GEOGRAPHICALLY WEIGHTED REGRESSION (GWR) MODEL FOR ANALYZING FACTORS OF LAND SUBSIDENCE IN JAKARTA PROVINCE

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ABSTRACT

Land subsidence was a serious issue affecting infrastructure, water resources and human safety on various countries in the world, including Indonesia. Jakarta as one of the Capital cities in Indonesia is also experiencing land subsidence at varying rates which has many impacts. This study aims to analyze the influence of built-up areas, population density, groundwater, elevation, and distance from the coastline against land subsidence in Jakarta. Data was obtained using the InSAR method, Landsat 8 imagery, Statistic Central Bureau, Indonesian Geospatial Bureau, and Water Resources Agency. The analysis was conducted using Geographically Weighted Regression (GWR). The results indicate that land subsidence in Jakarta is influenced by several parameters, including groundwater levels, population density, built-up areas, elevation, and distance from the coast. The overall R^2 value of the Geographically Weighted Regression (GWR) model was 0.566, suggesting a moderate explanatory power. Among the variables, groundwater exhibited the strongest correlation with land subsidence ($R^2 = 0.829$), whereas elevation ($R^2 = 0.255$) and distance from the coast ($R^2 = 0.249$) showed the weakest correlations. These findings suggest that anthropogenic factors, particularly related to human activities, have a more significant impact on land subsidence than natural topographic features. High GWR values were primarily concentrated in several districts, including Penjaringan, Pademangan, Cilincing, Tanjung Priok, and Kalideres.

Key-words: *Geographically Weighted Regression, Jakarta, Land Subsidence, InSAR Method, Landsat 8 Imagery*

1. INTRODUCTION

Land subsidence has emerged as a critical issue that spans multiple disciplines due to its widespread and multifaceted impacts across various regions of the world. It poses significant threats to infrastructure, including road networks, power grids, water supply systems, substations, farmland, sewage systems, railways, aquifer layers, and even human safety (Choubin et al., 2023; Sadeghi et al., 2023). Land subsidence refers to the gradual or rapid downward movement of the Earth's surface, which can occur over hours or extend across decades, and may affect areas ranging in size from a few square meters to several square kilometers (Botey i Bassols et al., 2023; Bremard, 2022; Declercq et al., 2021).

Land subsidence stems from combination of natural processes and human activities (Gao et al., 2019; Wang et al., 2023). Contributing factors include low annual rainfall, climatic and topographic conditions, soil characteristics, geological structures, underground mining activities, and large-scale infrastructure development (Bagheri-Gavkosh et al., 2021; Sadeghi et al., 2023). Moreover, rapid urbanization and population growth have led to increased groundwater extraction, which significantly contributes to land subsidence (Gao et al., 2019; Tirmizi & Khan, 2023; Younas et al., 2023).

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Excessive groundwater withdrawal, especially when combined with extensive infrastructure expansion, exacerbates the rate and severity of land subsidence (Z. Du et al., 2018; Gao et al., 2019; Tran et al., 2022).

Several studies have identified numerous countries around the world that are experiencing land subsidence, including Belgium, Mexico, the United States, Taiwan, Thailand, China, Japan, Egypt, Iran, Pakistan, and many others (Declercq et al., 2021; Kamh et al., 2016; Khan et al., 2023; Sadeghi et al., 2023; Tirmizi & Khan, 2023). In Belgium, subsidence rates of approximately 2.1 mm/year have been recorded across various districts along the Scheldt River (Declercq et al., 2021). In Mexico, several states such as Mexico, Jalisco, and Chihuahua have been affected (Figueroa-Miranda et al., 2018). Specifically, in the Toluca Valley and Mexico City, land subsidence is notably prevalent in industrial areas, with rates reaching up to 10 cm/year (Calderhead et al., 2011). In the United States, land subsidence has been reported from Louisiana to the Mexican border, affecting at least 56 counties. Between 1970 and 2010, the average subsidence rate in Montgomery, Harris, Karnes, and Fort Bend counties was approximately 1.4 mm/year (Younas et al., 2023). Houston is one of the most affected areas, with downtown subsidence rates reaching 7 cm/year between 1996 and 2003, and recent rates of 2 cm/year in the western areas (Khan et al., 2022; Tirmizi & Khan, 2023), Additionally, in Katy, Texas, subsidence has been recorded at a rate of 1.4 mm/year from 2017 to 2023 (Tirmizi &; Khan, 2023).

In Asia, numerous areas in China are experiencing land subsidence. The Hangzhou‑Jiaxing‑Huzhou Plain has recorded subsidence depths of up to 1.1 meters and 0.5 meters (Wang et al., 2023; Zhu et al., 2015). The Yellow River Delta has experienced a subsidence with 250 mm/year, while the Northern Region (Beijing Plain) has a subsidence rate 52 mm/year (Higgins et al., 2013; Pang et al., 2022; Zhu et al., 2015). In Thailand, Bangkok experiences subsidence of approximately 120 mm/year (Aobpaet et al., 2013; Bremard, 2022). Vietnam's Mekong Delta records an average subsidence rate of 6–7 mm/year in forest and swamp areas, while rates reach 18–20 mm/year in mixed agricultural and urban zones (Minderhoud et al., 2018). In Iran, several cities including Yazd, Qom, Kerman, Isfahan, and Mashhad experience subsidence rates of 15–20 cm/year (Sadeghi et al., 2023).

Indonesia has experienced setbacks including Jakarta, Semarang, Bekasi, Tangerang, Surabaya and Bandung (Asmadin et al., 2021; Bagheri-Gavkosh et al., 2021; Bott et al., 2021; Z. Du et al., 2018; Illigner et al., 2021; Minderhoud et al., 2019; H. Sari et al., 2023; Situmorang et al., 2021). A similar phenomenon has occurred in Jambi, where the city experiences a high subsidence rate, averaging 11.28 cm per year (Akbar & Setiawan, 2022). Other coastal cities in Indonesia, such as Padang, have also been affected, with land subsidence ranging from 0 to 40 mm across residential areas (Syafriani et al., 2022). Meanwhile, Semarang records one of the highest land subsidence rates, reaching 1.795 cm per year (Syafriani et al., 2022).

Jakarta is a major metropolitan area where several locations have experienced land subsidence at varying rates (Bott et al., 2021; Rahman et al., 2018; Yudhistira et al., 2020). It is among the fastest-subsiding cities globally, with subsidence rates reaching up to 28 cm per year (Abidin et al., 2011; Agustan et al., 2021; Bott et al., 2021; Z. Du et al., 2018; Minderhoud et al., 2019; H. Sari et al., 2023). Land subsidence that occurs in these areas is caused by many changes in land use from open field to built-up area as a result of increasing demand land availability for development, such as residential areas, toll roads, and infrastructure for industrial and economic activities (Bott et al., 2021; Dewi et al., 2020; Kurnianti et al., 2015; Rachma et al., 2022; Rahman et al., 2018; Rashid et al., 2022; D. P. Sari et al., 2021). The increasing density of the built-up area can also occur on the large growth of the population in Jakarta Metropolitan Area, the excessive use of land use has been a ground water exploitation that may cause some land subsidence in Jakarta.

Land subsidence has become a serious problem in the Jakarta Metropolitan Area in recent decade, especially in the Jakarta (Bott et al., 2021; Illigner et al., 2021; Rahman et al., 2018). The Damage to building infrastructure, increased risk of building collapse, flooding, and some areas have been below sea level (Bott et al., 2021; Cao et al., 2021; Hasibuan et al., 2023; Kamh et al., 2016; Koto & Negara, 2018). This event was caused by several factors, including excessive exploitation of groundwater, compaction of clay deposits underneath, and excessive load addition due to rapid urbanization in the Jakarta Metropolitan Area (Hasibuan et al., 2023; Rahman et al., 2018; Tambunan, 2017).

Rapid population growth and massive infrastructure development have led the area to higher groundwater demand resulting in overexploitation and land subsidence (Sajjad et al., 2023). The government has worked to address this problem, including by limiting groundwater exploitation, adopting soil reinforcement technologies, and building water retention infrastructure. However, these efforts have not yet provided a comprehensive solution to the problem. Therefore, there is a pressing need for more innovative and integrated approaches to effectively address land subsidence in the Jakarta Metropolitan Area. While various studies have explored the causes of land subsidence in Jakarta, most have not yet utilized spatial statistical approaches such as Geographically Weighted Regression (GWR) to examine how each contributing factor varies across different locations. In this context, this study seeks to fill that gap by using the GWR method to analyze the spatial relationships between land subsidence and several influencing variables, including built-up areas, population density, groundwater, elevation, and distance from the coastline.

2. STUDY AREA

This research focuses on Jakarta Province. Geographically, Jakarta is located between 6°12′ South Latitude and 106°48′ East Longitude. Jakarta City is located in a lowland area with an average elevation of approximately +7 meters above sea level. Geographically, it is bordered by the Java Sea to the north, West Java Province to the south and east, and Banten Province to the west (**Fig. 1**).

