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Climate variability and land-use dynamics: Spatiotemporal relationships in Mangochi District, Malawi

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Abstract

Climate variability is increasingly recognized as an important driver of land-use transformation in climate-sensitive regions of Sub-Saharan Africa. This study examined the spatial-temporal effects of climate variability on land-use dynamics in Mangochi District, Malawi. An integrated analytical framework combining statistical trend analysis, geospatial modelling, and remote sensing was employed to characterize spatial and temporal patterns. Climatic trends for 2000–2025 were assessed using the Mann–Kendall trend test and Sen’s slope estimator, while land-use and land-cover (LULC) changes were analysed from multi-temporal Landsat and Sentinel satellite imagery through supervised classification and GIS-based change detection. Spatial interpolation of climatic variables was conducted using ordinary kriging, and climate–land interactions were evaluated using Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR). Results reveal pronounced interannual rainfall variability and a statistically significant warming trend, with annual mean temperature increasing at approximately 0.032 °C year⁻¹. Land-use analysis indicates substantial expansion of wetland cultivation (+34.25%), accompanied by marked declines in marshes (–83.60%), woodland (–65.52%), and rainfed cultivation (–17.30%) between 2000 and 2020. The decline in woodlands and marshes indicates a broader contraction of important natural ecosystems, suggesting potential hydrological responses to climatic variability. The integrated spatial-temporal analysis indicates that land-use transformation occurred within a changing climatic context, with climate–land relationships varying spatially and climate variability providing only a partial explanation of the observed land-use changes. These findings provide empirical evidence of climate–land interactions at the local scale and underscore the importance of climate-informed land management, sustainable agricultural planning, and adaptation strategies to enhance resilience in smallholder farming systems in Malawi and other similar climate-vulnerable regions.

Keywords Climate variability · Geographically Weighted Regression (GWR) · GIS; Land-use change · Spatiotemporal analysis · Malawi

40 1. Introduction

41 Climate variability and change are major drivers of environmental and socioeconomic
42 change. These changes are particularly important in Sub-Saharan Africa (SSA), where
43 many livelihoods depend on climate-sensitive sectors such as agriculture. Rising
44 temperatures and changing rainfall patterns are increasingly affecting agricultural
45 production and water resources (Lazurko et al. 2024; Pophiwa et al. 2025). The frequency
46 and intensity of some extreme weather events are also increasing. These changes pose
47 significant risks to livelihoods and food security across the region (Omotoso et al., 2023).

48 SSA is particularly vulnerable to climate change due to its heavy reliance on rain-
49 fed agriculture and limited adaptive capacity (Connolly-Boutin and Smit, 2016). Existing
50 socioeconomic and development challenges further increase this vulnerability (IPCC,
51 2022). Climate variability can reduce agricultural productivity, increase food insecurity,
52 and place additional pressure on water resources and livelihoods (Omotoso et al., 2023).
53 Its effects also extend beyond environmental and economic outcomes. Floods, droughts,
54 and extreme heat can affect population health and psychosocial well-being, particularly
55 among already vulnerable populations (Deglon et al., 2023). Despite growing evidence of
56 these impacts, their effects are not uniform across locations, populations, and livelihood
57 systems. Local-level evidence on these variations remains limited. Climate variability can
58 influence how land resources are used and managed, particularly in rural areas where
59 livelihoods depend heavily on rain-fed agriculture. Changes in rainfall and temperature can
60 affect crop production and water availability, which may influence decisions on land
61 cultivation and management. At the same time, population growth, socioeconomic
62 conditions, and other human activities contribute to changes in land use and land cover
63 (LULC). These interactions underscore the importance of examining LULC dynamics
64 across space and time (Mogonong et al. 2024). Remote sensing and geographic information
65 systems (GIS) provide effective tools for detecting and quantifying such changes over large
66 areas and across different periods. Recent studies have demonstrated their value in
67 assessing agricultural and other LULC changes in Africa and in examining their
68 relationships with climatic conditions (Mogonong et al. 2024; Kerner et al., 2024)

69 Malawi is highly vulnerable to climate variability due to its heavy reliance on rain-
70 fed agriculture. Changes in temperature and rainfall patterns have important implications
71 for agricultural production and rural livelihoods (Ngongondo et al., 2011; World Bank
72 Group, 2022). Recent droughts and floods have further demonstrated the sensitivity of
73 Malawi's agricultural systems to climatic shocks (World Bank, 2024). Concurrently,
74 LULC changes are occurring through agricultural expansion, population growth,
75 settlement development, and other forms of resource use. These changes can interact with
76 climatic conditions to alter cropland, vegetation, forests, and water resources.

