Journal of Contemporary Academic Research and Methodologies

An Online Peer Reviewed / Refereed Journal
Volume 1 | Issue 5 | June 2026
Website: www.journal.jcarm.in

Case Study

RAINFALL VARIABILITY, LAND USE CHANGES AND URBAN GROWTH IN OSOGBO, NIGERIA: A DECISION SUPPORT SYSTEM FOR CLIMATE RESILIENT URBAN PLANNING

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Article No: 045 | **Accepted**: 03 July 2026 | **Published:** 10 July 2026

Abstract: Osogbo faces challenges from rainfall variability, rapid urbanization, and shifting land use. These pressures compromise the resilience of cities, infrastructure, and communities. Addressing them requires sophisticated urban planning that integrates rainfall variability and risk-mitigation strategies. Data were sourced from rainfall records by the Nigeria Meteorological Agency (NiMet) and land-use classifications from Landsat and Sentinel satellites. Analyses employed GIS platforms and regression and correlation analyses. The study revealed that April and October have higher annual rainfall in Osogbo, with the maximum in 2010 with 1700mm and the lowest in 2001 with 1000mm. The land-use data from 1990 to 2025 shows significant ups and downs across all categories. Agriculture and total land area change a lot without a clear pattern. Bare land and built-up areas grew significantly at times, suggesting city growth or land damage. Forest and water areas increased in the late 1990s and early 2000s but have since mostly decreased, which could harm the environment The multiple regression analysis conducted in this study revealed shortcomings in both the data and model dependability. While the model explains a substantial proportion of variance (R Square = 0.75), the negative Adjusted R Square, non-significant F-statistic, and uniformly high p-values for all predictors indicate a lack of statistical significance and soundness. The presence of errors in certain variables and the very small sample size further undermine the credibility and acceptability of the findings.The decision-support system targets regional vulnerabilities to land-use change and rainfall variability, aiming to guide policy and planning for greater urban climate resilience.

Keywords: DSS, Land uses, Urban Growth and Rainfall Variability

Copyright © 2026 by the authors https://doi.org/10.5281/zenodo.21300737

Background to the Study

Climate change and urbanization are major threats to sustainable development (Intergovernmental Panel on Climate Change, IPCC 2024). These impacts are especially pronounced in developing countries like Nigeria, where fast urbanization intensifies rainfall variability and alters land use (Adebanji, 2025). The interactions among rainfall variability, land-use changes, and urban growth have increased vulnerability and reduced resilience in many urban areas (IPCC, 2024; UN, 2022). The effects of rainfall variability and land-use change are expected to be more severe in countries like Nigeria, where fast urbanization and inadequate planning have increased vulnerability to natural hazards (UN, 2022).

Osogbo, Nigeria, is a case study for the links between rainfall variability, land-use change, and urban growth. This study explores these links and builds a decision-support system for climate-resilient planning (Keamey, 2022). Rapid urbanization and land-use change in Osogbo have raised climate risks (IPCC, 2024). Rainfall variability, in particular, poses risks to water resources (FAO, 2020). Without effective strategies, Osogbo could face severe impacts, including flooding and drought (IPCC, 2024). These events can cause property damage, loss of life, and economic decline (Dijk, 2022).

Few studies have addressed the impacts of rainfall variability, land-use change, and urban growth in Nigeria. Urban planning efforts often focus on mitigation and response. Integrating land-use change and rainfall variability into resilient planning is essential for Osogbo's sustainability. Osogbo's landscape includes rainforests and savannas, and it is seeing rapid urbanization. The city is at 7°50'N, 4°53'E, covers 8,884 sq km, and has a population of nearly 4 million. It has a tropical climate, with an average temperature of 28°C and annual rainfall of 1,200-1,800 mm. (Oluwadare and Oluwadare, 2023) Rainfall variability is a concern. The rainy season runs from April to October, but recent changes have led to extreme rainfall in some areas.