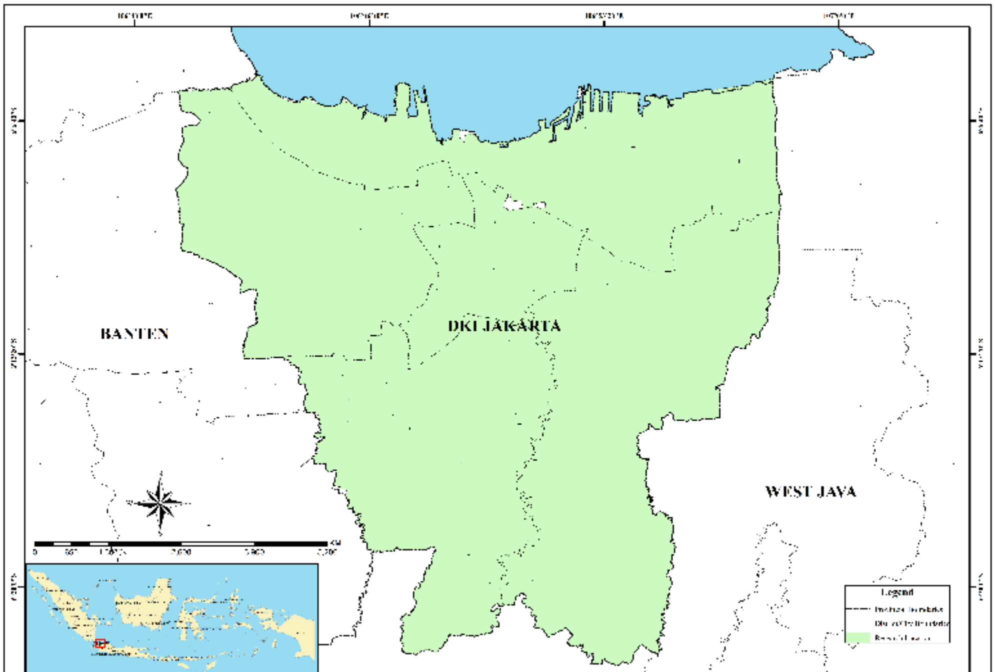

Fig. 1. Location of Jakarta.
(Source: InaGeospatial)

The administrative and geographical layout of Jakarta, including its boundaries with neighboring provinces and coastal positioning along the northern part of Java Island (**Fig.1**). Based on information from the official portal of the Jakarta Provincial Government, the Special Capital Region of Jakarta (DKI Jakarta) is administratively divided into five municipalities: Central Jakarta, North Jakarta, West Jakarta, East Jakarta, and South Jakarta. In addition to these, there is one administrative regency, namely the Thousand Islands (Kepulauan Seribu). The total area of the province covers approximately 662.33 square kilometers.

3. DATA AND METHODS

3.1. Land Subsidence Data

The data used is InSAR data obtained using the Small Baseline Area Subset (SBAS) method in generating land subsidence data. This InSAR SBAS method was proposed by Berardino in 2002 in producing spatial-temporal movements of several interferometric pairs with short spatial and temporal baselines (Berardino et al., 2002; Chang et al., 2022). InSAR (Interferometric Synthetic Aperture Radar) is a remote sensing method that works by combining pixel values from two radar datasets. This study uses Sentinel-1 imagery with the InSAR method. The Sentinel-1 data used in this study were obtained from the Copernicus Open Access Hub. Sentinel-1 is a satellite pair consisting of Sentinel-1A and Sentinel-1B, launched by ESA with the main goal of monitoring land and ocean surfaces. Sentinel-1 uses a C-SAR sensor, which offers medium to high-resolution imaging in all weather conditions (Sunu et al., 2019). This method is used to monitor land surface movements that occur by maintaining interferometric coherence in eliminating the effects of temporal decorrelation and atmospheric disturbances (Chang et al., 2022). The data used is LOS (Line of Sight) data from two recording directions which we can call ascending and descending data. The ascending data ranges from August 26, 2016 to August 31, 2022, while the descending data spans from February 17, 2015 to December 13, 2022. The data were then decomposed to generate vertical displacement data using the following formula (Fuhrmann & Garthwaite, 2019) (Eq. (1)). Data usage begins in 2015, as this year marks the overlapping period between the ascending and descending tracks.

$$\begin{pmatrix} V^{asc} \\ V^{desc} \end{pmatrix} = \begin{pmatrix} cos\theta^{asc} & -\ cos\alpha^{asc}\ sin\theta^{asc} \\ cos\theta^{desc} & -\ cos\alpha^{desc}\ sin\theta^{desc} \end{pmatrix} \begin{pmatrix} V^{UD} \\ V^{EW} \end{pmatrix} \quad (1)$$

where:

V^{asc}	-LOS displacement from ascending satellite pass (in mm/year)
V^{desc}	-LOS displacement from descending satellite pass (in mm/year)
V^{UD}	-Vertical displacement component (Up-Down), representing land subsidence (in mm/year)
V^{EW}	-Horizontal displacement component in the East-West direction (in mm/year)
$\theta^{asc}, \theta^{desc}$	-Incidence angles of the radar signal for ascending and descending paths (in degrees)
$\alpha^{asc}, \alpha^{desc}$	-Azimuth angles (or satellite heading angles) for ascending and descending tracks (in degrees)
cos, sin	-Trigonometric functions used to project LOS displacements onto vertical and horizontal planes

With the formula, it is able to provide a vertical value by using a data slice between ascending and descending data which will be used as a land subsidence variable. The decomposition data contains the recording results from August 26, 2016 to December 13, 2022 in the Jakarta area.

3.2. Built-Up Area Data

Landsat imagery, including data from Landsat 8, provides multispectral remote sensing information with a medium spatial resolution of 30 × 30 meters. This spatial resolution is sufficient for detecting changes in land cover, including the identification of Built-Up Areas. In this study, Landsat 8 OLI imagery is used to obtain Built-Up Area data in Jakarta for the period 2015–2022. Landsat 8 OLI was selected due to its higher accuracy in mapping Built-Up Areas (Bhatti & Tripathi, 2014). The method used to process Landsat 8 OLI imagery is supervised classification, which transforms multispectral image data into specific land cover classes based on spatial characteristics and training samples (Prahasta, 2008a). This method is widely used and considered suitable for land cover mapping, including the delineation of Built-Up Areas in urban environments like Jakarta (Septiani et al., 2019). To extract Built-Up Area data from Landsat 8 OLI imagery, several spectral bands were utilized, including Band 4 (Red), Band 5 (Near Infrared/NIR), and Band 6 (Shortwave Infrared 1/SWIR1). These bands were chosen because built-up surfaces generally reflect more strongly in the SWIR band and less in the Red and NIR bands, allowing for clearer differentiation from vegetation and bare soil. The combination of these bands, processed through supervised classification, enhances the accuracy of identifying land cover types, especially built-up areas (Bhatti & Tripathi, 2014; Prahasta, 2008).

Furthermore, supervised classification allows for temporal analysis of Landsat imagery, enabling the detection of spatial trends and the growth of urban areas over time (Mailendra & Buchori, 2019). In addition, this method also has the advantage of having better accuracy than the unsupervised method. Below is the overall accuracy formula used to measure accuracy in the built-up area (Eq.(2)).

$$Overall\ Accuracy = \frac{\Sigma Xii}{N}\ x\ 100\% \tag{2}$$

where:

ΣXii	-Total number of correctly classified pixels (sum of diagonal values in the confusion matrix)
N	-Total number of sample pixels tested
$x\ 100\%$	-Converts the result to a percentage

3.3. Population Density Data

Population density data at the sub-district level in Jakarta was obtained from secondary sources, specifically from Statistics Indonesia (Badan Pusat Statistik, BPS) in 2022. BPS serves as the central government agency responsible for conducting statistical surveys, compiling data, and providing official statistics to support national development planning and policy-making in Indonesia. The data processing began by collecting population figures for each sub-district in Jakarta. These figures were then imported into ArcGIS software and joined with the administrative boundary data of Jakarta's sub-districts. To visualize population distribution, a choropleth technique was applied using a color gradient, where darker shades represent areas with higher population density. This method enables a clear spatial interpretation of population concentration patterns across Jakarta.

3.4. Groundwater Data

The groundwater map utilizes secondary data from the Water Resources Agency of Jakarta Province. The agency's official website provides various publicly accessible datasets, including groundwater data, which in this study specifically refers to the number of wells in Jakarta in 2022. The process of creating the groundwater map begins with collecting and processing the 2022 well data by sub-district. This data is then input into ArcGIS software and combined with the administrative boundary data of Jakarta's sub-districts to display the number of wells per sub-district, symbolized using a color gradient based on the level of usage intensity.

3.5. Elevation Data

The elevation data used in this study is based on secondary data derived from the Digital Elevation Model (DEM) SRTM, sourced from the Geospatial Information Agency. The DEM from the Shuttle Radar Topography Mission (SRTM) has a spatial resolution of 30 × 30 meters, meaning each pixel represents a 30-meter square on the ground. This resolution is considered adequate for regional-scale topographic analysis, such as identifying elevation and slope patterns in urban areas like Jakarta. To analyze elevation, the data was processed using the Slope Tool in ArcGIS, which calculates the steepness or degree of slope from each cell in the elevation raster. The resulting slope values were then classified based on the minimum and maximum elevation found in Jakarta, allowing for the interpretation of terrain variation across the study area. The 30-meter SRTM data is commonly used in geospatial studies due to its balance between detail and manageable data volume (Prahasta, 2008)

3.6. Distance from the Coast for Land Subsidence Data

The land to coast distance map utilizes secondary spatial data from the Jakarta Satu website, including administrative boundaries for each sub-district in Jakarta and toponymic data for these sub-districts. The method for creating this coastal distance map employs an overlay technique, where the administrative boundary data is overlaid with the sub-district toponymic data. Then, a line is drawn from the centroid point of each sub-district to the coastline to obtain the distance from the land to the coast.