77 Evidence from southern Malawi shows substantial LULC changes over the past
78 three decades, including expansion of cropland and built-up areas and reductions in forest,
79 shrubland, and water areas (Nkolokosa et al., 2023). These landscape changes reflect the
80 combined influence of climate, agricultural expansion, and socioeconomic factors.
81 However, district-level evidence on how temporal climate variability corresponds with
82 spatial and temporal LULC dynamics remains limited. This gap is particularly important
83 in Mangochi, where climatic and agro-ecological heterogeneity may produce spatially
84 differentiated land-use responses. These characteristics make the district a particularly

85 suitable case for examining climate-LULC relationships, yet empirical evidence on these
86 relationships remains scarce.

87 Given these gaps, this study examines the spatiotemporal relationship between
88 climate variability and LULC dynamics in Mangochi District, Malawi. Specifically, it aims
89 to: (i) analyse temporal trends and variability in selected climate variables; (ii) assess
90 spatial and temporal patterns of LULC change; and (iii) evaluate associations between
91 climate variability and LULC dynamics. By integrating long-term climate records with
92 geospatial LULC data, the study provides district-level evidence to improve understanding
93 of landscape responses to climatic variability and support climate adaptation and
94 sustainable land management.

95 **2. Study Area**

96 The study was conducted in Mangochi District (**Fig. 1**), located in the southern region of
97 Malawi along the southern shoreline of Lake Malawi. The district lies between
98 approximately 14°20'–14°55' S and 34°30'–35°10' E, covering an area of about 6,673 km².
99 Mangochi is characterized by diverse physical landscapes, including lakeshore plains,
100 escarpments, and plateau regions. The proximity to Lake Malawi plays a significant role
101 in shaping local climatic conditions through lake–atmosphere interactions, influencing
102 rainfall distribution and humidity (Koseki and Mooney, 2019). The climate is tropical sub-
103 humid, with annual rainfall ranging between 700 *mm* and 1,200 *mm* and a distinct rainy
104 season from November to April. Agriculture is predominantly rain-fed, making the district
105 highly vulnerable to climate variability. The district lies within two major agro-ecological
106 zones: the lakeshore, middle and upper Shire valley zone and the mid-elevation upland
107 plateau zone, which together represent the most dominant agro-ecological systems in
108 Malawi (FAO, 2005; Nalivata et. al., 2017). This dual agro-ecological setting provides a
109 strong basis for examining climate–land interactions across contrasting environmental
110 conditions.

