distance has been rising constantly. Since line y_2 (85.086) has a larger slope than line y_3 (34.071), the price of land has been rising more quickly with distance from the train. This gives an indication of the changes in the price of land both near and far from the train after its construction. While (**Figure 6**) shows the change in the average price for each division separately (An, Am, and Af) along with the regression line of the price over the time (equations y_1, y_2 and y_3), **Appendix B** confirms the correctness of the results. Thus, sufficient evidence exists to conclude that a significant increase has taken place in the average price per m2 for residential and commercial properties in the regions far and a middle distance from the track, as compared to the prices of nearby regions. That is, prices have changed from one region to another. Therefore, hypothesis H3 can be accepted.

Table 8 presents a heatmap showing the correlation between real estate prices in the different neighborhoods. While positive correlation coefficients (red color) appear between the neighborhoods far and a middle distance from the train track, negative correlation coefficients (green color) appear between the neighborhoods near and far from the train. This confirms the results obtained earlier in this study.

To further validate the accuracy of the results, the study conducted an ANOVA test. Univariate analysis of variance (ANOVA) is a statistical method used to evaluate the differences between two or more groups of data and to assess whether these differences are significant. In addition, ANOVA can be used to compare the means of two or more variables across several levels of another variable, such as comparing the means of two or more groups across different levels of a categorical variable. This study used price as a dependent variable, year as an independent variable, and distance and property type as categorical variables. The results are shown in (**Table 9**), below.

The results revealed a significant main effect of distance from the train, such that $F(1.7181) = 23.305$, $p < 0.001$, and partial eta squared = 0.28. However, there was no significance for time, type, time * distance, and time * type status interaction, with $F(1.7181) < 0.7$ and $p > 0.6$, suggesting that the relationship interaction between time, type, and price does not matter to the buyer. According to the value of partial eta squared (0.28), the 28% price increase is due to distance from the train. These results reinforce and confirm the findings from the previous analyses.

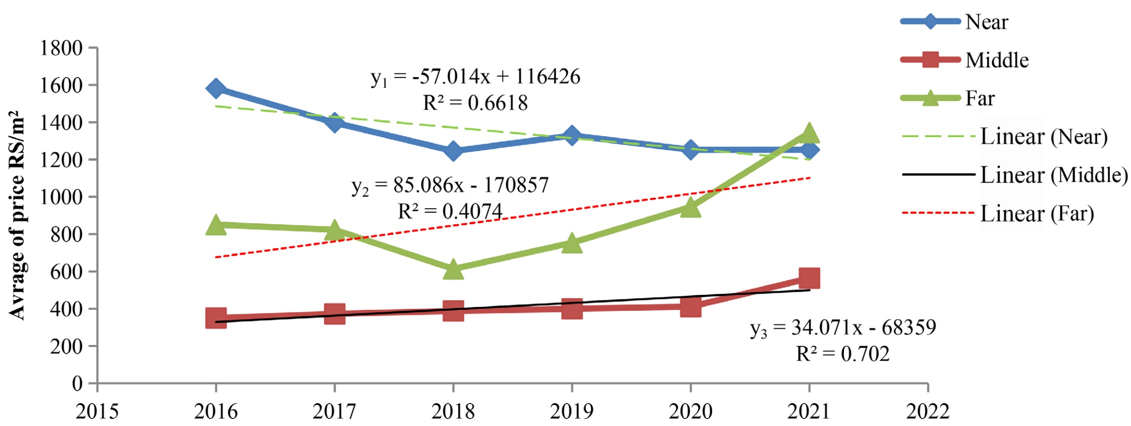


Figure 6. Change in the average price per m² over time for each neighborhood.

Table 8. Heatmap of the correlation between real estate prices in different neighborhoods.

	year	An	Am	Af
year	1	−0.67	0.68	0.61
An		1	−0.48	−0.29
Am			1	0.80
Af				1

Table 9. ANOVA results (Tests of between-subject effects; dependent variable: average price).

Source	*Type III sum of squares*	*df*	*Mean square*	*F*	*Sig.*	*Partial eta squared*
Corrected model	22077994.551	23	959912.8	2.525	0.001	0.326
Intercept	1.07E+08	1	1.07E+08	281.142	0.000	0.701
Time	1198595	5	239719.1	0.631	0.677	0.026
Distance	17719321	2	8859661	23.305	0.000	0.280
Type	4251.053	1	4251.053	0.011	0.916	0.000
Time * distance	2248984	10	224898.4	0.592	0.818	0.047
Time * type	238563.4	5	47712.69	0.126	0.986	0.005
Error	45619195	120	380160			
Total	1.9E+08	144				
Corrected total	67697189	143		R squared = 0.326		