3.7. Data processing method with GWR (Geographically Weighted Regression)

Geographically weighted regression (GWR) is a modelling technique designed to deal with spatial non-stationarity, e.g., the mean values vary by locations. It has been widely used as a visualization tool to explore the patterns of spatial data (Leong & Yue, 2017). The GWR model has advantages over standard regression models, namely that it can offer a local model at each location and can display variables that influence the response variable in relation to spatial characteristics (Dur et al., 2023). The general formulation of the GWR model which reflects the localized nature of this method (Eq.(3)).

$$\hat{y}^0 = \beta_0 (u_0, v_0) + \sum_{k=1}^{p} \beta_k (u_0, v_0) \chi_{0k} \tag{3}$$

where:

$\hat{y}^0$	-Predicted value of the dependent variable at location
$\beta_0 (u_0, v_0)$	-Intercept term estimated at location
$\beta_k (u_0, v_0)$	-Coefficient of the k independent variable at location
χ_{0k}	-Value of the k independent variable at location
p	-Number of independent variables
(u_0, v_0)	-Spatial coordinates of the observation point

This study uses the Geographically Weighted Regression method, which analyzes spatial data by extending global regression to local models that create parameter estimates at each Geographic location (Bivand & Yu, 2015). This technique uses weighting functions, such as Gaussian Kernel and bi-square, to include spatial effects. In this research, the bi-square weighting function is applied, as it offers localized weighting that is effective in capturing spatial heterogeneity. This method is suitable for application in various fields, including land subsidence assessment (Blachowski & Gutkowski, 2016). This study will analyze the influence of Built-Up Area factors, Population Density, Groundwater, Elevation, and Distance from the Coast to Land Subsidence in several districts in Jakarta.

4. RESULTS AND DISCUSSIONS

4.1. Land Subsidance Rate

The map illustrates the land subsidence rate in Jakarta from 2016 to 2022, measured in millimeters per year (mm/year). This map was produced using InSAR (Interferometric Synthetic Aperture Radar) technology, utilizing data from the Sentinel-1 satellite. The colors on the map represent different levels of land subsidence, where blue indicates lower subsidence rates, while yellow, orange, and red indicate higher rates (**Fig. 2**).

Fig. 2 illustrates the spatial distribution of land subsidence rates in Jakarta between 2016 and 2022, measured in millimeters per year (mm/year). The map was generated using InSAR (Interferometric Synthetic Aperture Radar) data from the Sentinel-1 satellite. The color gradient represents varying levels of land subsidence: areas in dark blue indicate low subsidence rates (between 0 and 5 mm/year), while areas shaded in lighter blue, cyan, yellow, orange, and red represent increasingly higher rates of subsidence.

Red areas experience the most severe subsidence, exceeding 50 mm/year. Based on the Land Subsidence Rate (2016–2022) map, the highest land subsidence rates (marked in red) are primarily concentrated in the northern part of Jakarta, particularly in Penjaringan and the surrounding coastal area. Moderate to high subsidence rates (30–50 mm/year, marked in orange) are also observed in parts of Kalideres, Kembangan, and Cengkareng in West Jakarta. Subsidence in the range of 19–30 mm/year (marked in yellow) occurs in the same general vicinity, gradually decreasing in intensity toward the central and southern regions. The majority of South Jakarta and parts of East Jakarta experience lower subsidence rates between 0 and 11 mm/year (shaded in dark to light blue), with some areas even showing slight uplift (white areas).

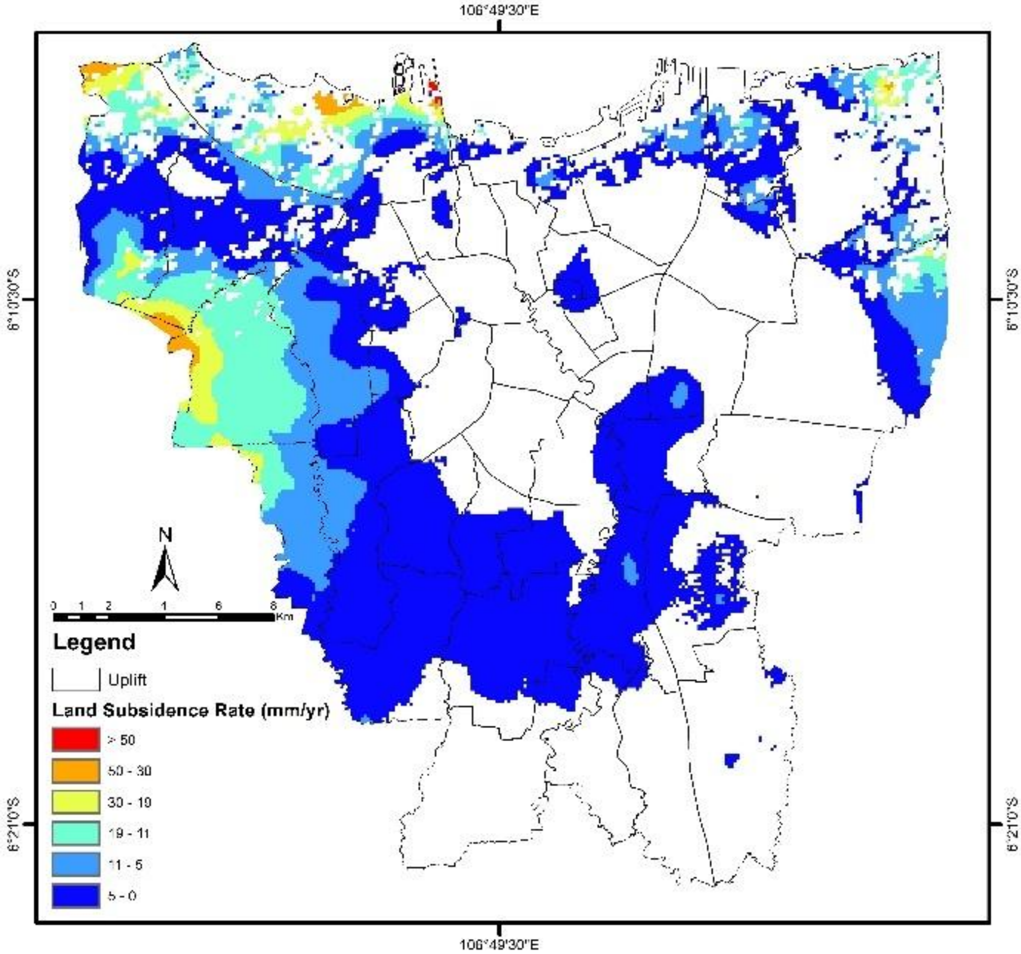

Fig. 2. Land Subsidance Rate (2016-2022).

4.2. Classification of Land Subsidence Parameters

The spatial distribution of five key variables, built-up area, population density, groundwater, elevation, and distance from the coastline shows considerable variation across different sub-districts in Jakarta (**Fig. 3**). Each of these factors varies from one region to another. By looking at these maps, we can get a better understanding of how these five factors are spread across Jakarta. These factors will be analyzed to see how they contribute to land subsidence in the Jakarta Metropolitan Area. The goal of this study is to understand the relationship between urban development (built-up land) and land subsidence, which can help in making better decisions for future urban planning.

Based on the land subsidence parameters map in the **Fig. 3**, the first parameter (**Fig. 3a**) illustrates built-up area in Jakarta. The land subsidence parameter map was used to generate the land subsidence rate map for Jakarta Province from 2016 to 2022. The green color represents settlement areas with the least coverage. The red-colored areas represent built-up land across Jakarta Province, covering most of the city. The second parameter (**Fig. 3b**) shows population density in Jakarta, using a color gradient to indicate the range of population per square kilometer. The lightest color (pink) represents a population density ranging from 8,490,000 to 12,970,000 people per km², indicating areas with low population density. In contrast, the dark red color represents a population density between 39,040,001 and 49,970,000 people per km², indicating areas with very high population density. The third parameter, shown in **Fig. 3c**, represents groundwater in Jakarta using a color gradient to indicate different consumption levels. The lightest color (light blue) represents the lowest groundwater consumption, ranging from 0 to 5,043 liters. In contrast, the dark blue color represents higher groundwater consumption, ranging from 412,790 to 1,456,582 liters. The fourth parameter, shown in **Fig. 3d**, presents a map of the distance from the coast. The blue lines indicate the distance to the coastline, illustrating the spatial distribution of areas based on their proximity to the shore. These lines provide a visual representation of how close different regions are to the coast, while building symbols mark the locations of each district in Jakarta Province. The fifth parameter, shown in **Fig. 3e**, is a map representing elevation in Jakarta Province using color variations to indicate different heights above sea level. Dark green to light green represents the highest elevations, ranging from 92 to 60 meters, primarily located in the southern and eastern parts of Jakarta. The yellow areas indicate an elevation of 50 meters, also found in the south and east. Meanwhile, orange to red shades represent lower elevations, ranging from 40 to 1 meter, which are concentrated in northern Jakarta.