A decision support system (DSS) plays a key role in climate-resilient urban planning. It combines spatiotemporal data on rainfall variability, land-use changes, and urban growth. This helps identify vulnerabilities and pathways for sustainable development. Climate change is a global risk to cities. Using a DSS enables decision-makers to identify and rank adaptation strategies that meet local needs. Climate adaptation is complex and involves many stakeholders. Uncertain climate impacts add to this complexity. A DSS helps decision-makers test scenarios and adaptation choices under different climate possibilities.

Research Questions

1. What are the trends and patterns of rainfall in Osogbo over the past 35 years, based on available meteorological data?

2. How has land use in Osogbo changed over the past 35 years, and what are the main drivers of these changes?

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3. What is the quantitative relationship between rainfall patterns and land use changes in Osogbo, and how can this relationship inform the development of a decision support system (DSS)?

Literature Review

In recent years, urban areas have been affected by rainfall variability (Adger, 2025). Changes in precipitation and extreme weather have made urban ecosystems, infrastructure, and populations more vulnerable (McPhearson, 2020). Rapid City growth and land-use change have worsened these problems, altering city environments and affecting sustainability (Wu, 2024). More cities now see changing rainfall patterns. This brings more flooding, droughts, and landslides. Extreme rainfall events and shifting seasons are becoming common (Fekere, 2022).

Rainfall variability can significantly affect urban ecosystems by modifying the hydrological cycle and influencing urban water resources and biodiversity (Vorosmary, 2022).

Rainfall variability shapes urban ecosystems. It alters the hydrological cycle, affecting water resources and biodiversity (Vorosmary, 2022). Urban infrastructure, energy, water supply, health, food security, and poverty are all impacted (Dijk, 2022). The link between land-use change and city growth was recently studied (Liu, 2025). Fast urbanization changes agricultural land, forests, and other natural spaces into urban areas. This alters landscapes and creates environmental and social challenges. Climate resilience and urban growth go hand in hand. Climate change increases hazards and vulnerability in cities (Perri, 2023).

Development strategies are needed to reduce vulnerability and improve resilience to rainfall variability. Achieving climate-resilient planning requires a decision support system. A DSS is a computer-based tool with integrated data models. It guides decision-making by providing information on risks, vulnerability, and adaptation, and helps evaluate planning choices.

This study uses systems thinking theory, developed by Jay Wright Forrester in 1950. He introduced a structure for modeling complex systems, such as cities and ecosystems. This perspective is holistic and integrative. It helps study the links between rainfall variability, land-use change, and urban growth. The theory states that each factor can be separate but is also interconnected. The study also uses resilience theory. This theory, developed in the 1970s by ecologists and soil scientists, holds that ecosystems may be resilient to change rather than remaining static. It is a frame for understanding, guiding, and evaluating complex systems and their response to disturbances. Resilience is a measure of system capacity, making it a good basis for developing a climate-resilient urban planning system.

Urban ecology theory, introduced by Henry Cowles and Charles Elton in the early 1800s, is a scientific field examining the relationships between cities and their natural environments. It conceptualizes cities as ecological systems with distinct biophysical and

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social attributes. The theory is applicable to this study, as it clarifies the structure and environmental interactions of urban ecosystems.

Research Method

Data for this study come from secondary sources, such as the Nigerian Meteorological Agency (NiMet) and Landsat satellite imagery. A geospatial and remote-sensing approach was used to analyze Land Use and Land Cover (LULC) changes in Osogbo. From 1990 to 2025, multi-temporal USGS imagery was used to classify land-use types. The method included image collection, pre-processing, supervised classification, post-classification processing, and trend analysis. GIS techniques helped map each land-use class's area. The Landsat series provided long-term data for analysis. The study used Landsat 5 TM for earlier years (1990, 2000), Landsat 7 ETM+ for intermediate years (2010), and Landsat 8 OLI for recent years (2020, 2025). Images were chosen based on year, 30-meter resolution, and similar seasonality to ensure consistent vegetation features.

All satellite images were downloaded in GeoTIFF format for further processing and analysis. Additional spatial datasets used in this study included the Administrative boundary map of Osogbo, Reference imagery from Google Earth, and base maps for visual interpretation. These datasets were used to clip satellite images to the study area and to assist in identifying different land-use types during classification. Image pre-processing was conducted to prepare the satellite imagery for classification and to ensure consistency across years. Satellite imagery for the selected years was downloaded from the USGS Earth Explorer database using the images' geographic coordinates. Images with minimal cloud interference were selected to guarantee clarity and improve classification correctness.

