EFFECTS OF TRANSPORT CORRIDOR ADVANCEMENT ON AGGLOMERATION AND INDUSTRIAL RELOCATION – A CASE STUDY OF DISTRICT 3 IN DALLAS

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Abstract

Cities serve as hubs for various activities that necessitate comprehensive transportation connectivity. This study examines the decadal urban agglomeration patterns from 2001- to 2020 and critically assesses the relationship between freeway developments, industrial relocation, and population density in the DFW (Dallas Fort Worth) metropolitan area. Landsat satellite imageries, US census, and open-source GIS datasets have been utilized in the study. Maximum Likelihood Classification (MLC) algorithm helped generate the vector database, using which Land Use/ Land Cover (LULC) variations were assessed. The calculated overall accuracies of the classified images for 2001, 2011, and 2020 were 93.12%, 91.87%, and 93.12%, and their corresponding kappa coefficients were 0.90, 0.89, and 0.90, respectively. Eventually, buffer generation techniques and summary statistics helped detect potential boom hotspots. Our results indicate that the highway advancement project lures industries, leading to population migration. The LULC variations suggest that the increase in highway infrastructure resulted in a surge in built-up and a decrease in open spaces in District-3 of DFW.

Keywords: urban agglomeration, transportation, LULC

1. Introduction

Cities rely on transit to stay afloat; hence, the transportation system is the city's lifeblood (Vuchin 2002). The transportation network is a complex system (Lu & Tang 2004). The growth of the transportation system can be explained in terms of the city's socio-economic development and the region's geographical location (AlQuhtani and Anjomani, 2021). Transportation infrastructure advancements and innovation are closely related to transportation costs, impacting the volume and pattern of commerce, industrial structure, and factor pricing across the region.

One of the instant aftereffects of highway expansion is corridor development (Dincer et al., 2019). As a highway advancement project is approved, industries aim to relocate to cheaper agricultural properties, resulting in the steady transformation of rural areas into industrial/residential/suburban plots, as Thunen's model explains. Property prices decline with an increase in distance from the key commercial wards (Bluestone, Stevenson & Williams, 2008). Also, localities near the transit corridors develop rapidly owing to which estate cost hikes with immediacy to transport corridors as indicated by Newling & Clark (McCann 2013).

Marshallian Externalities state that expansion of an area is a direct cause of industrialized establishments, leading to a snowball effect (Fujita, 2010). Entrepreneurs look for probable areas to reposition the industries in the optimism of plummeting extreme shipment expenses, thereby preferring an area near the vicinity of well- advanced transit systems, which eventually nurtures local advancement near the conveyance link nominated to reposition the businesses (Chapman 1991).

Our study intends to detect decadal modifications in Land Use/ Land Cover (LULC) with decadal expansion in highway links within the study area. This study plays a vital role in urban planning literature. It establishes the link amid clustering and transportation grid developments expending Remote Sensing and GIS practices.

2. Objectives

i. To study urban agglomeration patterns over two decades, i.e., 2001-2020

ii. To identify a potential booming region in the District 3 of DFW

3. Data Employed

The following satellite images were employed for performing the LULC classification within the study area.

I. Landsat 4-5 Thematic Mapper (TM) of 2001

II. Landsat 4-5 TM of 2011

III. Landsat 8 Operational Land Imager (OLI) of 2020

Other data sources include the Open Street Maps (OSM) data and the US Census database.

4. Study Area

The study area selected for the research was City Council District-3 of Dallas, illustrated in Figure 1. The motivation behind selecting this region was because this district has expanded freshly, with freshly authorized transit infrastructures projects.