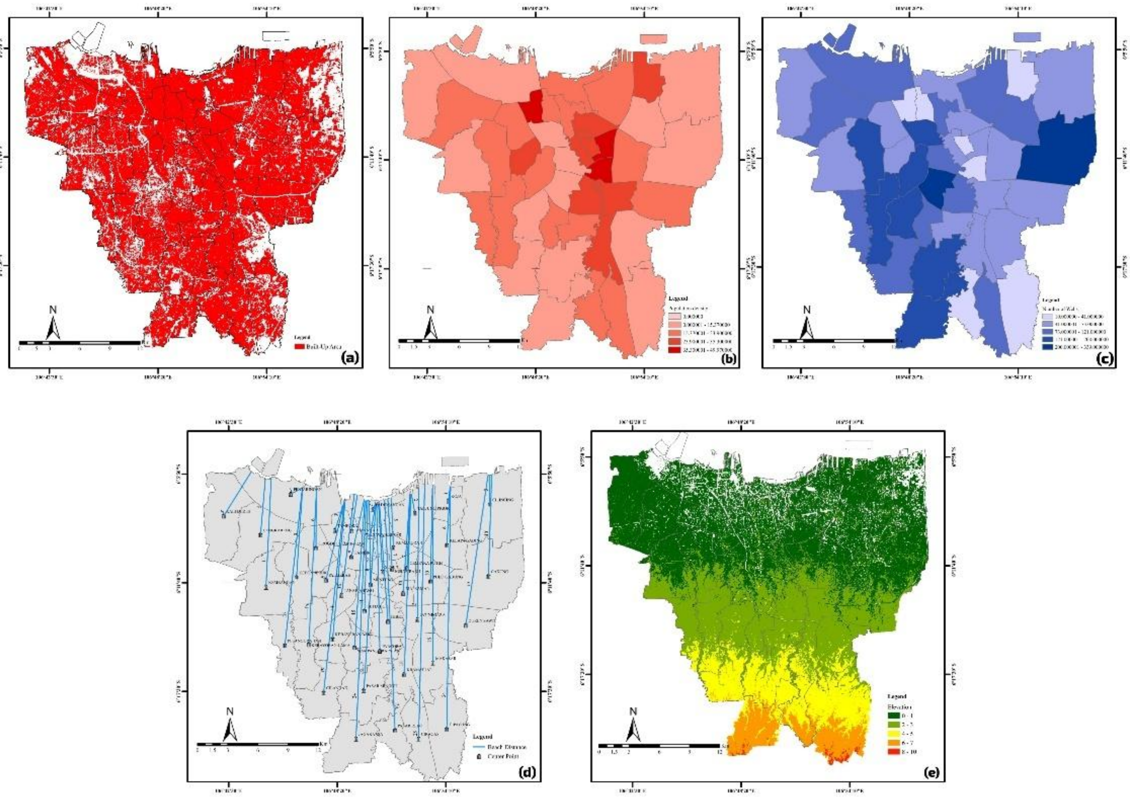

Fig. 3. Land Subsidence Parameters for (a) built-up area, (b) population density, (c) groundwater, (d) distance from the coast, (e) elevation.

4.3. GWR Model of the Distance from the Coast for Land Subsidence

The land to coast variable is a factor that cannot be separated, as Jakarta Province is defined by the coastal city of Jakarta, which has a large population in Indonesia. Development in Jakarta is continuously driven by massive infrastructure projects, which contribute to changes in the distance toward the coastline due to sediment compaction. This process contributes to land subsidence and increases the effects of tidal flooding in Jakarta (Erban et al., 2014). Even though land subsidence in Jakarta will continue, it can affect areas that are more vulnerable to sea level rise (Du et al., 2020; Abidin et al., 2011) Therefore, it is not impossible that in the coming decades, coastal areas with higher population densities will be more affected by tidal flooding in the long term, which will impact settlements and infrastructure in those areas.

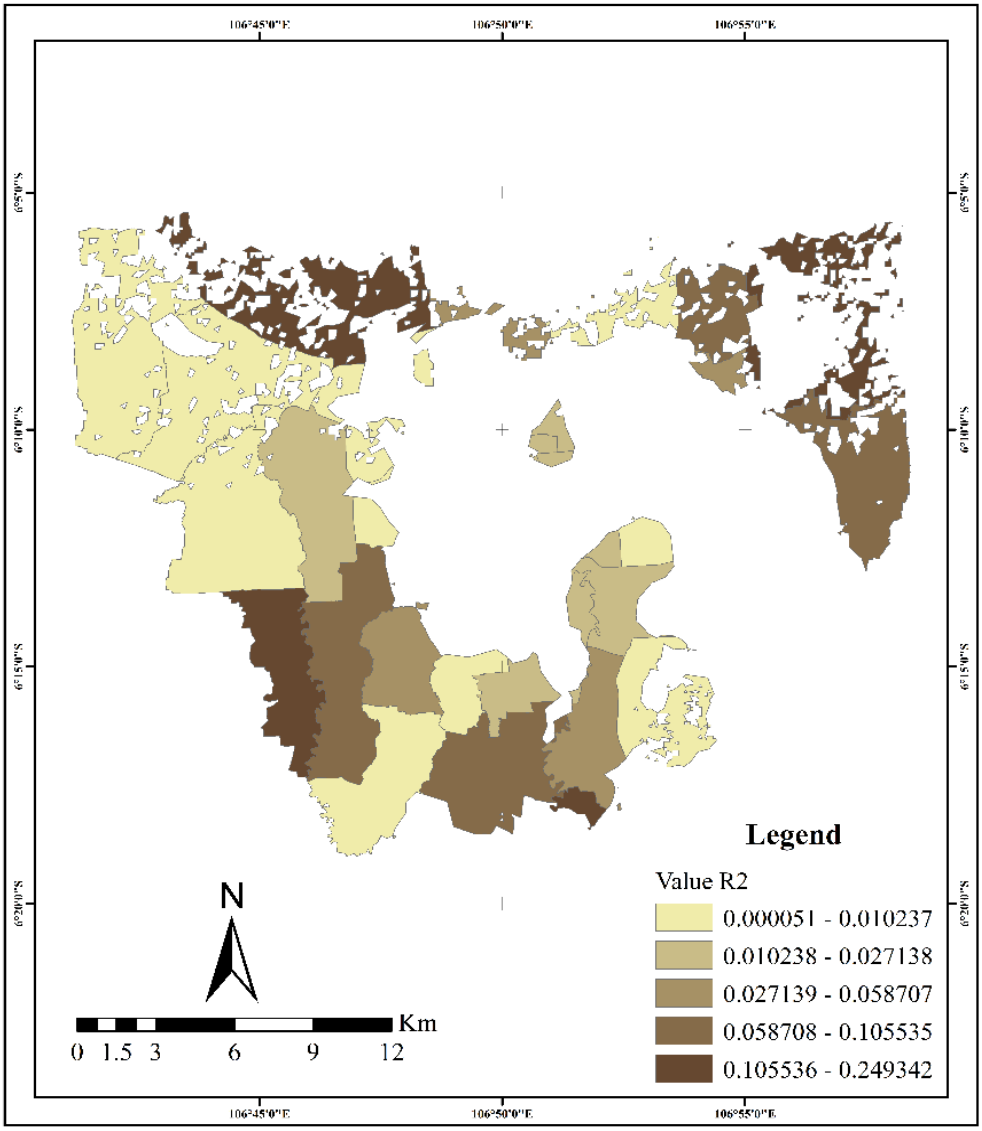

Fig. 4. $R^2$of the Distance from the Coast Variable.

To measure the distance from the coastline, this study utilized the centroid point of each administrative boundary polygon of sub-districts in Jakarta, ensuring a more spatially representative calculation. The map in **Fig. 4** presents the GWR results for the coastline distance variable. The local R^2 values for this variable range from as low as 0.00 to as high as 0.24, with notable concentrations in North and South Jakarta. The highest spatial correlation was observed in the districts of Penjaringan and Pesanggrahan. From the map, we can see differences in color across the areas of Jakarta. The color variations represent the different R^2 values from the GWR, indicating that there is a correlation between one location and another, with different R^2 values for each district. A few areas in Jakarta province have already experienced tidal flooding during high tide, which typically occurs in areas with biggest land subsidence (Abidin et al., 2015). Because of this, sea level rise will worsen land subsidence, with the potential continuation of rising sea levels along Jakarta's coastal areas, which are increasing at a rate of about 4–5 mm per year (Nurmaulia et al., 2010).

Jakarta's coastline generally has low wave energy, but sedimentation still occurs, especially in delta areas. Evidence of land growth over thousands of years can be seen in shoreline changes. The Cisadane and Citarum rivers have shifted their flow over time, but both have played a key role in shaping the land around Jakarta, especially in building coastal landforms. Marunda is one of the most affected areas, with the coastline retreating up to 750 meters over the past 40 years. Without adequate protection, around 225 hectares of land have been submerged by seawater, forcing thousands of residents to relocate. Tanjung Pasir, located in the northwest of Jakarta Bay, has also experienced severe coastal erosion. Once part of the old Cisadane River delta, this area is exposed to southwest monsoon winds, worsening erosion between 1948 and 1982, causing the coastline to recede by 250 meters and resulting in the loss of approximately 150 hectares of land. (Verstappen, 2000).

Based on the research of Zoysa et al., (2021) the rate of land subsidence along the Jakarta coastline varies significantly. When averaged over a 10-year period, the Penjaringan area shows a subsidence rate of up to 85 mm/year. This is similar to the changes in the distance from the coast observed in Muara Gembong, Bekasi, and Legon Kulon, Subang, where the distance from the coast has increased at rates of 200 and 150 meters per year, over the past two decades (2000-2020). This phenomenon is attributed to coastal inundation, coupled with hydrological changes and the expansion of built-up areas. (Solihuddin et al., 2021).