The downloaded satellite images were clipped to the Osogbo boundary; this step ensured that only the area of interest was analyzed and reduced the data size for productive processing. Band combinations and contrast enhancement techniques were applied to improve the visual quality of the satellite images. This made it easier to distinguish different land cover features such as agricultural fields, forest areas, and built-up zones.

A supervised classification technique was used to classify satellite imagery into different land-use and land-cover categories. This method was selected because it allows the classification process to be guided using known land cover information. Training samples were selected based on polygon features representing known land-use types within the study area. These training polygons were created for each land use class based on visual interpretation of satellite imagery and reference data. Care was taken to ensure that the selected training samples accurately represented the spectral characteristics of each land-use category.

The classification process assigned each pixel to a specific land use class based on its spectral attributes. The output of this process consisted of classified raster maps representing the spatial distribution of different land-use categories for each study year. Post-classification processing was performed to derive spatial information and quantify the

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area of each land-use class. The classified raster images were converted into polygon format. This conversion enabled precise measurement of the geographical extent of each land-use class. The area of each land use class was calculated in hectares using GIS measurement tools. This enabled a quantitative comparison of land-use distribution across different years. Accuracy assessment was carried out to evaluate the reliability of the classified maps.

Reference points were selected from high-resolution images and known land features. These reference points were compared with the classified results to generate an error matrix. Overall classification correctness was calculated to determine the reliability of the classification results. All spatial analysis and map production were carried out using GIS software tools. The classified land-use maps were symbolized with appropriate colors to represent each land-use class. Final outputs produced in this study included: a simple bar chart was used to determine the trend in rainfall between 1990 and 2025, while regression and correlation models were used to derive the Decision Support System.

Results and Discussion

April and October have higher annual rainfall in Osogbo, with the maximum in 2010 with 1700mm and the lowest in 2001 with 1000mm (Fig.1). (Adewoye, 2023) Understanding the rainfall trends and patterns will explain how rainfall variability affects sustainable economic growth in Osogbo, Nigeria. Food insecurity resulting from rainfall variability in crop yields will lead to poverty and hunger, hindering sustainable economic growth. Flooding from heavy rains and water shortages during droughts, which limit both industrial and domestic water use, will damage economic activity and compromise sustainability. Heavy rainfall has a significant impact on infrastructure, damaging roads, bridges, and other structures, thereby hindering economic activity and increasing the costs of doing business.

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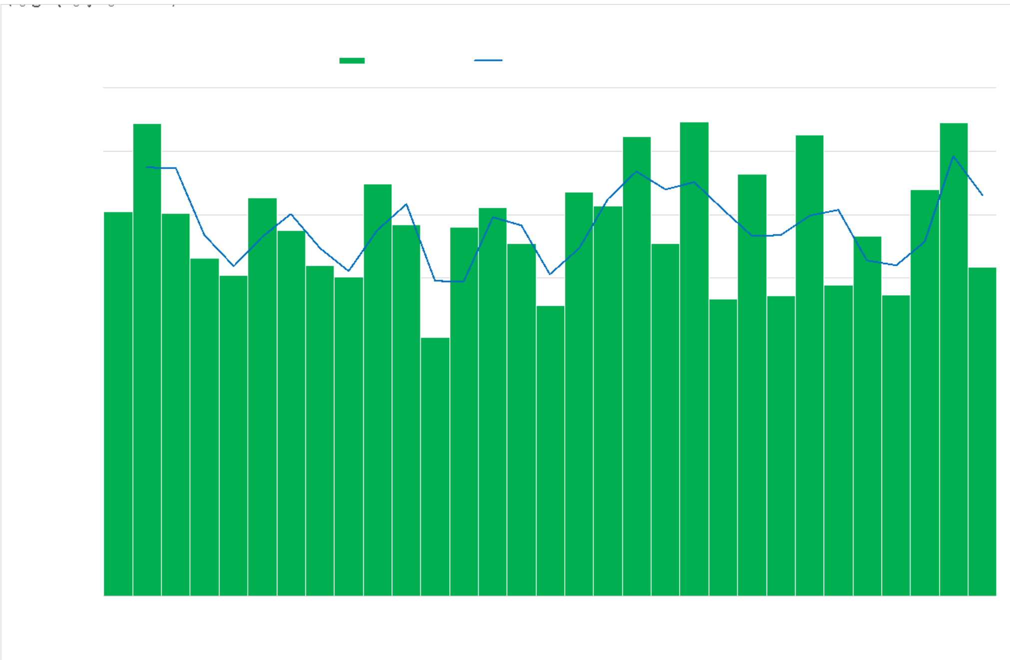