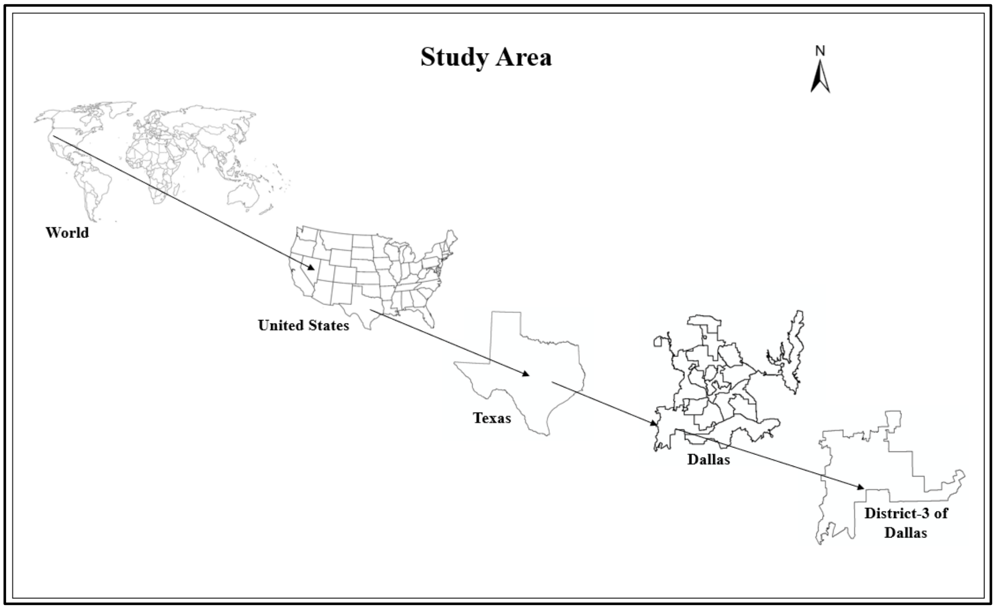


Figure 1: Study Area

5. Methodology

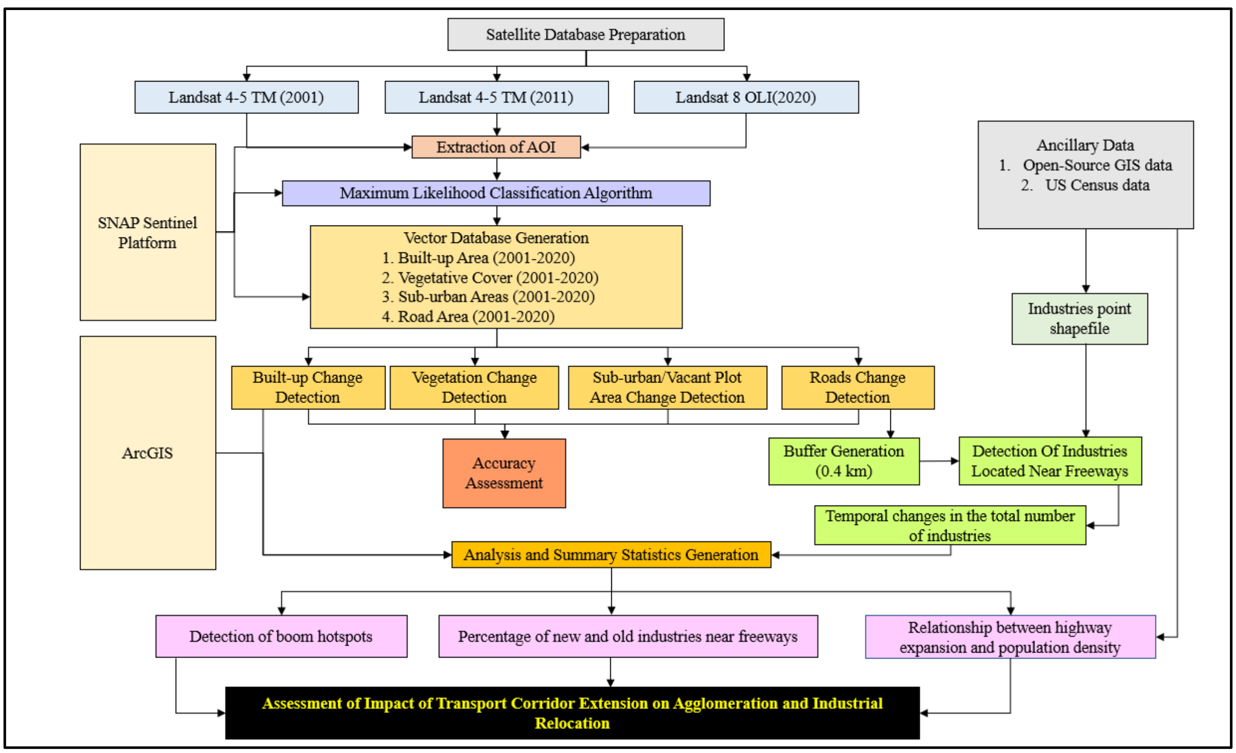


Figure 2: Methodology

The methodology employed in the study is depicted in Figure 2. The Landsat series data (Landsat 4-5 TM for 2001 and 2011, Landsat 8 OLI for 2020) was downloaded from the Earth Explorer. The Maximum Likelihood Classification (MLC) algorithm helped classify the satellite images using SNAP. MLC compensates for over-classification of image objects highly represented in the training data and other classes (Hagner & Reese, 2007). For executing the classification, detection, and training, several testers were chosen for every class, i.e., built-up, vegetation, suburban regions, and roads. Then MLC helped retain the object information in a classified image (Rana & Kharel, 2019). Subsequently, change detection examinations were carried out for the entire area to foresee the overall variations in land cover.

The accuracy of the classified images was assessed employing 160 testing sites obtained from Google Earth images. The following equations helped evaluate the accuracy of the classified images:

<u>Equation 1</u>: User Accuracy = (CCP/TCP) *100

<u>Equation 2</u>: Producer Accuracy = (CCP/TRP) *100

<u>Equation 3</u>: Overall Accuracy = (CCPD/TS) *100

<u>Equation 4</u>: $K = [\{(TS*TCS)-\Sigma(CT*RT)\} / \{TS^2 - \Sigma(CT*RT)\}] *100$