4.4. GWR Model of the Elevation

The elevation topography of a region is a key parameter that influences many processes in coastal changes (Gesch, 2009). As a result of low elevation areas or subsidence occurring in several regions in Jakarta, the city and low-lying coastal areas are now vulnerable to flooding triggered by seawater and sea level rise, with projections indicating increasing vulnerability by 2100 (Lakshmi, 2024). High-risk areas are characterized by low coastal relief, easily erodible substrates, evidence of past and present subsidence, widespread shoreline retreat, and high wave energy (Gornitz & Kanciruk, 1989).

The GWR analysis results of the elevation variable in relation to land subsidence in Jakarta are illustrated in **Fig. 5.** The R^2 values range from 0.00 to 0.25, indicating varying degrees of spatial correlation across sub-districts, The strongest spatial relationships with R^2 values approaching 0.25 are concentrated in North Jakarta and West Jakarta, particularly in Koja, Cilincing, Kalideres, Kembangan, and Pesanggrahan, with Koja and Cilincing standing out as the sub-districts with the highest values. In contrast, the lowest R^2 values close to 0.00 are generally found in the central and southern parts of Jakarta, suggesting a minimal influence of elevation on land subsidence in those areas. Jakarta's geomorphology plays a crucial role in these patterns. The city is traversed by 13 rivers that discharge into Jakarta Bay, with the Cisadane River in the west and the Citarum River in the east being the most significant in shaping sediment distribution. Historical shifts in the Citarum River's course and the accumulation of sediment in estuarine areas such as Gembong have significantly influenced the elevation profile along the coast (Verstappen, 2000). This shows high geomorphological activity in the area, where changing river patterns and river mouth shifts can affect the shape and elevation of the coastal areas (Holzer & Galloway, 2005).

In eastern Jakarta, the land is wider (60 km) due to the influence of the Citarum Delta. In contrast, Jakarta itself has a narrower coastal plain (only 7 km) because there are fewer large rivers carrying sediment to the shore. Meanwhile, the western part is lower, swampy, and has been affected by urban waste and housing projects over the past few decades. Areas with low elevation, especially near or below sea level, are more prone to flooding and tidal inundation. Coastal areas with low elevation are at high risk of sea-level rise. Low-lying coastal areas are at high risk of sea level rise due to the combination of low elevation. As a result, these materials will compact over time, especially with human activities and development occurring in the coastal areas. The dominant processes that determine the fate of the coastline are inundation (elevation loss due to sea level rise) and accretion/sedimentation (Chu, et.al. 2011). The sea level rise causes flooding in coastal areas, as seen in the coastal region of Semarang, which has already experienced coastal hazards due to tidal flooding and land subsidence (Marfai & King, 2008).

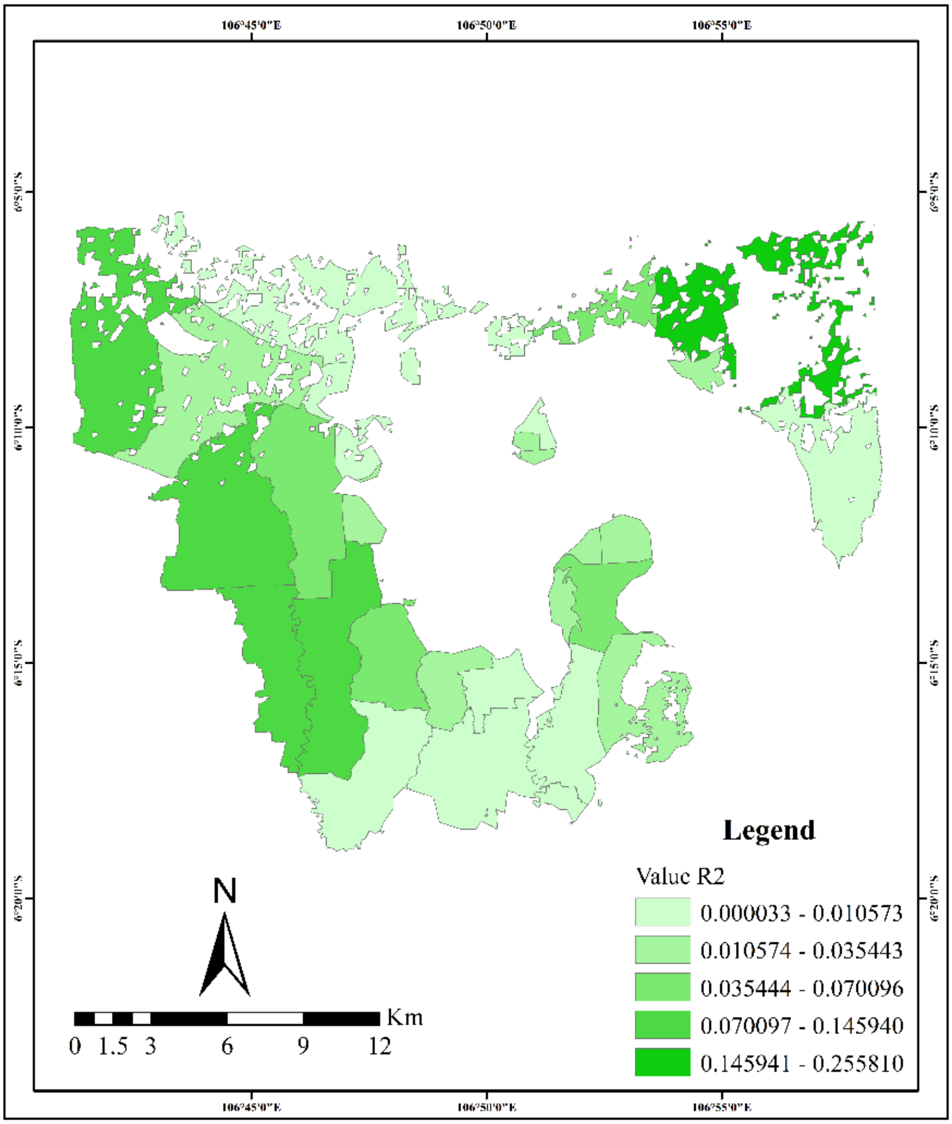

Fig. 5. $R^2$of Elevation Variable.

Coastal areas that have already experienced subsidence will continue to sink and worsen. As a result, seawater infiltrating the aquifer causes groundwater contamination (Gornitz, 1991). Based on the research of Nicholls et al., (2021) it is stated that the global average for relative sea level rise is 2.6 mm per year over the past two decades. However, because coastal populations tend to live in areas that are experiencing subsidence, they experience relative sea level rise at a rate up to four times faster, ranging from 7.8 to 9.9 mm per year.

Coastal wetlands are at risk from accelerated sea level rise because their ability to build up vertically is limited. This can lead to flooding, which causes sand to settle in tidal deltas and erosion of the coastline (Kanciruk, 1989). In the United States, approximately 26,000 km^2 of land has permanently subsided. Land subsidence causes permanent inundation, worsens flooding, changes topographic gradients, damages the land surface, and reduces the capacity of aquifers to store water (Galloway et al., 2008).

4.5. GWR Model of the Groundwater

Groundwater extraction, indicated by the number of wells in use, has increased due to the declining availability of surface water. This has led to a drop in groundwater levels and has accelerated the rate of land subsidence (Zhou et al., 2020; Faunt et al., 2016). Wells are widely used not only to meet household water needs but also to support industrial and factory operations in Jakarta. Approximately 64% of Jakarta's water consumption is still fulfilled through groundwater extraction from wells (Ali, 2011). The expansion of industrial activities and residential areas has contributed to a rise in groundwater use, resulting in land subsidence in many regions (Guzy & Malinowska, 2020; Chiao et al., 2014). This study finds a similar pattern in organic settlements, where many households rely on groundwater wells for more than 80% of their daily water use. Households frequently affected by flooding also tend to have higher water demand during the rainy season, particularly for cleaning purposes after flood events (Setiawan et al., 2017). The GWR map for the variable representing the number of wells used in Jakarta shows varying levels of spatial correlation with land subsidence across different regions, as illustrated in **Fig. 6**. The R^2 values for this variable range from 0.00 to 0.82, indicating that groundwater has a significant spatial influence in certain areas.