5.2. Post-Classification Images

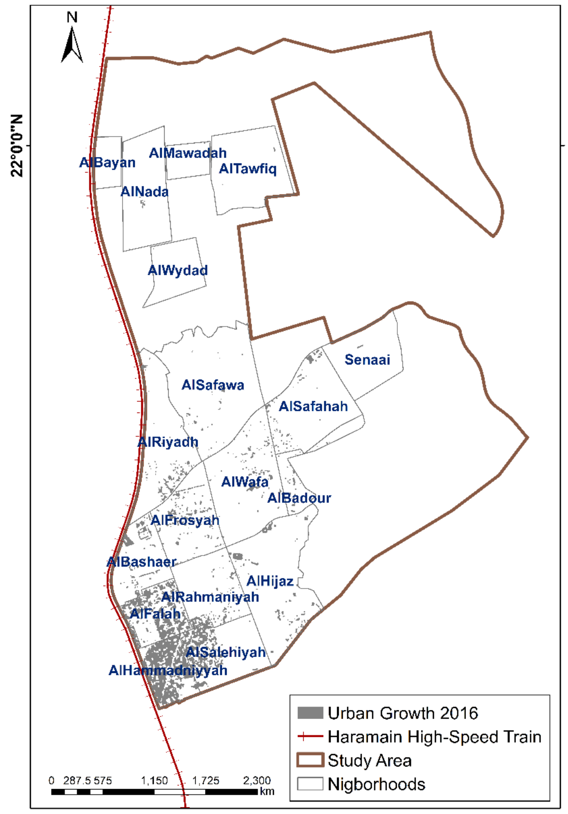
Based on the study results, the images categorized using the supervised maximum likelihood classification method in the study area showed that urban land use occupied a larger area than the total study area. The category area (land use) was calculated based on the area of the pixels in the selected category divided by the total area of the region under study. By analyzing (Table 10), a discrepancy was found in the urban scale area of the study area from 2016 to 2021. The urban scale area in 2016 was 15.51 km^2, and the most residential neighborhood in terms of urban growth was Al Hammadniyyah (Anr) at a percentage of 47.71%, while Al Wydad (Afr) neighborhood was the least residential neighborhood area in terms of urban growth, at 0%. However, 2018 witnessed urban growth of approximately 25.62 km^2, with the Al Hammadniyyah (Anr) neighborhood characterized by remarkable growth at 48.4%, while the Al-Wydad (Afr) neighborhood was still one of the slowest growing neighborhoods, estimated at 0%. The most likely reason behind this neighborhood's slow urban growth was its newly established status and a shortage of services to attract residents. In 2021, the urban use area of the study region was estimated at 42.1 km^2, which is a larger area than in the earlier years of the study. The urban growth of the Al Hammadniyyah (Anr) neighborhood was relatively stable at 49.75%, while the Al Wydad (Afr) neighborhood demonstrated almost negligible growth at 0.02%, as shown in (Figure 7).

5.3. Accuracy Assessment

Table 11 illustrates the results of the accuracy assessment via the Landsat satellite

Table 10. Urban growth in neighborhoods of Tibah municipality.

Neighborhoods	Area in km^2 2016	rate %	Area in km^2 2018	rate %	Area in km^2 2021	rate %
AlBadour	0.2	1.29	0.2	0.78	0.3	0.71
AlBashaer	0.8	5.16	0.9	3.51	0.7	1.66
AlFalah	2.4	15.47	1.5	5.85	0.4	0.95
AlFrosyah	1	6.45	1.6	6.25	1.8	4.26
AlHammadniyyah	7.4	47.71	12.4	48.40	21	49.75
AlHijaz	0.9	5.80	1	3.90	1.6	3.79
AlMawadah	0.01	0.06	0.04	0.16	0.1	0.24
AlNada	0.05	0.32	0.03	0.12	0.1	0.24
AlRahmaniyah	0.4	2.58	1	3.90	0.5	1.18
AlRiyadh	0.6	3.87	3.6	14.05	7.2	17.06
AlSafahah	0.4	2.58	1.1	4.29	1.4	3.32
AlSafawa	0.2	1.29	0.7	2.73	4.7	11.13
AlSalehiyah	0.5	3.22	0.3	1.17	0.1	0.24
AlTawfiq	0.02	0.13	0.05	0.20	0.3	0.71
AlWafa	0.6	3.87	0.8	3.12	1.5	3.55
AlWydad	0	0.00	0	0.00	0.01	0.02
Senaai	0.03	0.19	0.4	1.56	0.5	1.18
Total	15.51	100	25.62	100	42.21	100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Urban Growth 2016
Haramain High-Speed Train
Study Area
Nigborhoods
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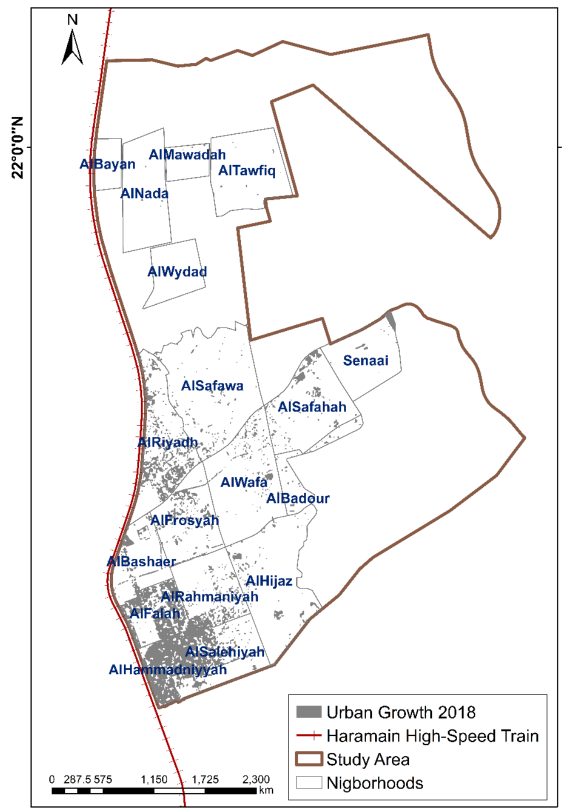
(a)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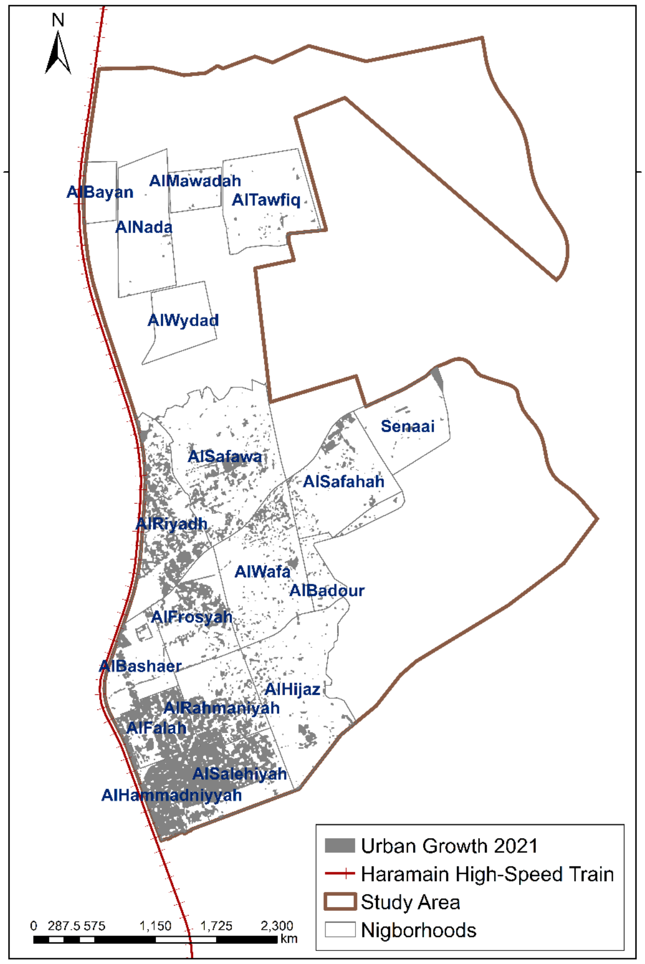