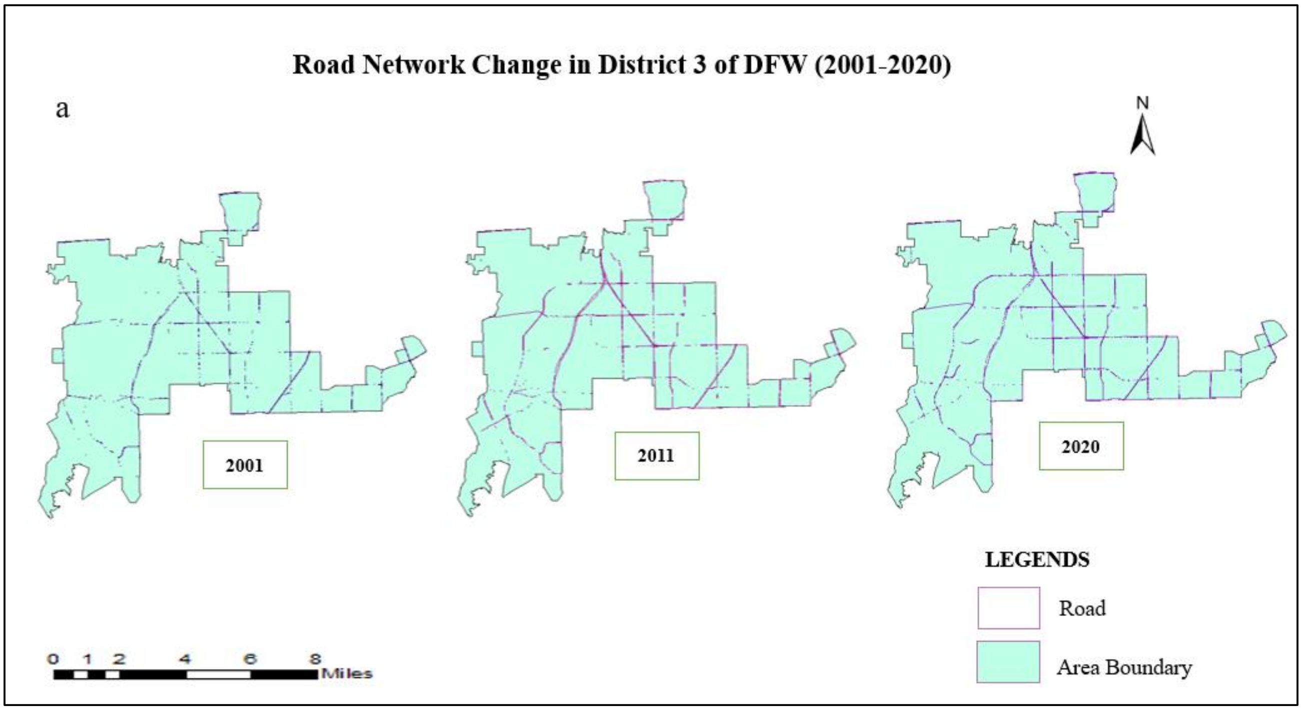
Here,

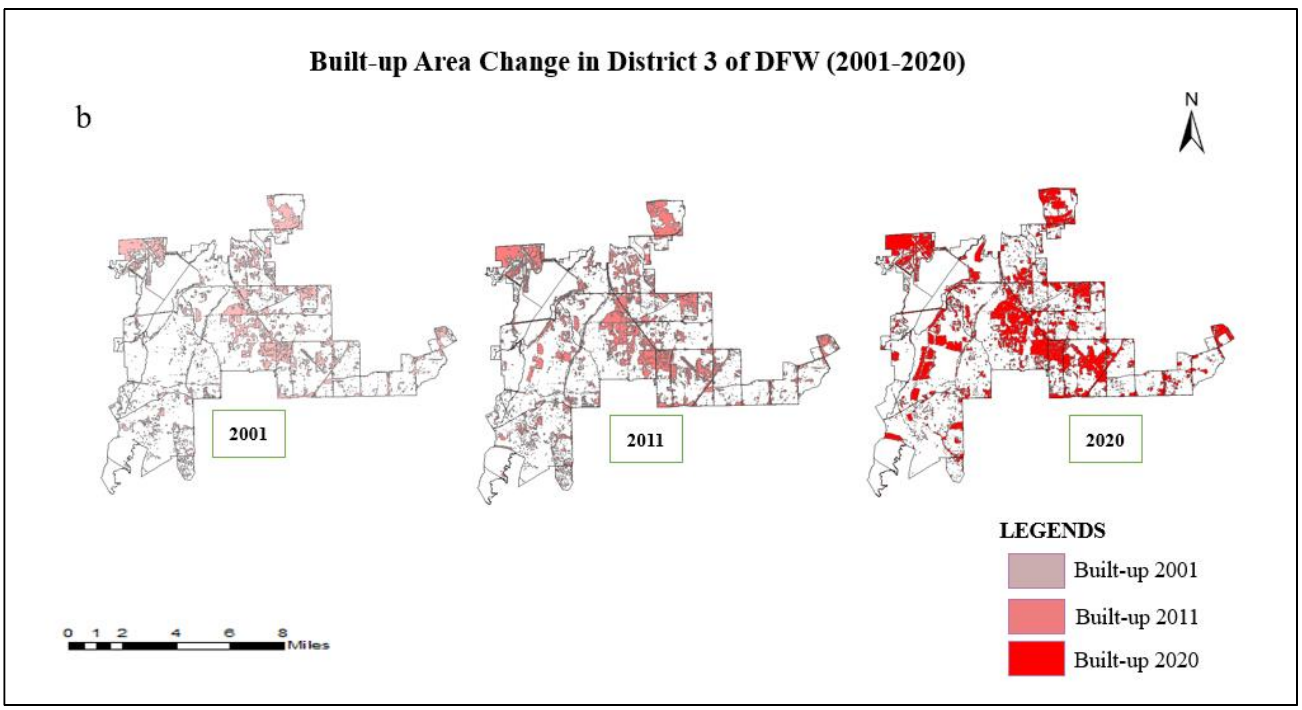
CCP= Correctly Classified Pixels in each category; TCP = Total Classified Pixels in that category; TRP= Total Reference Pixels in that category; CCPD= Correctly Classified Pixels (Diagonal); TS= Total Sample; TCS= Total Correctly Classified Samples; CT= Column Total; RT= Row Total; K= Kappa Coefficient