Figure 1: Trend of Annual Rainfall in Osogbo (1992-2025) in mm

Source: Fieldwork (2026).

The analysis revealed five different land uses these include Agriculture, Forestry, Bare-land, Built –up Areas and water bodies. Agriculture (Km²) starts at 32.854 (1990-1995), drops to 5.970 (1995-2000), then fluctuates, peaking again at 32.859 (2005-2010) before generally declining to 15.55 (2020-2025). There is considerable variability with sharp increases and decreases rather than a consistent trend (Fig 2-9). Bare-land (Km²) starts at 18.213, stays similar in 2005-2010, then jumps to 49.241 (2010-2015), 59.208 (2015-2020), and slightly decreases to 54.634 (2020-2025) (Fig 2-9). Bare-land area increased significantly after 2005-2010, possibly due to changes in other land types or land deterioration. (Eresanya et al., 2019)

Built-up Areas (Km²) start at 13.203, surge to 50.477 (1995-2000), then drop and stabilize around 13-14 across several periods, with a considerable spike (27.880) in 2000-2005. There is a big jump in 1995-2000, due to city growth or changes in land classification, but overall, this remains fairly steady in most years. Forest (Km²) starts at 3.179, increases to 15.949 (1995-2000), then varies, reaching 12.650 (2000-2005), but generally remains below 7 in later years. (Fig 2-9)Forest area grew in the late 1990s and early 2000s but declined afterward, possibly due to tree cutting or changes in land use. Water bodies (Km²) start at 3.179, peak at 15.949 (1995-2000), then gradually decline to 3.608 (2020 2025). (Eresanya et al., 2019)

Water bodies grew significantly during 1995-2000 and 2000-2005, but then began to shrink after 2005.The land-use data from 1990 to 2025 shows significant ups and downs

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across all categories. Agriculture and total land area change a lot without a clear pattern. Bare land and built-up areas grew significantly at times, suggesting city growth or land damage. Forest and water areas increased in the late 1990s and early 2000s but have since mostly decreased, which could harm the environment. (Eresanya et al., 2019)

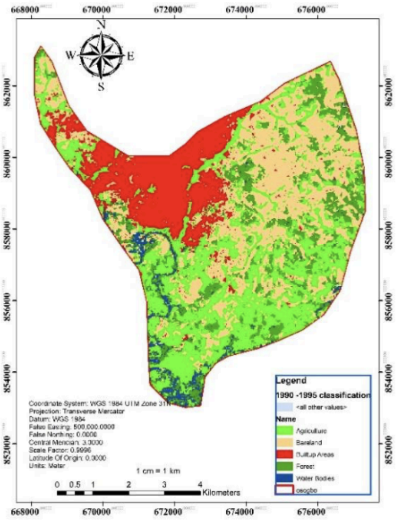

Fig 2:Land use changes in Osogbo from (1990-2005)
Authors' computation (2026)

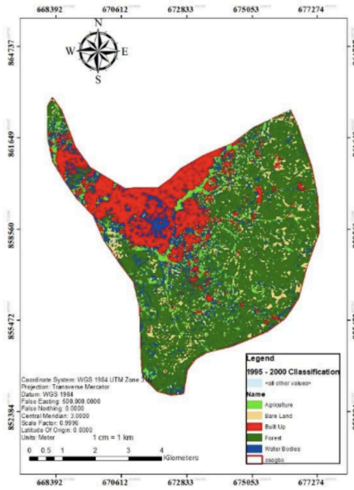

Fig3:Land use changes in Osogbo from (1995-2000)
Authors' computation (2026)