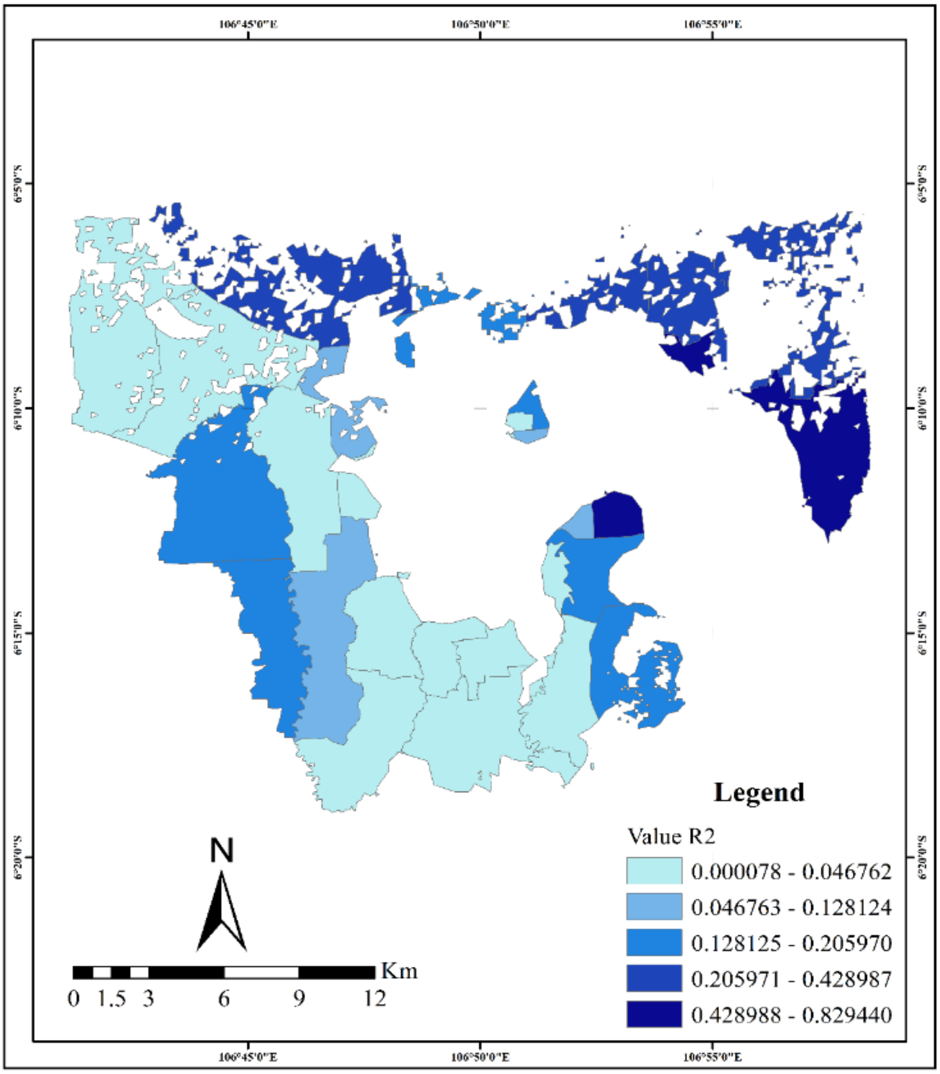

Fig. 6. $R^2$of Groundwater Variables.

The highest GWR values are observed in North Jakarta, particularly in the sub-districts of Penjaringan, Pademangan, and Cilincing, lower GWR values close to 0.00 are generally found in South Jakarta, East Jakarta, and parts of West Jakarta, suggesting weaker spatial relationships in these areas. Jakarta has experienced rapid development in land use change, from areas covered with vegetation to built-up areas. The increasing development of residential, industrial, and office areas, along with supporting infrastructure, has driven large-scale land conversion. Rising population density has contributed to the growing number of wells in use, and this trend continued in the following years (Setiawan et al., 2017). In this study, the groundwater variable is represented by the number of registered wells in Jakarta in 2022. The underlying assumption is that a higher number of wells reflects greater demand for groundwater due to densely populated residential areas. As built-up areas expand, the land's capacity for natural groundwater recharge declines, further accelerating the rate of land subsidence in affected regions.

Land subsidence shows a positive correlation with groundwater, particularly in urban city (Sajjad et al., 2023). This can lead to a decrease in the capacity of deep groundwater supply and groundwater storage resources (Liu et al., 2022; Ghazifard et al., 2016). Groundwater in North Jakarta, in addition to residential needs, has also significantly increased due to the tourism sector. This is similar from the reasearch by Teatini et al. (2006) in their study in Italy, which revealed that the southern region of the Po River Delta experienced dramatic land subsidence. This subsidence was largely caused by large-scale groundwater exploitation linked to economic development and the local tourism sector since the early 1950s could lead to sustained land subsidence. The land subsidence observed today is likely the result of past groundwater exploitation, further exacerbated by delayed compaction processes in clay aquitard layers between the depleted aquifers (Hutabarat, 2017; Abidin et al., 2004). In addition to sea water inundation many are unaware that low-lying coastal areas are also susceptible to groundwater inundation, which causes coastal flooding due to the rise in groundwater levels with sea level rise.

Apart from sea water inundation, many are unaware that low-lying coastal areas are also vulnerable to groundwater inundation, which occurs due to the rise in groundwater levels along with the increase in sea level. This also contributes to land subsidence, making the area increasingly saturated and leading to waterlogging. A sea level rise of 0.6 meters could cause significant flooding, and a 1-meter rise could inundate 10% of the densely populated coastal zone, with a width of 1 km. A study by Marfai & King (2008) in Hawaii found that the submerged area, including groundwater inundation, is more than twice the area submerged by seawater alone. Based on research in Shanghai city, groundwater exploitation and rapid urbanization are the main causes of most land subsidence. Although urbanization accelerates economic growth, human activities such as large-scale construction of skyscrapers, metro lines, and highways also contribute to this issue (Dong et al., 2014).

4.6. GWR Model of the Population Density

Land subsidence does not happen accidentally without reason. It results from a combination of natural and human activities (Gao et al., 2019; Wang et al., 2023). Jakarta Province, with its high population density, leads to increased human activities that impact water consumption (Setiawan et al., 2017). Meanwhile, limited groundwater resources are being over-exploited to meet these needs. This excessive exploitation leads to land subsidence, which affects soil stability and infrastructure, posing a risk of damage to buildings and drainage systems in the city. This happens in Jakarta's coastal areas, where the high population density increases the building load each year (Delinom et al., 2009) contributing to land subsidence (Hutabarat, 2017). The GWR analysis of the population density variable uncovers spatial variations in its influence on land subsidence across Jakarta, as represented in **Fig. 7.** The R^2 values for this variable range from 0.00 to 0.63, with higher values observed predominantly in North Jakarta, and in the northern areas of East and West Jakarta. Coastal areas with high population density, including population growth, unprecedented urbanization, and climate change, require significant amounts of groundwater, leading to excessive exploitation and resulting in land subsidence (Jia et al., 2019; Abidin et al., 2004). Excessive groundwater extraction, combined with large-scale infrastructure development, will have a major impact on land subsidence (Z. Du et al., 2018; Gao et al., 2019; Tran et al., 2022).

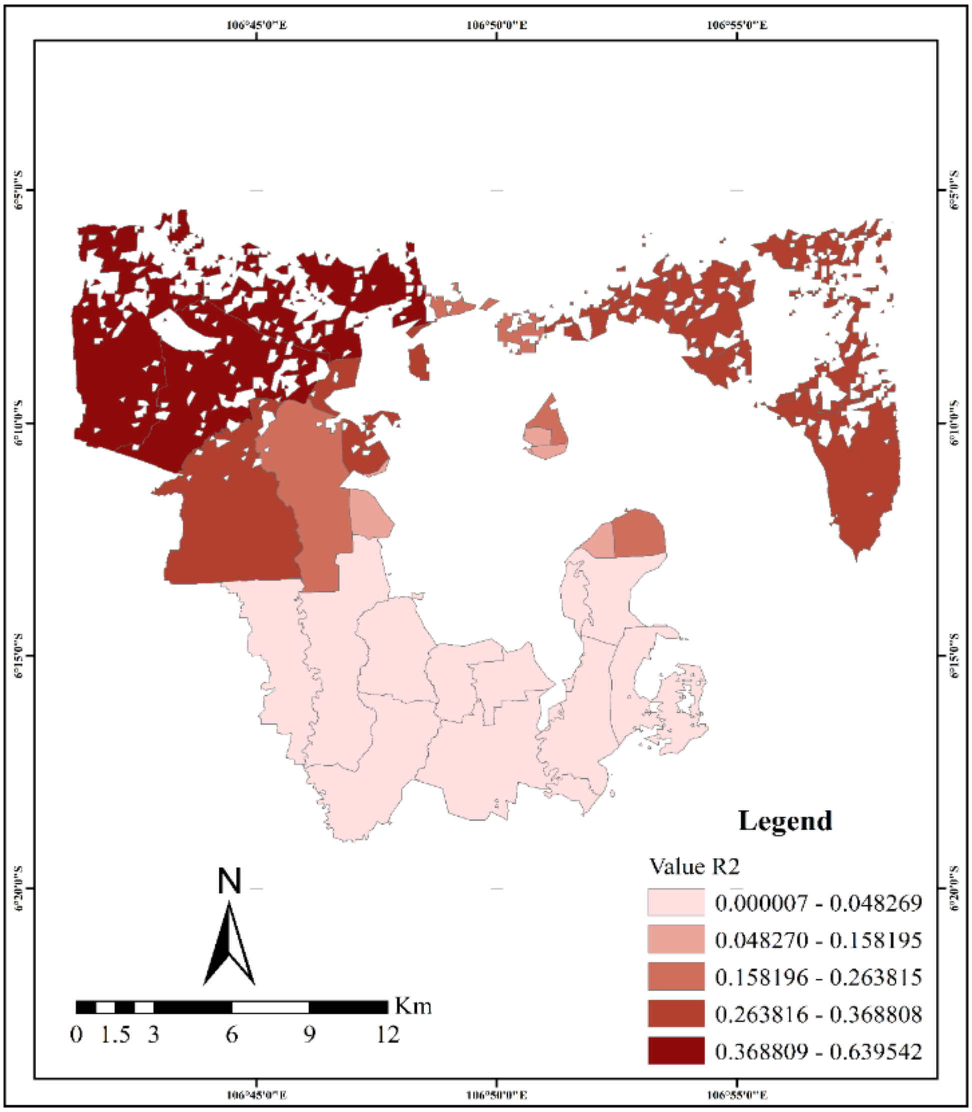

Fig. 7. R^2 of Population Density Variables.