(c)

Figure 7. Urban growth in (a) 2016, (b) 2018, and (c) 2021.

Table 11. Accuracy assessment of urban growth.

Data	Producer's	User's	Overall	Kappa
2016	93.7	90	92	0.84
2018	93.8	92	93	0.86
2021	97.8	92	95	0.9

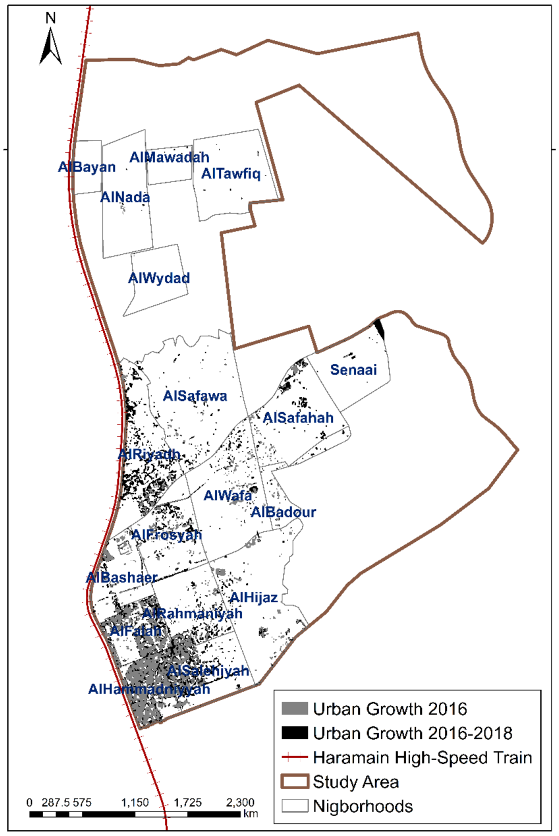
images of the study area for the years 2016, 2018 and 2021 based on the data obtained by the coefficient matrix that calculated both urban use and non-urban use categories. This showed an agreement in the overall accuracy—that is, in both the producer's and the user's accuracy—and in the kappa coefficient from 2016 to 2021. The results for 2016 indicated that the overall accuracy assessment was 92, while the producer's accuracy score was 93.7, the kappa coefficient was 0.84, and the user's score was 90. In 2018, the overall accuracy was 93, with a producer's accuracy score of 93.8, a kappa coefficient score of 0.86, and a user's score of 92. The results of the accuracy analysis in 2021 showed that overall accuracy was 95, while the producer's accuracy score was 97.8, the kappa coefficient score was 0.90, and the user's score was 92, indicating that the results of the accuracy assessment were high in the years chosen for the study.

5.4. Change Detection in Urban Growth over Time

Temporal and spatial changes were noted in the study neighborhoods based on satellite images for 2016, 2018, and 2021, as shown in (Figure 8). Table 12 shows the rate of change in the urban areas for all study periods; notably, urban growth in 2016 reached about 12.89%, which is a low percentage compared to the years following HHST construction. The study area witnessed a high rate of urban growth in 2018, as urbanization increased at a rate of 20.71% in the study area neighborhoods. However, most of the expansion that occurred in the study area can be attributed to the main factor, the inauguration and operation of HHST in Jeddah. Moreover, during the period from 2018 to 2021, neighborhoods continued to expand in the same direction, to the extent that some neighborhoods began to expand more rapidly than before, such as the Al Hammadniyyah (An) neighborhood at 36.76% and the Al-Riyadh (An) neighborhood at 20.61%.

Table 12. Change detection in urban growth during the years 2016, 2018, and 2021.