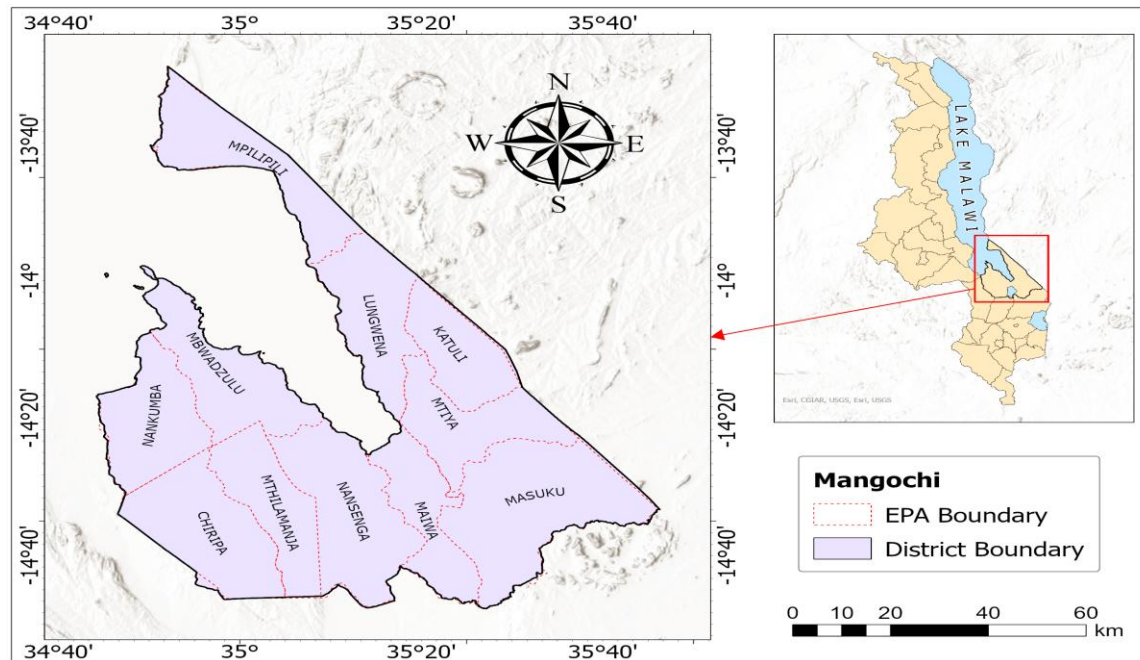


Fig. 1. Location of Mangochi District within Malawi and the spatial distribution of Extension Planning Areas (EPAs) in the study area.

3. Methodology

This study applied an integrated spatiotemporal analytical framework to examine temporal climate variability, LULC change, and spatial variation in climate-LULC associations in Mangochi District, Malawi. The analytical sequence was hierarchical: climate trend and variability analyses first characterized the climatic context; multi-temporal remote sensing quantified LULC patterns and transitions; and global and local regression models were then used to evaluate whether spatial variation in rainfall and temperature was statistically associated with LULC change. Because land-use outcomes are also shaped by socioeconomic, biophysical, and institutional factors not represented in the models, the regression results were interpreted as associations rather than causal effects.

The methodological framework therefore comprised three linked components: (i) temporal analysis of climate trends and rainfall anomalies, (ii) spatial and temporal analysis of LULC patterns and transitions, and (iii) global and geographically varying regression analysis of climate-LULC relationships, followed by residual spatial diagnostics.

3.1 Data sources and pre-processing

Climatic data, including precipitation and temperature, were obtained from meteorological stations for the period 2000 – 2025. To address spatial gaps, supplementary gridded datasets (CHIRPS and ERA5-Land) were incorporated where necessary.

LULC data were derived from multi-temporal satellite imagery, including Landsat TM (30 m resolution), Landsat OLI (30 m resolution), and Sentinel-2 (10–20 m resolution) for 2000, 2005, 2010, 2015, and 2020.

Climate variability was evaluated over 2000 – 2025, whereas the available LULC imagery extended through 2020. This distinction is important because climatic conditions were characterized over a longer period than the observed land-cover change interval. A multi-decadal climate record was used to distinguish persistent monotonic trends from short-term interannual fluctuations, while repeated satellite observations were used to characterize longer-term landscape transitions (Ngongondo et al. 2011; Lambin et al. 2003; Verburg et al. 2015). The two temporal components were therefore integrated as complementary, but not temporarily identical, lines of evidence.

Climate data pre-processing included screening for missing values, gap filling were required, outlier detection, and homogeneity testing before annual summaries were derived. Satellite imagery was subjected to atmospheric and geometric correction and clipped to the study boundary before classification. These quality-control steps were applied to reduce artefacts that could otherwise be mistaken for temporal or spatial variability (Ngongondo et al., 2011; Li and Heap, 2014; Chen et al., 2015).

Administrative boundary data at district level (ADM2) were used to define the study area.