Population growth in Jakarta has driven an increase in population density, accompanied by a rise in economic activities. This density has contributed to the expansion of various sectors, including entertainment, education, and the economy, even extending to reclaimed coastal areas designed to accommodate more infrastructure and residential developments. Even though Jakarta's economy is growing, there are also negative effects. One big problem is land subsidence, which means the ground is sinking. This can damage buildings and make floods worse, especially in coastal areas. The demand for water keeps increasing, but most of the water supply still comes from groundwater. Taking too much groundwater makes the land sink even more, especially in North Jakarta (Y. Du et al., 2020). Tanjung Priok and its surrounding areas have undergone significant changes due to erosion, seawater intrusion, and human activities. To the west of the port, the area mainly consists of wetlands, while to the east in Marunda, seawater intrusion has worsened due to river mouth changes and land subsidence (Verstappen, 2000). The same thing happened in Riyadh, Saudi Arabia. Because the city's population grew quickly, the land started sinking a lot up to 21 mm per year (Aljammaz et al., 2021).

4.7. GWR Model of the Built-Up Area

Land subsidence is closely linked to the expansion of built-up areas, which continues to grow due to population growth, economic activities, and industrialization. This issue is particularly evident in residential, industrial, and agricultural land use. Land subsidence happens mostly because of big changes in how land is used. At first, open land is used for farming or green spaces. But as more land is needed, these areas are turned into houses, roads, and factories. This change makes the ground heavier and more compact, causing it to sink over time. This happens because buildings and roads put extra weight and pressure on the ground (Faunt et al., 2016). As cities grow quickly, the land sinks even faster (Abidin et al., 2011). Areas with lots of houses and factories tend to sink more than other places (Zhou et al., 2020). To support spatial analysis related to land subsidence, built-up area data was extracted using Landsat 8 OLI imagery and processed with a supervised classification method. This approach produced a high overall accuracy of 95.45%, indicating that the classification results are highly reliable and closely match actual land cover conditions.

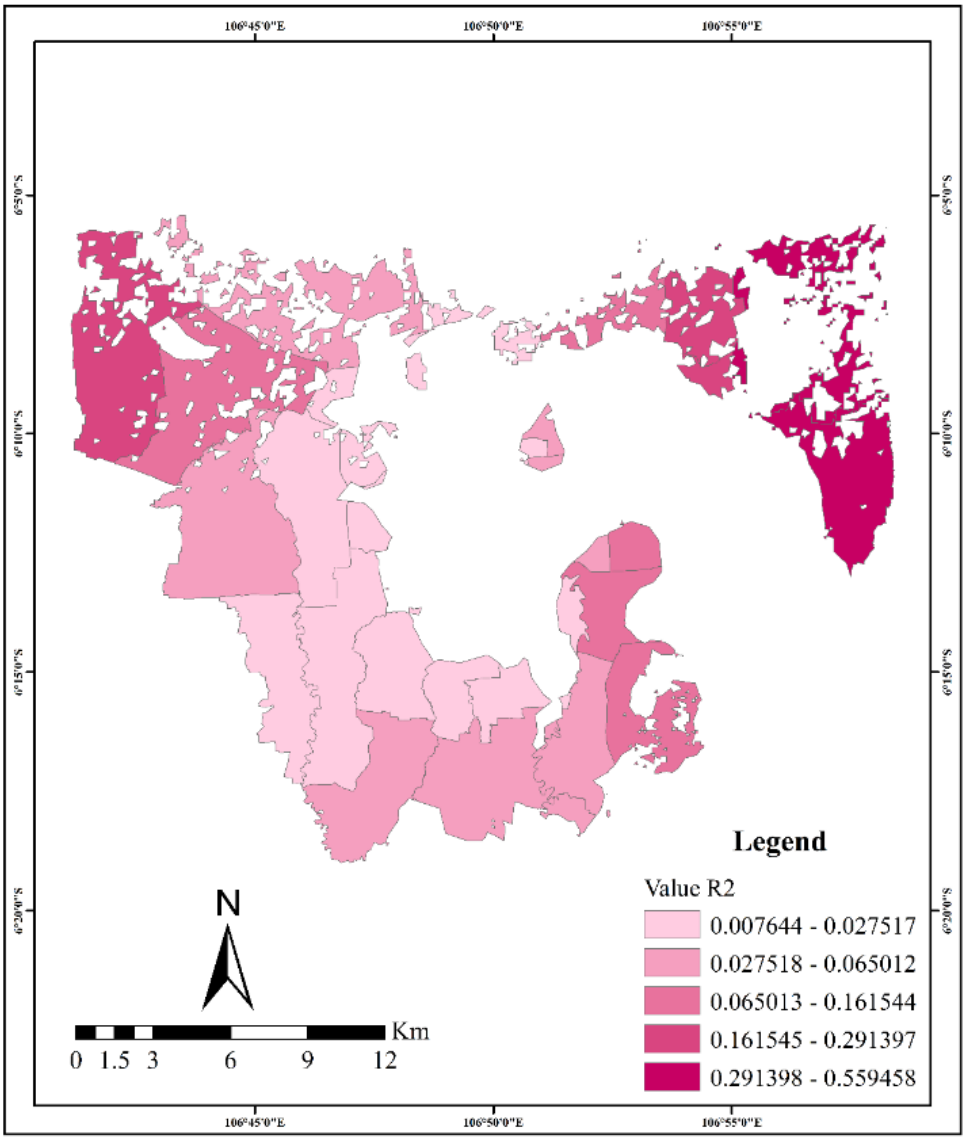

Fig. 8. R^2 of Built Up Area Variables

The GWR analysis results for the built-up land variable show R^2 values ranging from 0.00 to 0.55, with relatively even distribution across various areas, particularly in North Jakarta, East Jakarta, and West Jakarta (**Fig. 8**). The highest GWR values are observed in Cilincing, Cakung, and Kalideres Districts, indicating a strong spatial relationship between built-up land and land subsidence in these regions. Urban development in these districts appears to play a significant role, likely due to increased surface pressure and reduced natural groundwater recharge. If this trend continues, many densely populated coastal zones could sink below sea level in the coming decades, increasing the risk of coastal flooding, endangering infrastructure, and posing serious challenges for sustainable development in Jakarta's coastal areas (Chaussard et al., 2013).

There is a strong relationship between built-up land use and land subsidence (Minderhoud et al., 2018). Land subsidence can significantly impact soil stability and its ability to support buildings. If subsidence continues, the risk of structural damage to infrastructure, buildings, and public facilities will increase, especially in densely populated areas with extensive urban development (Delinom et al., 2009). In North Jakarta, land subsidence can be observed through various physical indicators, such as cracks in permanent buildings and roads, changes in river and drainage flow patterns, and the expansion of flood-prone areas. These signs indicate significant subsidence in the region, affecting both coastal and inland areas (Abidin et al., 2015).

Similar to what has happened in Pakistan, land subsidence is classified based on land cover types, showing a strong correlation between variables. Urban areas and plantation vegetation, which require large amounts of groundwater extraction, also experience significant land subsidence (Ahmad et al., 2019). A similar situation is occurring in Iran, where the demand for groundwater resources continues to rise uncontrollably, particularly for domestic, agricultural, and industrial needs. As a result, the depletion of groundwater supplies has led to severe consequences. Per capita water resources in Iran have already decreased by more than 65% over the past four decades and are expected to decline by another 16% by 2025 (Motagh et al., 2008).

4.8. GWR Model for the Impact of Land Subsidence with All Parameters

Based on data processing using the Geographically Weighted Regression (GWR) model, the R-squared values were obtained and categorized into different ranges. This map serves as a model to illustrate the relationship between land subsidence and the selected variables or parameters. These variables include Built-Up Area, Population Density, Groundwater, Elevation, and Distance from the Coast, analyzed across several districts in Jakarta. The resulting R-squared values represent the strength of the relationship between land subsidence and these variables, which varies across different areas within the province of Jakarta.

The highest GWR values ranged from 0.00 to 0.56, indicating a strong spatial relationship between these variables and the rate of land subsidence (**Fig. 9**). Almost all areas in Jakarta exhibit high GWR influence values, with the highest observed ranging from 0.42 to 0.56, primarily in North Jakarta. Meanwhile, the lowest GWR values range from 0.17 to 0.22, showing spatial relationships between different regions. These interactions reflect a mutual influence between land subsidence and variables such as distance from the coast, elevation, groundwater, population density, and built-up area. The other research also shows similarities in that the variables of population density (Gao et al., 2019; Tirmizi & Khan, 2023; Younas et al., 2023), groundwater, and built-up area affect the rate of land subsidence (Faunt et al., 2016).

To verify the land subsidence data, GPS data from CORS (Continuously Operating Reference Station) stations were used as a reference dataset. This verification is crucial to clarify and ensure the quality and accuracy of the land subsidence measurements obtained from the SBAS-InSAR method. **Table 1** presents the verification results of land movement at several locations in Jakarta during the period 2017–2021, using data from the Sentinel-1 satellite and the GNSS CORS system managed by the Geospatial Information Agency (BIG) (Harintaka et al., 2024).

To verify the accuracy of the land subsidence data used in the GWR analysis, additional validation was conducted using GPS data measuring vertical displacement. Two monitoring points, UD and CORS CJKT, both located in the northern area of Jakarta, showed positive vertical displacement values.