	2016-2018 area in km^2		2018-2021 area in km^2		2016-2021 area in km^2	
Neighborhoods	Changed	%	Changed	%	Changed	%
AlBadour	0.1	0.78	0.2	0.97	0.2	0.69
AlBashaer	0.4	3.1	0.3	1.45	0.5	1.72
AlFalah	0.5	3.88	0.4	1.93	0.4	1.37
AlFrosyah	1.1	8.53	1.2	5.79	1.5	5.15
AlHammadniyyah	3.7	28.7	7	33.8	10.7	36.76
AlHijaz	0.5	3.88	1	4.83	1.3	4.47
AlMawadah	0.03	0.23	0.1	0.48	0.1	0.34
AlNada	0.03	0.23	0.1	0.48	0.1	0.34
AlRahmaniyah	0.7	5.43	0.4	1.93	0.5	1.72
AlRiyadh	3.1	24.05	3.8	18.35	6	20.61
AlSafahah	0.8	6.21	0.6	2.9	1.1	3.78
AlSafawa	0.6	4.65	3.9	18.83	4.5	15.46
AlSalehiyah	0.3	2.33	0.1	0.48	0.1	0.34
AlTawfiq	0.03	0.23	0.3	1.45	0.3	1.03
AlWafa	0.6	4.65	1.1	5.31	1.3	4.47
AlWydad	0	0	0.01	0.05	0.01	0.03
Senaai	0.4	3.1	0.2	0.97	0.5	1.72
Total	12.89	100	20.71	100	29.11	100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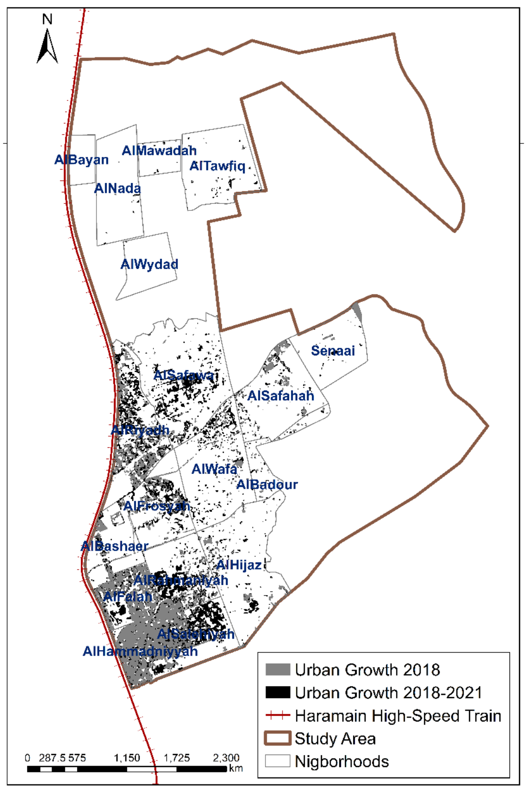
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Study Area
Nigborhoods
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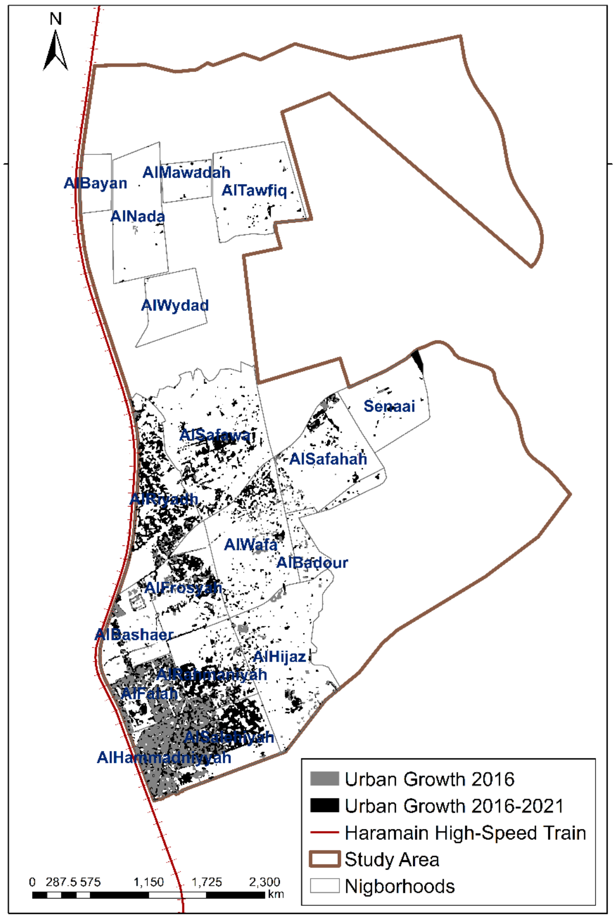
(b)



(c)

Figure 8. Change detection in the study area in 2016 to 2018 (a), 2018 to 2021 (b), and 2016 to 2021 (c).

6. Discussion

A variety of statistical approaches were used, such as analysis of variance (ANOVA), as one of the most beneficial statistical procedures, which provides statistical inference for comparing multiple group means in the study to assess and validate the accuracy of the results of the average land prices in terms of near, middle, and far distance from HHST. Moreover, the study adopted the classification of maximum likelihood, in which accuracy assessment and change detection were reported regarding urban growth during the specified years. In this study, the results of the impact of HHST on the neighborhoods of Tibah municipality showed variations in the values of the average land prices for each of the neighborhoods. Land prices and urban growth during the years 2016, 2018, and 2021 showed differences in terms of the rate of change occurring before, during, and after the inauguration of the train. The findings indicated a negative correlation between the closeness of neighborhoods to the train and land prices in 2016, 2018, and 2021. However, this finding contrasts with those of previous studies conducted in China (Zhou et al., 2017), which have suggested that HSR positively impacts land prices in neighborhoods near the train. This is the case even though China's HSR (Zhou et al., 2017) and the HHST lines are both recently constructed passenger lines and not dedicated freight transportation routes (Kozicki, 2016). Additionally, the previous study and the current research both confirmed the same hypothesis, namely that HSR causes an increase in land prices. However, in the current study, land prices increased in the areas far from the train track and in the middle areas more than in lands close to the train track. The reason for this may be that people prefer to live in quiet places away from noise and bustle; perhaps the noise caused by the train led Saudi people to choose to live in neighborhoods far from the train. These results are consistent with the findings of Paulo et al. (Trombetta Zannin & Bunn, 2014), in which 69% of survey respondents expressed the impression that train sounds can lower the value of their property. In addition, Fields and Walker (Fields & Walker, 1982) stated that "noise is rated as the most serious environmental nuisance caused by railways." This observation is supported by the study results, which showed a positive impact on land prices in middle-distance and far neighborhoods over the course of the study. Another possible reason involves the location of the University of Jeddah in the middle-distance neighborhoods of the municipality. The availability of this educational service may have played a decisive role in attracting residents and increasing property values in this area.