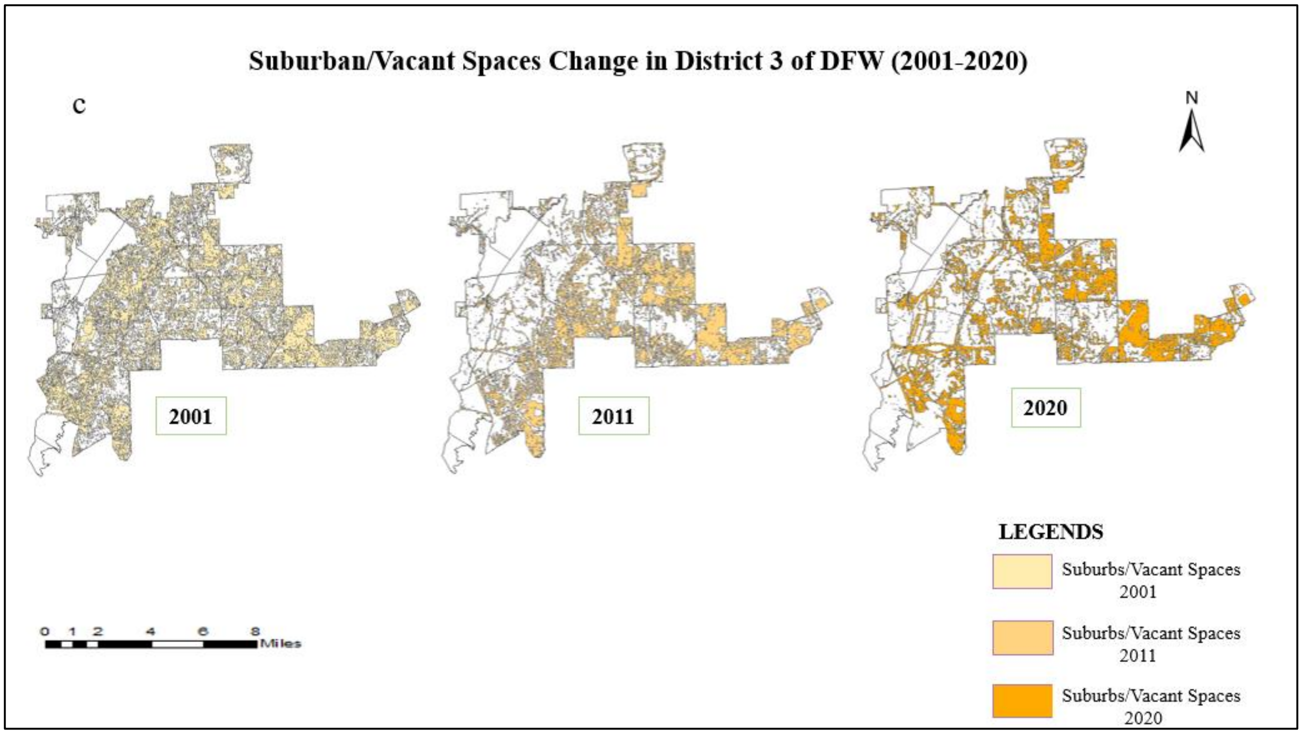
Next, the built-up layer was overlayed along with the transportation network shapefiles, and summary statistics were calculated which helped locate areas where high built-up variations were observed within the study area during the time frame of 2001-2020. Thereafter, a buffer of 0.4km was generated around the transportation network using a buffer analysis tool to detect industries relocated within a radius of 0.4km from the freeways. Eventually, summary statistics helped quantify the total area occupied by industries and by freeways, using which the plot between the total area occupied by relocated industries and the total freeway area was derived. The booming built-up was calculated by comparing the increase/decrease in the built-up area within each census tract to the increase/decrease in the road area for that census tract for the three decades. The census tracts which had the highest built-up recorded within a time span of three decades had the highest booming built-up and vice-versa.

6. Result and Discussion

Change detection analysis was conducted for the District 3 of DFW utilizing ML classifiers. Figure 3 illustrates the land-use dynamics from 2001- 2020.