3.2 Climate variability analysis

Temporal trends in annual climatic variables were assessed using the Mann–Kendall trend test (Mann, 1945; Kendall, 1975), a non-parametric method used to test for a monotonic trend without requiring normally distributed observations.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

where S is the Mann–Kendall test statistic, x_i and x_j are sequential observations of climatic variables, n is the total number of observations, and $\text{sgn}(\cdot)$ is the sign function.

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases}$$

The magnitude of the trend was estimated using Sen’s slope estimator (Sen, 1968):

$$Q = \text{median} \left(\frac{x_j - x_i}{j - i} \right)$$

where the Sen’s slope represents the median rate of change in the climatic variable per unit time. Mann-Kendall significance and Sen’s slope magnitude were interpreted jointly: the test statistic was used to determine whether evidence of a monotonic trend was present while Sen’s slope quantified the direction and physical rate of that trend. A significance level of $p < 0.05$ was used. Importantly, a non-significant Mann-Kendall result was not interpreted as an absence of variability; rainfall trend results were therefore

considered together with annual anomalies and the Standardized Rainfall Anomaly Index (SRAI) (Ngongondo et al., 2011; Nkhoma et al., 2025).

3.3 Spatial interpolation of climate data

To generate continuous spatial surfaces of climate variables, ordinary kriging interpolation was applied (Goovaerts, 1997; Ngongondo et al., 2011; Li and Heap, 2014; Rodrigues et al., 2024; Bojago et al., 2024; Ahmed et al., 2025).

$$Z(x_0) = \sum_{i=1}^n \lambda_i Z(x_i)$$

where $Z(x_0)$ is the estimated value at an unsampled location, $Z(x_i)$ represents observed values, and λ_i are weights determined from the spatial covariance structure.

The kriging system satisfies the unbiasedness condition:

$$\sum_{i=1}^n \lambda_i = 1$$

Semivariogram models (spherical, exponential, and Gaussian) were evaluated to determine the best representation of spatial dependence.

Model performance was assessed using cross-validation metrics:

$$ME = \frac{1}{n} \sum_{i=1}^n [Z^*(x_i) - Z(x_i)]$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Z^*(x_i) - Z(x_i))^2}$$

where $Z^*(x_i)$ is the predicted value, $Z(x_i)$ is the observed value, and n is the number of observations.

3.3.1 Spatial interpolation and kriging cross-validation

Ordinary kriging was used to interpolate mean annual temperature and rainfall across Mangochi District. The method was selected to estimate spatially continuous climate surfaces from the available observation points while accounting for the spatial dependence between observations. No deterministic trend was specified in either interpolation model. A stable semivariogram model was fitted to the spatial dependence structure for both temperature and rainfall.

A standard searching neighbourhood was used, with a maximum of 15 neighboring observations and a minimum of 5 observations included in the estimation. The search neighbourhood was divided into four sectors using a 45° sector angle. Isotropy was assumed, with no directional anisotropy specified. The semivariogram was fitted using 12 lags, with a lag size of approximately 0.107° for temperature and 0.208° for rainfall. The

fitted temperature model had a range of approximately 0.933°, whereas the rainfall model had a range of approximately 2.494°. The corresponding nugget, parameter, and partial-sill values were retained from the fitted ArcGIS Geostatistical Analyst models.

The predictive performance of the kriging models was evaluated using cross-validation. Cross-validation involved comparing the observed climate values at the available sampling locations with the corresponding values predicted by the kriging models. The assessment considered the mean error (ME), mean absolute error (MAE), root mean square error (RMSE), mean standardized error, and root mean square standardized error (RMSSE). Mean error and mean standardized error values close to zero were considered indicative of low systematic prediction bias, while RMSSE values approaching one indicated consistency between the magnitude of prediction errors and the estimated kriging uncertainty. These diagnostics were used to assess the reliability of the interpolated climate surfaces subsequently used in the spatial analysis of climate variability and its relationship with LULC dynamics.