Moreover, the impact of HHST on the rate of urban growth within the neighborhoods of Tibah municipality during the years selected for the study found that the neighborhoods near HHST grew over time, while the middle-distance and far neighborhoods experienced slow urban growth. This finding is consistent with Wang's (Wang, 2015) study, which demonstrated that HSR impacts urban growth because it improves accessibility in the region. Furthermore, the land near the HSR station has higher accessibility than land away from the HSR station. The study conducted by Wang (2015) examined the experiences of China's major cities and showed that large cities with good access have a chance of expanding towards the subcenters. This finding is relevant to Jeddah, one of the largest cities in Saudi Arabia, and the HHST, which encourages regional integration and development to promote better accessibility and regular, easy travel between cities (e.g., Makkah, Madina, and Jeddah). This growth might be partially explained by the Saudi government's actions to help citizens receive bank loans to buy residential and commercial land. That being said, the growth began to show signs of a gradual rise, especially after the inauguration of the HHST project, which boosted growth in the neighborhoods of Tibah municipality to 25.62 km^2 in 2018. However, some neighborhoods in the Tibah municipality, such as Al Wedad (Af), Al-Nada (Am), Al-Bayan (An) and Al-Tawfeek (Af), did not witness growth since they are newly established and not well planned in terms of the availability of services and distance from the city center. Direct relationships were noted between higher land prices and lower urban growth as well as lower land prices and greater urban growth.

It is clear that land prices were also strongly affected by several political decisions and international circumstances. One study has shown that a wide range of economic variables—including investment, expenditure, inflation, buying power, and the balance of trade—are strongly correlated with the introduction of the value-added tax (VAT) (Bogari, 2020). In 2016, an annual fee was imposed on undeveloped lands in cities at the rate of 2.5% of the value of land parcels larger than 5000 m^2 (Idle Lands, 2023), with the aim of preventing land hoarding and price drops. Furthermore, a general decline in oil prices began in early 2016, when it fell below $40 per barrel (see **Appendix C**), resulting in a drop in land values. In 2018, Saudi Arabia imposed a 5% VAT on all products and services, and following the recent worldwide COVID-19 epidemic, they increased this amount, levying a 15% VAT beginning in July 2020 (Sarwar et al., 2021). More importantly, according to the Housing Program Delivery Plan 2021-2025, the economic recession resulting from the general closures during the COVID-19 pandemic had a negative effect on the economy, caused by a drop in oil prices. With the lifting of the general ban in 2021 and the rise in oil prices, markets recovered. Real estate in Saudi Arabia is divided into three sectors—namely residential, commercial, and agricultural—and all of these have witnessed severe price fluctuations due to these events (General Authority for Statistics, 2023).

7. Conclusion

Through the adoption of various statistical methods and a GIS program, this study examined the relationships between HHST and the value of land prices and urban growth in the neighborhoods of Tibah and explored the reasons for these dynamics. The study confirmed a decrease in the average price of land close to the train, as the train had a negative impact on nearby neighborhoods. By contrast, the middle-distance neighborhoods and those far from the train were positively affected as land values rose. As for the rate of urban growth, the results indicated that the year 2016 witnessed urban expansion at a rate of 15.51 km^2, while in 2018, the growth rate increased to 25.62 km^2. In 2021, growth significantly increased, reaching 42.1 km^2. The study also found that the neighborhoods near HHST have experienced a significant increase in urban growth over time, while the middle-distance and far neighborhoods have grown more slowly.

More importantly, the study found that a number of governmental decisions and international circumstances (i.e., VAT, an annual fee on undeveloped lands, oil prices, and the COVID-19 pandemic) had a significant effect on land prices. This study provides vital information on the effects of the HHST development project on Jeddah city's urban development, particularly in Tibah municipality's neighborhoods, and therefore contributes to existing knowledge on the effects of HHST on land prices and urban growth. However, further research should be undertaken to investigate the economic impact of the train in Jeddah city in terms of employment and commercial investments, and future studies regarding the economic impact of the train network on the growth and expansion of the city should be considered.

Conflicts of Interest

The author declares that there is no conflict of interest to disclose.

References

Aburas, M. M., Abdullah, S. H., Ramli, M. F., & Ash'aari, Z. H. (2017). Measuring and Mapping Urban Growth Patterns Using Remote Sensing and GIS Techniques. *Pertanika Journal of Scholarly Research Reviews, 3,* 55-69.

Alkan, M., Oruc, M., Yildirim, Y., Seker, D., & Jacobsen, K. (2013). Monitoring Spatial and Temporal Land Use/Cover Changes; a Case Study in Western Black Sea Region of Turkey. *Journal of the Indian Society of Remote Sensing, 41,* 587-596. https://doi.org/10.1007/s12524-012-0227-2

Alkaradaghi, K., Ali, S. S., Al-Ansari, N., & Laue, J. (2018). Evaluation of Land Use & Land Cover Change Using Multi-Temporal Landsat Imagery: A Case Study Sulaimaniyah Governorate, Iraq. *Journal of Geographic Information System, 10,* 247-260. https://doi.org/10.4236/jgis.2018.103013

Arzaghi, M., & Henderson, J. V. (2008). Networking off Madison Avenue. *The Review of Economic Studies, 75,* 1011-1038. https://doi.org/10.1111/j.1467-937X.2008.00499.x

Banister, D., & Lichfield, N. (2003). The Key Issues in Transport and Urban Development. In *Transport and Urban Development* (pp. 11-26). Routledge. https://doi.org/10.4324/9780203451328

Bhatta, B. (2009). Analysis of Urban Growth Pattern Using Remote Sensing and GIS: A Case Study of Kolkata, India. *International Journal of Remote Sensing, 30,* 4733-4746. https://doi.org/10.1080/01431160802651967

Blanquart, C., & Koning, M. (2017). The Local Economic Impacts of High-Speed Railways: Theories and Facts. *European Transport Research Review, 9,* 1-14. https://doi.org/10.1007/s12544-017-0233-0

Bogari, A. (2020). The Economic and Social Impact of the Adoption of Value-Added Tax in Saudi Arabia. *International Journal of Economics, Business and Accounting Research (IJEBAR), 4,* 62-74. https://doi.org/10.29040/ijebar.v4i02.991

Bowes, D. R., & Ihlanfeldt, K. R. (2001). Identifying the Impacts of Rail Transit Stations on Residential Property Values. *Journal of Urban Economics, 50,* 1-25. https://doi.org/10.1006/juec.2001.2214

Campbell, J. B., & Wynne, R. H. (2011). *Introduction to Remote Sensing*. Guilford Press.