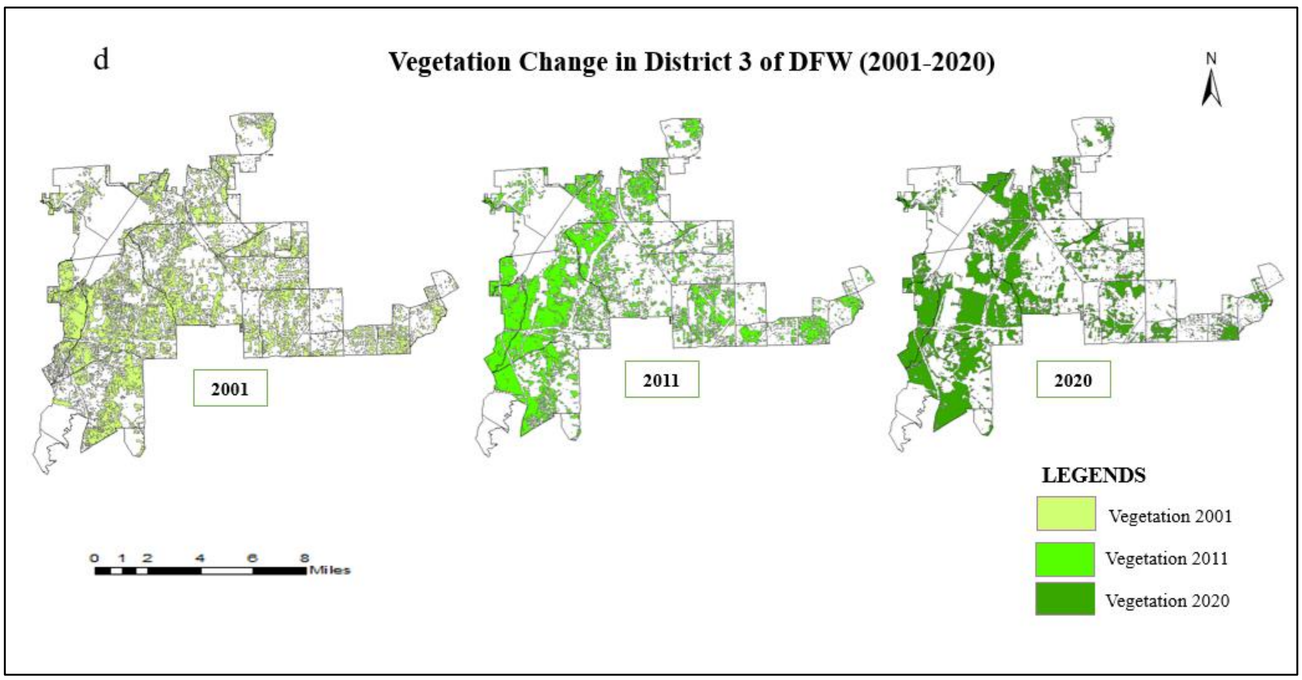


Figure 3: Spatial variation in the road network (a), built-up (b), suburban/vacant plot (c), and vegetation cover (d) in District-3 of DFW.

The substantial increase in highway spans due to the commissioning of significant highway development projects resulted in a considerable surge in built-up areas and a decrease in open spaces. Figure 4 depicts LULC variations in District 3 of the DFW metropolitan region over the last two decades. The results illustrate the human/industrial agglomeration fostered by freeway development.

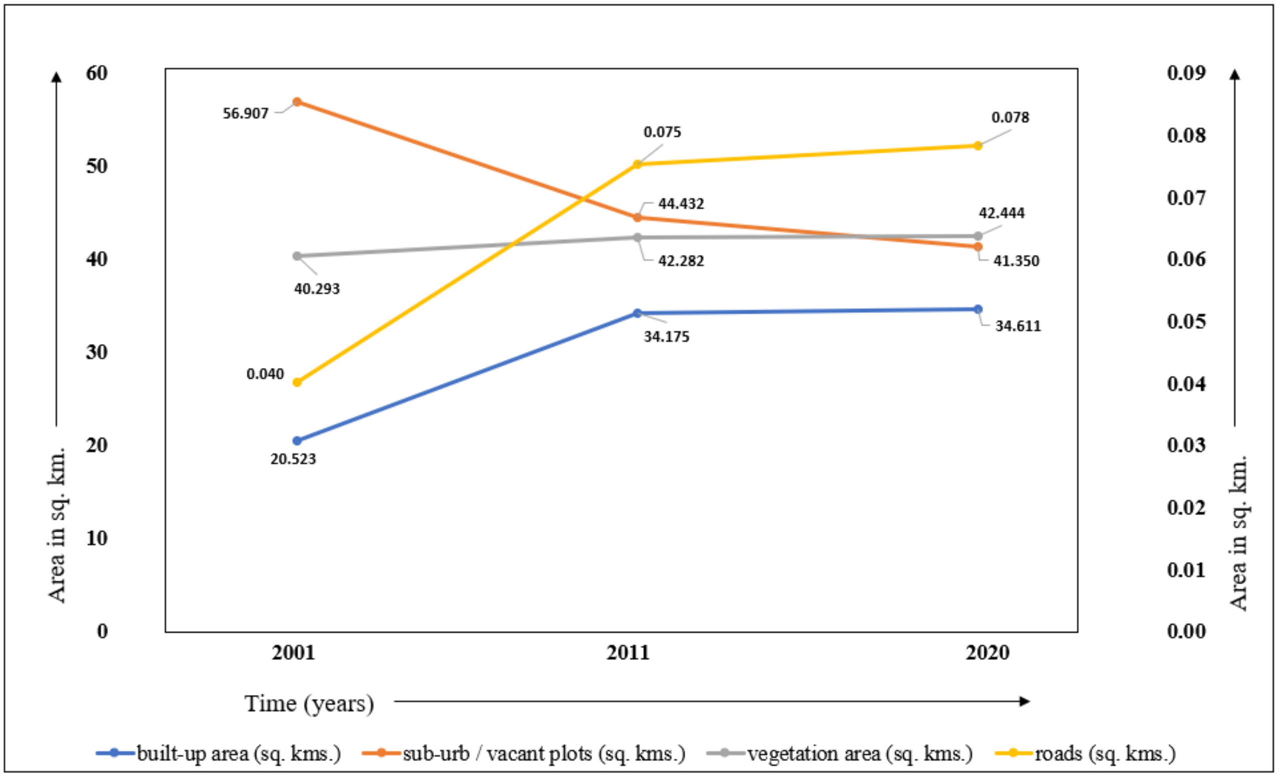


Figure 4: Road area increase and LULC in District 3 of DFW

Figure 4 illustrates a swift growth in metropolitan areas during 2001-2010, while there was a stagnant growth recorded in the next decade. The trend depicts the upsurge in property costs during 2001-2011, owing to which the building constructions may have been stagnated.