Table 1. Ordinary kriging model specifications used for climate interpolation

Parameter	Mean annual temperature	Mean annual rainfall
Kriging method	Ordinary	Ordinary
Trend	None	None
Semivariogram model	Stable	Stable
Number of lags	12	12
Lag size	0.10735°	0.20783°
Maximum neighbors	15	15
Minimum neighbors	5	5
Search sectors	4	4
Sector angle	45°	45°
Anisotropy	No	No
Major semiaxis	0.93301°	2.49398°
Minor semiaxis	0.93301°	2.49398°
Range	0.93301°	2.49398°
Nugget	0	0.000000614
Parameter	1.91387	2.00000
Partial sill	17,352.29905	0.000061402

3.4 Rainfall variability and standardized rainfall anomalies

Annual rainfall variability was assessed using both percentage rainfall anomalies and the Standardized Rainfall Anomaly Index (SRAI) over the 2000–2025 reference period.

Annual rainfall for each year was calculated as the arithmetic mean of observations from the six meteorological stations used in the study. Percentage rainfall anomalies were calculated as the departure of annual rainfall from the 2000–2025 mean, expressed as a percentage:

$$A_i(\%) = \frac{(P_i - \bar{P})}{\bar{P}} \times 100$$

where A_i is the percentage rainfall anomaly for year i , P_i is annual rainfall in year i , and $\bar{P}$ is the mean annual rainfall over the 2000 – 2025 reference period.

To provide a standardized measure of rainfall variability and facilitate comparison of wet and dry years, the Standardized Rainfall Anomaly Index (SRAI) was subsequently calculated as:

$$SRAI_i = \frac{P_i - \bar{P}}{\sigma}$$

where $SRAI_i$ is the standardized rainfall anomaly for year i , P_i is annual rainfall in year i , $\bar{P}$ is the mean annual rainfall over 2000 – 2025, and σ is the standard deviation of annual rainfall over the same reference period. Positive SRAI values represent wetter-than-average conditions, whereas negative values represent drier-than-average conditions. SRAI values were classified according to predefined standardized anomaly thresholds to distinguish near-normal, moderately dry/wet, very dry/wet, and extremely dry/wet conditions.

The SRAI was used as a descriptive standardization of annual rainfall departures rather than as a substitute for a seasonally fitted drought index. Accordingly, SRAI categories were used to compare relative wetness and dryness among years within the study period, while agricultural interpretation considered the limitations of annual aggregation.

3.5 Land -use and land-cover analysis

Land-use classification was conducted using supervised classification techniques based on multi-temporal satellite imagery (Lillesand and Kiefer 2000; Lambin et al. 2003; Chen et al. 2020). The classification process included image classification into major land-use classes, post-classification refinement, and accuracy assessment. Post-classification filtering using a sieve algorithm was applied to reduce isolated pixel noise and improve spatial coherence.

The LULC classes were defined into eight categories based on spectral characteristics and field-relevant land-use types. A consistent color scheme was applied across all classified maps to ensure comparability (**Table 2**).

Classification accuracy was evaluated for each mapped period using a confusion matrices, overall accuracy, and the Kappa coefficient (Congalton 1991; Foody 2002; Emediegwu et al. 2022; Niu et al. 2023). These diagnostics were also used to qualify the interpretation of subsequent area and transition estimated: changes involving classes with greater classification uncertainty were treated as indicative spatial patterns rather than exact measurements of change.

Land-use change was quantified using:

$$R = \frac{(A_2 - A_1)}{A_1 \times t} \times 100$$

where R is the rate of land-use change (%), A_1 and A_2 are the initial and final land-use areas, and t is the time interval. This method enables the assessment of temporal dynamics of land-use change (Lambin et al., 2003; Verburg et al., 2015).

Training samples were derived using a hybrid approach combining automated extraction from ESA WorldCover (2020) with manual refinement based on expert interpretation of Landsat imagery. This is because the reference product represents a contemporary land-cover condition while the analysis included historical imagery, the resulting historical classifications and inter-class transitions were interpreted cautiously, particularly where spectral confusion among classes were evident.