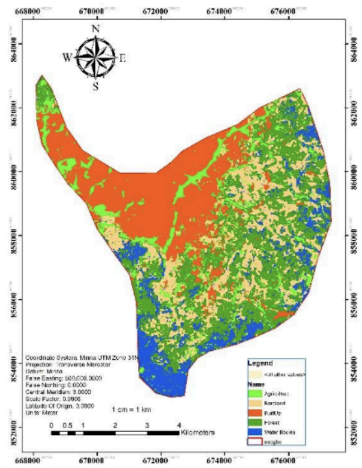

Fig4:Land use changes in Osogbo from (2000-2005)
Authors' computation (2026)

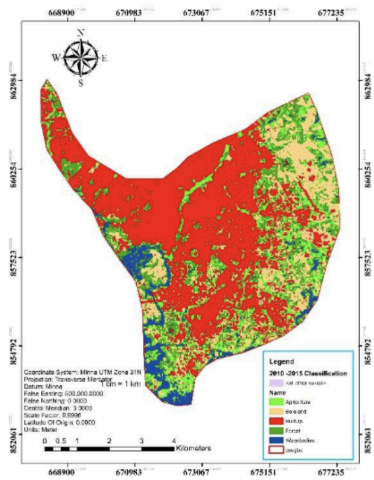

Fig 5:Land use changes in Osogbo from (2005-2010)
Authors' computation (2026)

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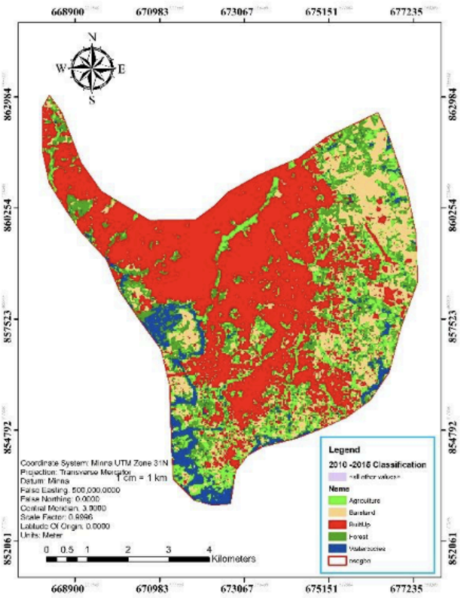

Fig 7:Land use changes in Osogbo from (2010-2015)
Authors' computation (2026)

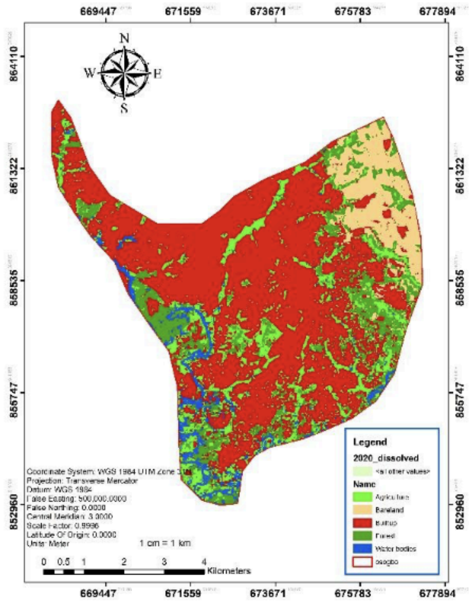

Fig 7:Land use changes in Osogbo from (2015-2020)
Authors' computation (2026)

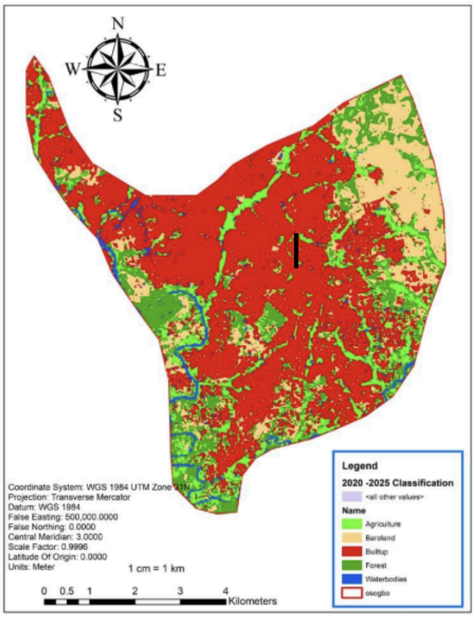

Fig 6 :Land use changes in Osogbo from (2015-2020)
Authors' computation (2026)