A confusion matrix was generated using the cross-referenced training samples to identify the degree of misclassified pixels during the image classification (Baig et al., 2022). Figure 5 illustrates the confusion which helped calculate the overall accuracy and kappa coefficient. The analysis of the generated confusion matrix resulted in an overall accuracy of 93.12%, 91.87%, and 93.12% for the years 2001, 2011, and 2020 and their corresponding kappa coefficient were calculated to be 0.90, 0.89, and 0.90 respectively.

	Class	Built-up	Vegetation	Suburb and Open Space	Road	(User)	User Accuracy
2001	Built-up	37	1	1	1	40	92.5
	Vegetation	0	37	3	0	40	92.5
	Suburb/Open	0	2	38	0	40	95
	Road	2	0	1	37	40	92.5
	(Producer)	39	40	43	38	160	
	Producer Accuracy	94.87	92.5	88.37	97.36		

	Class	Built-up	Vegetation	Suburb and Open Space	Road	(User)	User Accuracy
2011	Built-up	36	0	2	2	40	90
	Vegetation	1	37	2	0	40	92.5
	Suburb/Open	0	1	38	1	40	95
	Road	2	0	2	36	40	90
	(Producer)	39	38	44	39	160	
	Producer Accuracy	92.31	97.36	86.36	92.30		

	Class	Built-up	Vegetation	Suburb and Open Space	Road	Total (User)	User Accuracy
2020	Built-up	38	0	2	0	40	95
	Vegetation	0	38	1	1	40	95
	Suburb/Open	1	1	37	1	40	92.5
	Road	2	1	1	36	40	90
	(Producer)	41	40	41	38	160	
	Producer Accuracy	92.68	95	90.24	94.73		

Figure 5: Confusion Matrix

The booming built-up hotspots calculated from the data on built-up, population density, and road lengths showed that district 3 of the DFW metropolitan area was under speedy expansion during both the decades (Figure 6).