Table 2. LULC classification scheme and color representation used in the study

Class Code	LULC Class	Color (HEX)	Description
0	Rainfed Cultivation	#FFD700	Areas under rainfed agriculture, primarily seasonal cropping systems
1	Wetland Cultivation	#7CFC00	Agricultural activities occurring within seasonally or permanently moist wetland environments
2	Grassland	#F0E68C	Natural or semi-natural grass-dominated areas
3	Woodland	#006400	Areas dominated by trees and dense natural vegetation
4	Marshes	#00CED1	Permanently or seasonally waterlogged natural wetlands
5	Open Water	#0000FF	Lakes, rivers, and other permanent water bodies
6	Built-up Areas	#FF0000	Urban and settlement areas, including infrastructure
7	Rock Outcrops	#8B4513	Bare surfaces including exposed rock and sparsely vegetated land

3.6 Climate–land use relationship analysis

3.6.1 Ordinary Least Squares (OLS) regression and model diagnostics

To assess the overall relationships between climate variables and LULC change, Ordinary Least Squares (OLS) regression was applied as a global regression model:

269

$$Y_i = \beta_0 + \sum_{k=1}^p \beta_k X_{ik} + \varepsilon_i$$

270 where Y_i is the dependent variable at location i , X_{ik} are the independent variables,
 271 β_0 is the intercept, β_k are the regression coefficients, and ε_i is the error term.

272 The OLS provides a single district-wide coefficient for each explanatory variable
 273 and was used to estimate the average direction and strength of climate–LULC relationships.
 274 Model adequacy was evaluated using R^2 , adjusted R^2 , $AICc$, VIF , and residual diagnostics.
 275 OLS results were used as a global benchmark before examining whether relationships
 276 varied geographically using GWR.

277 The OLS regression was used to quantify the global relationships between climate
 278 variability and LULC change across the 273 spatial grid cells of Mangochi District.
 279 Separate OLS models were estimated for changes in rainfed cultivation, wetland
 280 cultivation, grassland, and woodland between 2000 and 2020, using mean annual rainfall
 281 and mean annual temperature as explanatory variables. The general OLS formulation was:

282

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i$$

283 where Y_i represents the change in the respective LULC class at location i , X_{1i} and
 284 X_{2i} represent mean annual rainfall and temperature, respectively, β_0 is the intercept, β_1 and
 285 β_2 are regression coefficients, and ε_i is the error term.

286 Model performance and reliability were evaluated using R^2 , adjusted R^2 , Akaike
 287 Information Criterion corrected for small sample size ($AICc$), variance inflation factor
 288 (VIF), the Koenker (BP) test, and the Jarque–Bera test. VIF assessed redundancy
 289 predictors. When the Koenker test was significant, robust probability values were used for
 290 coefficient inference because non-stationarity and/or heteroskedasticity can make
 291 conventional standard errors unreliable. The regression coefficients were unstandardized;
 292 consequently, each coefficient represents the expected change in the LULC response per
 293 one-unit increase in the corresponding climate predictor, holding the other predictor
 294 constant, and coefficient magnitudes for rainfall and temperature were not directly
 295 compared because the predictors use different units.

296 Because the 273 observations were spatially distributed grid cells, Global Moran's
 297 I was applied to the OLS residuals using a row-standardized contiguity matrix
 298 (`CONTIGUITY_EDGES_CORNERS`). A significant positive Moran's I was interpreted as
 299 evidence that residuals were spatially clustered and that the assumption of the global model
 300 remained unmet. This diagnostic was used to assess whether a spatially varying model was
 301 warranted; Moran's I itself was not interpreted as identifying the omitted processes
 302 responsible for the clustering. A significance level of $p < 0.05$ was adopted for statistical
 303 inference.

304 3.6.2 Geographically weighted regression and model diagnostics

305 Geographically Weighted Regression (GWR) was employed to investigate spatial
 306 heterogeneity in the relationships between climate variability and LULC change across
 307 Mangochi District. GWR extends the global OLS framework by allowing regression

coefficients to vary spatially, thereby identifying locations where the magnitude and direction of climate–LULC relationships differ across the study area. The analysis used the same 273 grid-cell observations as the OLS models so that global and local results were directly comparable.