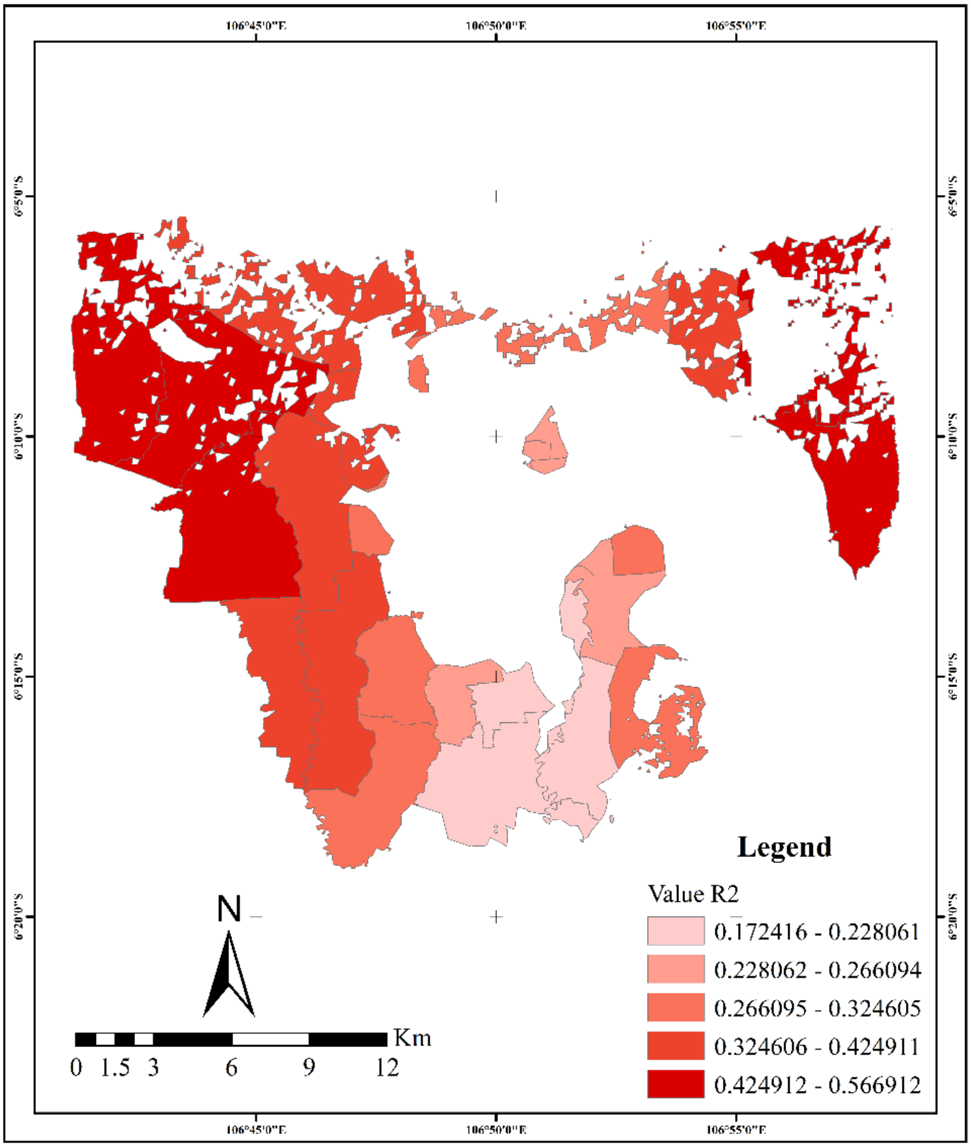

Fig. 9. R^2 of GWR Land Subsidence Variables

Table 1.
Verification of Land Subsidence Measurements from SBAS-InSAR with GNSS CORS Stations

Data	Long	Lat	Value (mm/year)
UD	106.8786°	-6.1101°	1.590
CORS CJKT	106.8845°	-6.1101°	1.154

(Source: Harintaka et al., 2024)

The UD point recorded a ground surface uplift of approximately 1.590 mm/year, while CORS CJKT recorded an uplift of about 1.154 mm/year. These positive vertical values, often referred to as up and down displacement, indicate that the ground surface at these locations moved upward. This condition can be caused by several factors such as reduced groundwater extraction resulting in natural soil rebound and land stabilization efforts.

The North Jakarta has the highest GWR values, particularly in districts such as Penjaringan, Pademangan, Cilincing, and Tanjung Priok. This indicates that these areas experience higher rates of land subsidence compared to other parts of Jakarta, based on variables such as distance from the coast, elevation, groundwater, population density, and built-up land. These factors collectively show that North Jakarta consistently has higher GWR values than other areas in the city (Du et al., 2020; Abidin et al., 2011). West Jakarta and the northern part of East Jakarta also show relatively high GWR values, although not as high as North Jakarta. Districts such as Kalideres, Cengkareng, and Duren Sawit are significantly affected by high population density and rapid built-up land expansion, which increase surface load and accelerate land subsidence. In contrast, Central Jakarta and most of South Jakarta have lower GWR values compared to North and West Jakarta.

Based on the GWR results shown that the Kalideres District in West Jakarta has the highest influence, with a GWR value of 0.56, indicating a strong relationship between built-up land, elevation, population density, groundwater, and distance from the coast. Pasar Rebo District in East Jakarta has the lowest influence, with a GWR value of 0.17, showing a weaker relationship with the same variables. Other areas display varying degrees of influence, as seen in the map, which categorizes the R^2 values into five groups, illustrating their interconnected effects. The GWR model for overall land subsidence in Jakarta Province is based on the variables built-up land, elevation, population density, groundwater, and distance from the coast. The GWR model for overall land subsidence in Jakarta Province, based on the variables of built-up land, elevation, population density, groundwater, and distance from the coast (Eq. (4)).

$$\hat{y} = 5.05 + 0.23BuiltUpArea + (-0.027)Elevation + (-0.182)Population + (-0.004)Groundwater + (-0.214)CoastDistance \tag{4}$$

This formulation is the result of GWR calculations using data sourced from Jakarta. Therefore, it is most suitable for application in Jakarta. However, the model may also be applied to other regions that have similar geographical, environmental, and socio-economic characteristics. The applicability of the model in other areas depends on how closely their spatial conditions resemble those of Jakarta. Jakarta, known as the most densely populated city in Indonesia, continues to grow rapidly, leading to increased human activities, especially in expanding built-up areas. The rising population has also caused excessive groundwater (Setiawan et al., 2017). Over-extraction of groundwater contributes to land subsidence, as sand deposits on the bay floor are gradually eroded by strong currents due to the abrasion of previously stable sand ridges and surrounding areas.This abrasion can lead to sedimentation, especially in Jakarta's delta areas, which is visible through changes in the coastline. Since Jakarta Bay is the mouth of 13 rivers, erosion has caused the coastline to retreat by up to 250 meters (Verstappen, 2000). This process is part of natural activity, which contributes to land subsidence in Jakarta. As a result, fine materials in delta areas compact over time, especially with human activities and coastal development.

Land subsidence in Jakarta is significantly influenced by various spatial variables, including groundwater, elevation, distance from the coast, population density, and built-up areas. Among these variables, groundwater showed the highest R^2 value at 0.829, indicating the strongest relationship with land subsidence in the region. This suggests that excessive groundwater extraction is the primary factor accelerating subsidence, especially in urban areas with high water demand. Population density emerged as the second most influential variable, with an R^2 value of 0.639. This finding aligns with previous research conducted in Wuhan, China, which employed the Geographically Weighted Regression (GWR) method to examine the impact of urbanization on land subsidence. The study analyzed the impact of urbanization variables on land subsidence and found that all urbanization indicators were significantly correlated with land subsidence across the study area (Wang et al., 2022). This supports the conclusion that human activitiesparticularly in densely populated zones are the main drivers of land subsidence in Jakarta Province.

Built-up areas also showed a strong correlation, with an R^2 value of 0.559. Meanwhile, elevation and distance from the coast exhibited lower R^2 values of 0.255 and 0.249 respectively. Nevertheless, these values still indicate a relationship, especially in coastal zones that are naturally more vulnerable to subsidence due to geological and hydrological conditions. The overall GWR model produced an R^2 value of 0.566, demonstrating a fairly strong spatial relationship between the combination of variables and land subsidence in Jakarta. The Geographically Weighted Regression (GWR) model produced an R^2 value of 0.566, indicating a moderately strong spatial correlation between the selected variables (such as distance from the coast, elevation, population density, groundwater, and built-up area) and land subsidence in Jakarta.This R^2 value means that approximately 56.6% of the variation in land subsidence across the study area can be explained by the combination of these variables included in the model.

5. CONCLUSIONS

Based on this study, Jakarta as a whole experiences significant land subsidence. Among the analyzed areas, North Jakarta has the highest subsidence rates, indicating a more severe impact in coastal regions. Groundwater shows the strongest correlation with land subsidence, suggesting that densely populated areas are more prone to ground sinking. In contrast, the distance from the coast and elevation has the least impact, implying that human activities play a more dominant role than natural topographic factors. The overall analysis highlights a strong relationship between land subsidence and factors such as groundwater, population density, built-up area, elevation, and the distance from the coast, emphasizing the urgent need for sustainable land and water resource management.

6. ACKNOWLEDGEMENT

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