Chen, Y. (2021). *High Speed Rail and China's New Economic Geography: Impact Assessment from the Regional Science Perspective*. Edward Elgar Pubing.

Congalton, R. G. (1991). A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sensing of Environment, 37,* 35-46. https://doi.org/10.1016/0034-4257(91)90048-B

Congalton, R. G., & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. CRC Press. https://doi.org/10.1201/9780429052729

Crawford, S. L. (2006). Correlation and Regression. *Circulation, 114,* 2083-2088. https://doi.org/10.1161/CIRCULATIONAHA.105.586495

de Rus Mendoza, G. (2012). *Economic Analysis of High Speed Rail in Europe*. Fundacion BBVA.

Debrezion, G., Pels, E., & Rietveld, P. (2005). The Impact of Rail Transport on the Prices

of Real Estate: Empirical Study of the Dutch Housing Market. https://www.researchgate.net/profile/Eric_Pels/publication/23731849_Impact_of_railway_station_on_Dutch_residential_housing_market/links/53f5ca060cf2888a7491e848.pdf
https://doi.org/10.2139/ssrn.895270

Donaldson, D. (2018). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *American Economic Review, 108,* 899-934. https://doi.org/10.1257/aer.20101199

Dornier Group (2023). Saudi Railway Organization. https://dornier-group.com/en/reference/saudi-railway-master-plan-up-to-year-2040/

Dubé, J., Thériault, M., & Des Rosiers, F. (2013). Commuter Rail Accessibility and House Values: The Case of the Montreal South Shore, Canada, 1992-2009. *Transportation Research Part A: Policy and Practice, 54,* 49-66. https://doi.org/10.1016/j.tra.2013.07.015

Fields, J. M., & Walker, J. (1982). The Response to Railway Noise in Residential Areas in Great Britain. *Journal of Sound and Vibration, 85,* 177-255. https://doi.org/10.1016/0022-460X(82)90519-3

Gashaw, T., Tulu, T., Argaw, M., & Worqlul, A. W. (2017). Evaluation and Prediction of Land Use/Land Cover Changes in the Andassa Watershed, Blue Nile Basin, Ethiopia. *Environmental Systems Research, 6,* Article No. 1. https://doi.org/10.1186/s40068-016-0078-x

General Authority for Statistics (2023). *Real Estate Price Index*. https://www.stats.gov.sa/ar/843

Geng, B., Bao, H., & Liang, Y. (2015). A Study of the Effect of a High-Speed Rail Station on Spatial Variations in Housing Price Based on the Hedonic Model. *Habitat International, 49,* 333-339. https://doi.org/10.1016/j.habitatint.2015.06.005

Guastella, G., Pareglio, S., & Sckokai, P. (2017). A Spatial Econometric Analysis of Land Use Efficiency in Large and Small Municipalities. *Land Use Policy, 63,* 288-297. https://doi.org/10.1016/j.landusepol.2017.01.023

Hamdy, O., Zhao, S., Salheen, M. A., & Eid, Y. (2017). Analyses the Driving Forces for Urban Growth by Using IDRISI® Selva Models Abouelreesh-Aswan as a Case Study. *International Journal of Engineering and Technology, 9,* 226-232. https://doi.org/10.7763/IJET.2017.V9.975

Hardin, P. J., Jackson, M. W., & Otterstrom, S. M. (2007). Mapping, Measuring, and Modeling Urban Growth. In R. R. Jensen, J. D. Gatrell, & D. McLean (Eds.), *Geo-Spatial Technologies in Urban Environments: Policy, Practice, and Pixels* (pp. 141-176). Springer. https://doi.org/10.1007/978-3-540-69417-5_8

Hazra, A., & Gogtay, N. (2016). Biostatistics Series Module 6: Correlation and Linear Regression. *Indian Journal of Dermatology, 61,* 593-601. https://doi.org/10.4103/0019-5154.193662

He, S. Y. (2020). Regional Impact of Rail Network Accessibility on Residential Property Price: Modelling Spatial Heterogeneous Capitalisation Effects in Hong Kong. *Transportation Research Part A: Policy and Practice, 135,* 244-263. https://doi.org/10.1016/j.tra.2020.01.025

Hensher, D., Li, Z., & Mulley, C. (2012). The Impact of High Speed Rail on Land and Property Values: A Review of Market Monitoring Evidence from Eight Countries. *Road & Transport Research: A Journal of Australian and New Zealand Research and Practice, 21,* 3-14.

Heuermann, D. F., & Schmieder, J. F. (2014). Warping Space: High-Speed Rail and Returns to Scale in Local Labor Markets. ECONSTOR. https://2u.pw/s4ktdr9

Idle Lands (2023). *The Executive Regulations of the Undeveloped Land Fee System*. https://idlelands.housing.gov.sa/ar/page/121

International Union of Railways (2022). *High-Speed Rail: The Right Speed for Our Planet*. https://uic.org/passenger/highspeed/

Jensen, J. R. (1996). *Introductory Digital Image Processing: A Remote Sensing Perspective*. Prentice-Hall Inc.