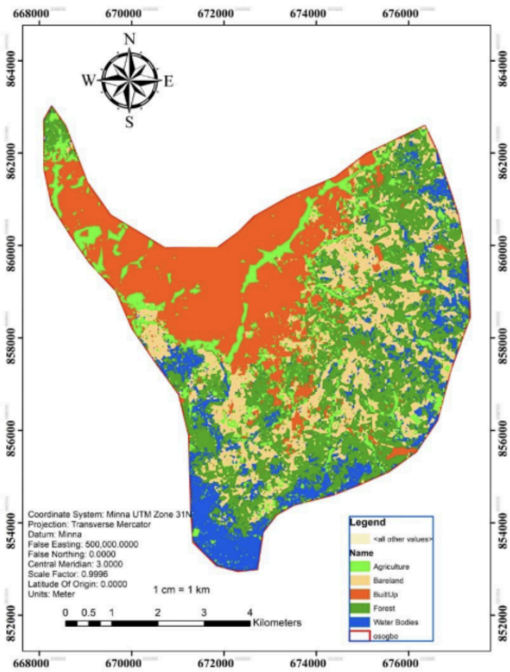

Fig 7:Land use changes in Osogbo from (2020-2025)
Authors' computation (2026)

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The multiple regression statistics revealed that R (0.86) is the correlation coefficient between the observed and predicted values. A value of 0.86 suggested a strong positive linear relationship. R Square (0.75): This means about 75% of the variation in the dependent variable is explained by the model. Adjusted R Square (-0.26) is negative, which is unusual. It happens when the model does not fit well, especially with few data points and many predictors. It suggested the model may be over-fitting or not explaining the variance meaningfully. Standard Error (4.30) measures the average distance between the observed values and the regression line. Lower values are better.

Observations have 7 data points, which is low for a multiple regression with 5 predictors. The F-statistic (1.48), Significance F (0.55): The F-test checks whether the regression model is significantly better than a model with no predictors. Here, the p-value (Significance F) is 0.55, well above the typical cutoff (0.05), suggesting the model is not statistically significant overall. P-values (P-value column): Indicate the probability that the coefficient is actually zero (no effect). All p-values are much larger than 0.05, meaning none of the predictors are statistically significant. Model Fit: The model appears to fit the data poorly (negative Adjusted R Square, non-significant F-statistic). This regression model does not provide statistically meaningful results, likely due to the very small sample size and possibly issues with the predictor variables.

The multiple regression analysis conducted in this study yielded an R-squared value of 0.75, indicating that approximately 75% of the variation in the dependent variable is explained by the selected predictors. While this suggests a potentially strong relationship, the negative Adjusted R Square (-0.26) and non-significant F-statistic ($p = 0.55$) indicate limitations in the model's reliability. Additionally, none of the independent variables, including Agriculture, Bare-land, Built-up Areas, Forest, and Water Bodies, were found to be statistically significant predictors, as indicated by their high p-values and wide confidence intervals. (Table 1and 2)

These outcomes contrast with those of Liu (2025), who found significant effects of land-use variables, such as Agriculture and Forest area, on rainfall variability using a larger dataset. Their study found that increases in forest cover, for example, were associated with improved environmental outcomes, and their regression models showed statistically significant coefficients ($p < 0.05$) for several predictors. Similarly, Keamy (2024) pointed out the importance of Built-up Areas in predicting rainfall, with results showing a strong positive association, supported by significant p-values and large sample sizes. In the findings, however, the coefficient for Built-up Areas was not statistically significant, possibly due to the small sample size and limited data variation, as evidenced by the regression output errors.