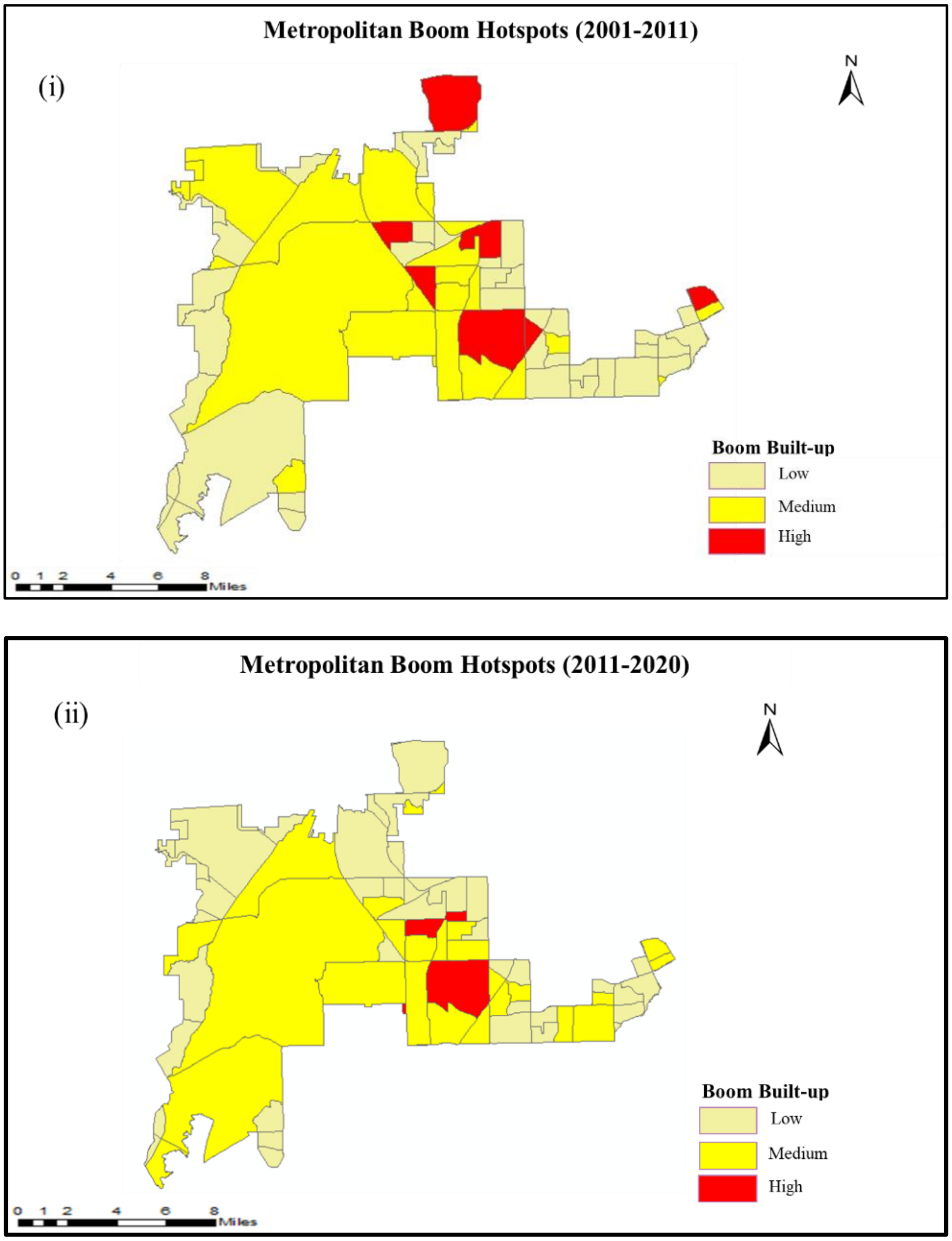


Figure 6: Metropolitan boom hotspot in District 3 of DFW

Figure 7 highlights that highway expansion ultimately fosters industrial relocation. We assume that all roads built before the year 2000 as old and those constructed after 2000 as new roads. We assume a radial distance of 0.4km buffer around the highway to ensure that all industrial clusters located very close to freeways are detected accurately. We assume this optimum figure because any radius beyond 0.4 or 0.5 km would not justify the study. According to our study, 79.16% of old industries were located near old freeways while 78.84% of new industries were located near new freeways. From this observation, we concluded that most industries were located near highways.

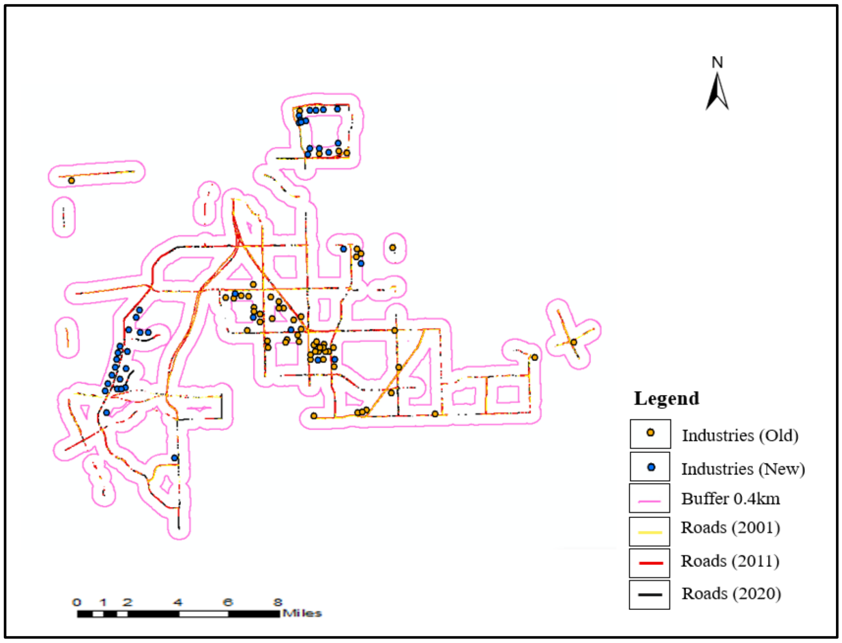


Figure 7: Buffer generation for identifying industrial clusters relocated near freeways

Figure 8 depicts the ratio between industrial area occupancy and the road area. Figure 8 shows that most industries were set up near transit corridors, showing a strong positive relationship between transportation infrastructure and industrial relocation.