Kilic, S., Evrendilek, F., Berberoglu, S., & Demirkesen, A. (2006). Environmental Monitoring of Land-Use and Land-Cover Changes in a Mediterranean Region of Turkey. *Environmental Monitoring and Assessment, 114,* 157-168. https://doi.org/10.1007/s10661-006-2525-z

Kim, T. K. (2017). Understanding One-Way ANOVA Using Conceptual Figures. *Korean Journal of Anesthesiology, 70,* 22-26. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5296382/pdf/kjae-70-22.pdf https://doi.org/10.4097/kjae.2017.70.1.22

Kozicki, M. (2016). Railway Development in Saudi Arabia. In Kończak I., Woźniak-Bobińska M.(red.), *Ciągłość i zmiana w świecie islamu, Wydawnictwo Uniwersytetu Łódzkiego, Łódź 2016*. Wydawnictwo Uniwersytetu Łódzkiego. https://doi.org/10.18778/8088-166-2.05

Landis, J. R., & Koch, G. G. (1977). A One-Way Components of Variance Model for Categorical Data. *Biometrics, 33,* 671-679. https://doi.org/10.2307/2529465

Lee, C.-M., Ryu, K.-M., Choi, K., & Kim, J. Y. (2018). The Dynamic Effects of Subway Network Expansion on Housing Rental Prices Using a Repeat Sales Model. *International Journal of Urban Sciences, 22,* 529-545. https://doi.org/10.1080/12265934.2018.1487331

Li, Z., & Xu, H. (2018). High-Speed Railroads and Economic Geography: Evidence from Japan. *Journal of Regional Science, 58,* 705-727. https://doi.org/10.1111/jors.12384

Liu, X., Jiang, C., Wang, F., & Yao, S. (2021). The Impact of High-Speed Railway on Urban Housing Prices in China: A Network Accessibility Perspective. *Transportation Research Part A: Policy and Practice, 152,* 84-99. https://doi.org/10.1016/j.tra.2021.08.006

Liu, Y., Nishiyama, S., & Yano, T. (2004). Analysis of Four Change Detection Algorithms in Bi-Temporal Space with a Case Study. *International Journal of Remote Sensing, 25,* 2121-2139. https://doi.org/10.1080/01431160310001606647

Lu, Y., & Zeng, L. (2022). How Do High-Speed Railways Facilitate High-Quality Urban Development: Evidence from China. *Land, 11,* Article 1596. https://doi.org/10.3390/land11091596

Luo, G., & Li, T. (2019). Dynamic Change and Driving Factors of Land Use Efficiency Differences Affected by Carbon Emissions at the Provincial Level in China. *Acta Ecologica Sinica, 39,* 4751-4760. https://doi.org/10.5846/stxb201903020389

Okamoto, C., & Sato, Y. (2021). Impacts of High-Speed Rail Construction on Land Prices in Urban Agglomerations: Evidence from Kyushu in Japan. *Journal of Asian Economics, 76,* Article 101364. https://doi.org/10.1016/j.asieco.2021.101364

Ollivier, G., Bullock, R., Ying, J., & Zhou, N. (2014). High-Speed Railways in China. *China Transport Topics No. 11.*

Perl, A., Deng, T., Correa, L., Wang, D., & Yan, Y. (2021). Understanding the Urbanization Impacts of High-Speed Rail in China. *Archives of Transport, 58,* 21-34. https://doi.org/10.5604/01.3001.0014.8795

Qiao, W., & Huang, X. (2021). Change in Urban Land Use Efficiency in China: Does the High-Speed Rail Make a Difference? *International Journal of Environmental Research and Public Health, 18,* Article 10043. https://doi.org/10.3390/ijerph181910043

Reggiani, A., Bucci, P., Russo, G., Haas, A., & Nijkamp, P. (2011). Regional Labour Markets and Job Accessibility in City Network Systems in Germany. *Journal of Transport Geography, 19,* 528-536. https://doi.org/10.1016/j.jtrangeo.2010.05.008

Renzhi, N. (2018). How High-Speed Rail Affects Local Land Prices: Evidence from Taipei, China. https://doi.org/10.2139/ssrn.3286235

Ross, A., & Willson, V. L. (2017). Paired Samples T-Test. In *Basic and Advanced Statistical Tests* (pp. 17-19). Springer. https://doi.org/10.1007/978-94-6351-086-8_4

Rungskunroch, P., Yang, Y., & Kaewunruen, S. (2020). Does High-Speed Rail Influence Urban Dynamics and Land Pricing? *Sustainability, 12,* Article 3012. https://doi.org/10.3390/su12073012

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *International Journal of Geosciences, 8,* 611-622. https://doi.org/10.4236/ijg.2017.84033

Sarwar, S., Streimikiene, D., Waheed, R., Dignah, A., & Mikalauskiene, A. (2021). Does the Vision 2030 and Value Added Tax Leads to Sustainable Economic Growth: The Case of Saudi Arabia? *Sustainability, 13,* Article 11090. https://doi.org/10.3390/su131911090

Sathya, P., & Deepa, V. B. (2017). Analysis of Supervised Image Classification Method for Satellite Images. *International Journal of Computer Science Research (IJCSR), 5,* 16-19.