The lack of statistical significance in the present study may be attributable to different factors. First, the small sample size reduces the analysis's statistical power and increases the risk of Type II errors (Keamy, 2024). Second, the presence of data issues, such as constant values for Bare-land and Built-up Areas, may have further limited the model's ability to detect real relationships, as also discussed by Liu (2024).

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To summarize, while the direction and magnitude of some coefficients in this study are consistent with previous research, the overall lack of significance suggests that further data collection and refinement of predictor variables are needed. For a strong Decision Support System. Future studies should aim to increase sample size and ensure variability in key predictors to yield more reliable and generalizable findings.

Regression Statistics	***Regression Statistics***
Multiple R	0.864442913
R Square	0.74726155
Adjusted R Square	-0.258215349
Standard Error	4.298730279
Observations	7

Authors Computation (2026)

Table 1: Summary of the output, source Author's computation

	df	*SS*	*MS*	*F*	*Significance F*			
Regression	5	109.2727	21.85454169	1.47833	0.551752675			
Residual	2	36.95816	18.47908201					
Total	7	146.2309						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	121.3129113	52.319	2.318716052	0.146263	-103.7975883	346.4234	-103.798	346.4234
Agriculture	-0.054717428	1.104586	-0.049536606	0.964994	-4.807366195	4.697931	-4.80737	4.697931
Bare-land	0	0	65535	#NUM!	0	0	0	0
Built-up Areas	-0.035617075	0.511884	-0.06958031	#NUM!	-2.238077835	2.166844	-2.23808	2.166844
Forest	0.503931903	0.468016	1.076741668	0.394225	-1.509776716	2.517641	-1.50978	2.517641
Water Bodies	-2.134196978	1.946357	-1.096508309	0.387256	-10.50869663	6.240303	-10.5087	6.240303

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Table 2:Multiple Regression Table

Years	Agric(Km2)	Bare-land(Km2	Builtup Areas(Km2)	Forest(Km2)	Water Bodies(Km2)	Rainfall(mm)
1990-1995	32.543	32.854	18.213	13.203	3.179	117.033
1995-2000	8.817	5.970	18.784	50.477	15.949	112.625
2000-2005	10.450	18.982	27.880	30.036	12.650	105.4278
2005-2010	32.543	32.859	18.213	13.203	3.179	120.2708
2010-2015	13.897	16.740	49.241	13.503	6.616	115.6278
2015-2020	13.581	9.211	59.208	13.0972	4.901	111.8958
2020-2025	12.450	15.55	54.634	13.748	3.608	118.061

Total Land Uses and Annual Rainfall (1990-2025)

Author's computation (2026)

Conclusion and Recommendations

The multiple regression analysis conducted in this study revealed shortcomings in both the data and model dependability. While the model explains a substantial proportion of variance (R Square = 0.75), the negative Adjusted R Square, non-significant F-statistic, and uniformly high p-values for all predictors indicate a lack of statistical significance and soundness. The presence of errors in certain variables and the very small sample size further undermine the credibility and acceptability of the findings.

These results show the importance of increasing sample size, improving data quality, and diligently selecting predictor variables in future research. Drawing stronger conclusions will require additional comprehensive data and thorough methodological approaches to ensure reliable and useful insights. The study recommends an Increased Sample Size to improve the statistical power and dependability of the regression analysis. Larger samples reduce the risk of spurious results and allow more accurate estimates of relationships.

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Address issues with predictors that show errors or lack of variation (e.g., Bare-land and Built-up Areas). Ensure that each variable has sufficient variability and that the data are accurately recorded. Refine Variable Selection, Re-examine the choice of predictor variables. Consider including other relevant factors from the literature, or removing those with consistently low significance or data quality issues. Compare with Previous Studies; contextualize findings by comparing them with existing research. Discuss similarities or differences in model significance, variable effects, and potential reasons for discrepancies. Consider Simpler Models. If data remains limited, use simpler models (e.g., with fewer predictors) to avoid over-fitting and improve interpretability. Perform Diagnostic Checks:Run additional diagnostics (e.g., residual plots, multicollinearity tests) to ensure the regression's underlying assumptions are met.

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