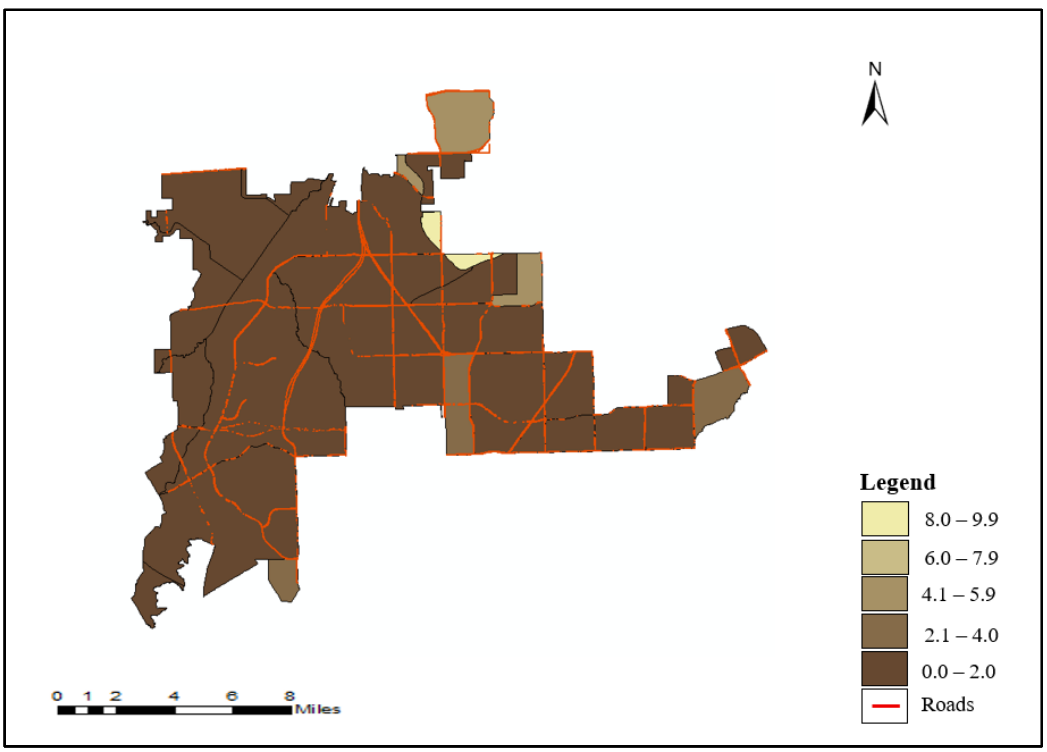


Figure 8: Ratio of industrial area occupancy to the road area

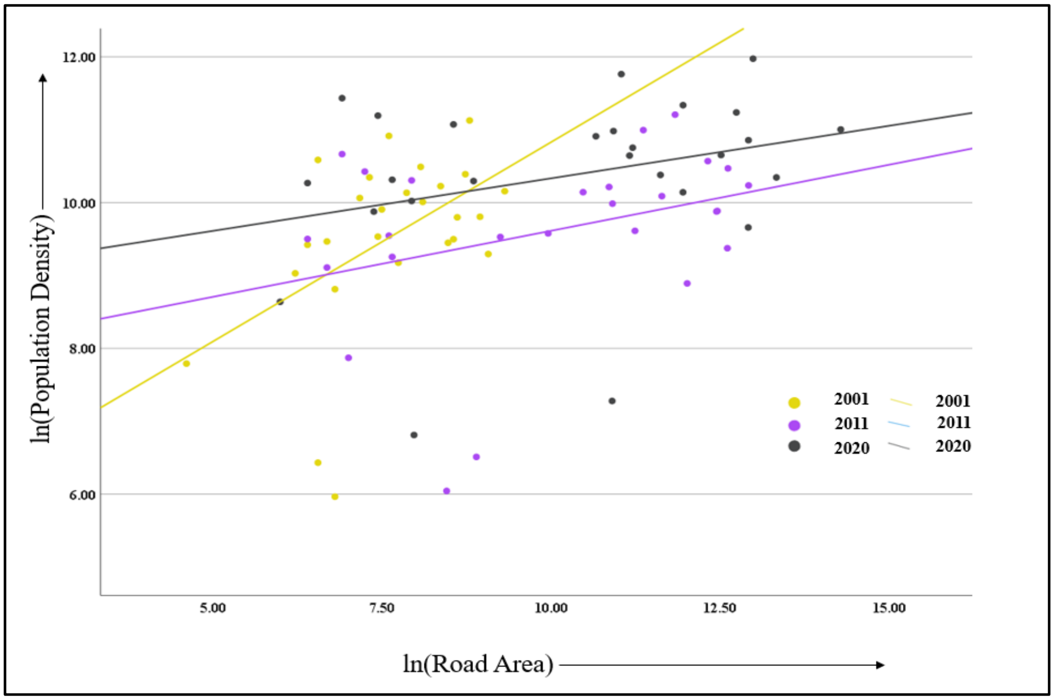


Figure 9: Plot of highway expansion vs. population density (2001-2020)

Further, Figure 9 clearly shows that with the increase in the total road area in a census tract, there is an increase in population density within that census tract, which confirms that highway expansion leads to population agglomeration. Also, we conclude from Figures 7, 8, and 9 that highway expansion, industrial relocation, and population agglomeration are interrelated.

7. Conclusion

This research compared decadal urban growth and decadal freeway expansions within the study area. Our study found that transportation development fosters urban growth. This research highlights the applications of geospatial data in urban studies. Such technologies integrated with automated learning approaches will become a boon to metropolitan planners. The generation of easy and valuable data eliminates the need for manual digitization of image objects (Kharel et al., 2019), thereby closing the time and labor barriers usually unavoidable in geospatial studies.

References

Dincer, S. E., Akdemir, F., Ulvi, H., & Duzkaya, H. (2019). Assessing Urban Sprawl Effect of Transportation Investments using Remote Sensing Data and GIS Methods: The case of Ankara Protocol Road. IOP Conference Series: Materials Science and Engineering, 471, 092079.

Vuchic, V. R. (2002). Urban public transportation systems. *University of Pennsylvania, Philadelphia, PA, USA*, *5*, 2532-2558.

Lu, Y., & Tang, J. (2004). Fractal dimension of a transportation network and its relationship with urban growth: a study of the Dallas-Fort Worth area. *Environment and Planning B: Planning and Design*, *31*(6), 895-911.

McCann, P. (2013). *Modern urban and regional economics*. Oxford University Press.

Bluestone, B., Stevenson, M. H., & Williams, R. (2008). *The urban experience: Economics, society, and public policy*. Oxford University Press, USA.

Chapman, K. (1991). *Industrial location: Principles and policies*.

Fujita, M. (2010). The evolution of spatial economics: From THÜNEN to the new economicgeography. *Japanese Economic Review*, *61*(1), 1-32.

Rana, M. and Kharel, S. (2019). Feature Extraction for Urban and Agricultural Domains Using Ecognition Developer, *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 423, pp. 609–615.

Kharel, S., Shivananda, P., Ramesh, K. S., Naga Jothi, K. and Raj, K.G. (2019). Use of transportation network analysis for bus stop relocation, depiction of service area and bus route details, *Journal of Geomatics,* 13(2) pp. 224-229.

Hagner, O., & Reese, H. (2007). A method for calibrated maximum likelihood classification of forest types. Remote Sensing of Environment, 110(4), 438-444.

AlQuhtani, S., & Anjomani, A. (2021). Do Rail Transit Stations Affect the Population Density Changes around Them? The Case of Dallas-Fort Worth Metropolitan Area. *Sustainability*, *13*(6), 3355.

Baig, M. F., Mustafa, M. R. U., Baig, I., Takaijudin, H. B., & Zeshan, M. T. (2022). Assessment of Land Use Land Cover Changes and Future Predictions Using CA-ANN Simulation for Selangor, Malaysia. *Water*, *14*(3), 402.