Sudhira, H., Ramachandra, T., & Jagadish, K. (2004). Urban Sprawl: Metrics, Dynamics and Modelling Using GIS. *International Journal of Applied Earth Observation and Geoinformation, 5,* 29-39. https://doi.org/10.1016/j.jag.2003.08.002

Sun, W., Wang, C., Liu, C., & Wang, L. (2021). High-Speed Rail Network Expansion and Its Impact on Regional Economic Sustainability in the Yangtze River delta, China, 2009-2018. *Sustainability, 14,* Article 155. https://doi.org/10.3390/su14010155

Suribabu, C., Bhaskar, J., & Neelakantan, T. (2012). Land Use/Cover Change Detection of Tiruchirapalli City, India, Using Integrated Remote Sensing and GIS Tools. *Journal of the Indian Society of Remote Sensing, 40,* 699-708. https://doi.org/10.1007/s12524-011-0196-x

Tan, K. C., Lim, H. S., MatJafri, M. Z., & Abdullah, K. (2010). Landsat Data to Evaluate Urban Expansion and Determine Land Use/Land Cover Changes in Penang Island, Malaysia. *Environmental Earth Sciences, 60,* 1509-1521. https://doi.org/10.1007/s12665-009-0286-z

Trombetta Zannin, P. H., & Bunn, F. (2014). Noise Annoyance through Railway Traffic—A Case Study. *Journal of Environmental Health Science and Engineering, 12,* Article No. 14. https://doi.org/10.1186/2052-336X-12-14

Ureña, J. M., Menerault, P., & Garmendia, M. (2009). The High-Speed Rail Challenge for Big Intermediate Cities: A National, Regional and Local Perspective. *Cities, 26,* 266-279. https://doi.org/10.1016/j.cities.2009.07.001

Varquez, A. C. G., Dong, S., Hanaoka, S., & Kanda, M. (2020). Improvement of an Urban Growth Model for Railway-Induced Urban Expansion. *Sustainability, 12,* Article 6801. https://doi.org/10.3390/su12176801

Venables, A. J. (2007). Evaluating Urban Transport Improvements: Cost-Benefit Analysis in the Presence of Agglomeration and Income Taxation. *Journal of Transport Economics and Policy (JTEP), 41,* 173-188.

Wang, T. (2015). *Effects of High-Speed Rail on Regional Development: Case Study of the Stockholm-Mälar Region and Yangtze River Delta Region*. KTH Kungliga Tekniska Högskolan.

Wang, W., Wang, Y., Wang, Q., Lian, D., & Wang, Z. (2011). Application of Decision Tree in Land Use Classification. In L. Jiang (Ed.), *Proceedings of the 2011, International Conference on Informatics, Cybernetics, and Computer Engineering (ICCE2011)* (pp. 567-573). Springer. https://doi.org/10.1007/978-3-642-25188-7_70

Wang, Y., Ruan, H., & Tian, C. (2022). Access to High-Speed Rail and Land Prices in China's Peripheral Regions. *Cities, 130,* Article 103877. https://doi.org/10.1016/j.cities.2022.103877

Zheng, H., & Wu, Y. (2019). A XGBoost Model with Weather Similarity Analysis and Feature Engineering for Short-Term Wind Power Forecasting. *Applied Sciences, 9,* Article 3019. https://doi.org/10.3390/app9153019

Zheng, S., & Kahn, M. E. (2013). China's Bullet Trains Facilitate Market Integration and Mitigate the Cost of Megacity Growth. *Proceedings of the National Academy of Sciences of the United States of America, 110,* E1248-E1253. https://doi.org/10.1073/pnas.1209247110

Zhou, Y., Yang, J., Hewings, G., & Huang, Y. (2017). Does High-Speed Rail Increase the Urban Land Price in China: Empirical Evidence Based on Micro Land Transaction Data. https://doi.org/10.2139/ssrn.3082657

Zhu, P. (2021). Does High-Speed Rail Stimulate Urban Land Growth? Experience from China. *Transportation Research Part D: Transport and Environment, 98,* Article 102974. https://doi.org/10.1016/j.trd.2021.102974

Zhu, S., Zhou, Z., Li, R., & Li, W. (2022). Impact of High-Speed Rail Construction on the Environmental Sustainability of China's Three Major Urban Agglomerations. *Sustainability, 14,* Article 2567. https://doi.org/10.3390/su14052567

Zhu, X., & Liu, D. (2014). Accurate Mapping of Forest Types Using Dense Seasonal Landsat Time-Series. *ISPRS journal of Photogrammetry and Remote Sensing, 96,* 1-11. https://doi.org/10.1016/j.isprsjprs.2014.06.012

Zou, W., Chen, L., & Xiong, J. (2021). High-Speed Railway, Market Access and Economic Growth. *International Review of Economics & Finance, 76,* 1282-1304. https://doi.org/10.1016/j.iref.2019.11.014

Appendix

Appendix A. Study Sample Distribution between Residential Areas and Commercial Areas

Table A1. Study sample distribution between residential areas and commercial areas.

Type	Frequency	%
Residential	73	50.7
Commercial	71	49.3
Total	144	100
Region		
Near	48	33.3
Middle	36	25.0
Far	60	41.7
Total	144	100

Appendix B. Statistical Analysis Confirming the Correctness of the Results

Table B1. Statistical analysis confirming the correctness of the results.

Regression statistics					
	Near	Far	Middle		
Multiple R	0.81	0.64	0.84		
R^2	0.66	0.41	0.70		
Adjusted R^2	−1.5	−1.5	−1.5		
Standard error	85.25	214.65	46.43		
Observations	1	1	1		
	ANOVA				
Section		df	SS	MS	F
Near	Regression	6	56886.00	9481.00	7.83
	Residual	4	29073.08	7268.27	
	Total	10	85959.08		
Far	Regression	6	20315.09	3385.85	9.42
	Residual	4	8623.29	2155.82	
	Total	10	28938.38		
Middle	Regression	6	126692.63	21115.44	2.75
	Residual	4	184301.18	46075.30	
	Total	10	310993.81		
		Coefficients	S.er	t Stat	P-value
Near y_1	Intercept	116426.38	41136.32	2.83	0.05
	Year	−57.01	20.38	−2.80	0.05

Continued

Far y_2	Intercept	−170856.95	103572.38	−1.65	0.17
	Year	85.09	51.31	1.66	0.17
Middle y_3	Intercept	−68359.10	22403.52	−3.05	0.04
	Year	34.07	11.10	3.07	0.04

Appendix C. Oil Prices during the Study Period