For each grid cell i , the GWR model was specified as:

$$y_i = \theta_0(u_i, v_i) + \theta_1(u_i, v_i)X_{1i} + \theta_2(u_i, v_i)X_{2i} + \varepsilon_i$$

where y_i represents the LULC-change variable at location i , X_{1i} and X_{2i} represent mean annual rainfall and mean annual temperature, respectively, (u_i, v_i) denote the spatial coordinates of location i , $\theta_0(u_i, v_i)$ is the local intercept, $\theta_1(u_i, v_i)$ and $\theta_2(u_i, v_i)X_{2i}$ are spatially varying coefficients, and ε_i represents the local error term.

Separate GWR models were estimated for rainfed cultivation, wetland cultivation, grassland, and woodland change. An adaptive spatial neighborhood based on the 31 nearest neighboring observations was used for each local regression. This approach allows the effective spatial scale of the regression to adjust to the distribution of observations while maintaining a consistent number of neighboring observations for each local estimate.

Local rainfall and temperature coefficients were examined with their statistical significance and local R^2 values. Positive and negative coefficients indicate the direction of the local associations, but coefficient sign or magnitude alone was not tested as evidence of a reliable local relationship. This is because GWR estimates many local models, the proportion and spatial coherence of statistically significant locations were considered when interpreting coefficient surfaces, and isolated or non-significant local estimates were treated cautiously.

Residual spatial dependence was subsequently assessed using Global Moran's I applied to the GWR residuals. A contiguity-based spatial weights matrix using the (CONTIGUITY_EDGES_CORNERS) criterion was used to define spatial relationships among neighboring grid cells. This criterion considers cells sharing either an edge or a corner as spatial neighbors. A significant positive Moran's I indicates clustering of similar residual values, suggesting that spatial structure remains unexplained by the model, whereas a non-significant Moran's I indicates that statistically significant residual spatial autocorrelation was not detected.

The median and range of local R^2 , together with Moran's I, associated z-scores, and p -values for GWR residuals were used to assess local model performance and remaining spatial dependence. Local R^2 values near 1 indicate stronger local fit, values near 0 indicate little improvement over a model without climate predictors, and negative values indicate locations where the fitted model performs worse than that baseline. These diagnostics were therefore interpreted jointly rather than using median local R^2 alone.

3.7 GIS-based spatial analysis and mapping

All spatial analyses were conducted using ArcGIS Pro. The GIS workflow included data preparation and georeferencing, spatial interpolation, land-use classification, change detection, overlay analysis, and map production.

Outputs included climate variability maps, rainfall anomaly maps, land-use change maps, and climate–land interaction maps.

3.8 Integration of spatiotemporal analysis

The integration of statistical and spatial techniques enabled the analysis of temporal trends in climate variables, identification of spatial patterns in land-use change, and modelling of localized climate–land interactions. This integrated framework provides a comprehensive understanding of how climate variability influences land-use dynamics in Mangochi District.

These approaches are widely used in recent studies on climate variability and spatial analysis, particularly in Sub-Saharan Africa, where spatial heterogeneity and climate-driven agricultural changes are prominent (Emediegwu et al. 2022; Niu et al. 2023; Ondiek et al. 2024).

4. Results

4.1 Climate variability and trends

Annual rainfall showed pronounced interannual fluctuations over 2000–2025, with alternating relatively wet and dry years (**Fig. 2a**). This pattern demonstrates substantial year-to-year variability but, by itself, does not establish a persistent long-term increase or decrease in rainfall. In contrast, temperature shows a clear, consistent upward trend throughout the study period (**Fig. 2b**). Spatial distribution of mean annual climate variables (**Fig. 3**) shows pronounced spatial heterogeneity in mean annual rainfall and comparatively limited spatial variation in mean annual temperature across Mangochi District during 2000–2025. Mean annual temperature ranged from approximately 22.4°C to 22.4°C, with relatively higher temperatures occurring in the northern and northwestern parts of the district and lower values toward the central and southeastern areas (**Fig. 3a**).

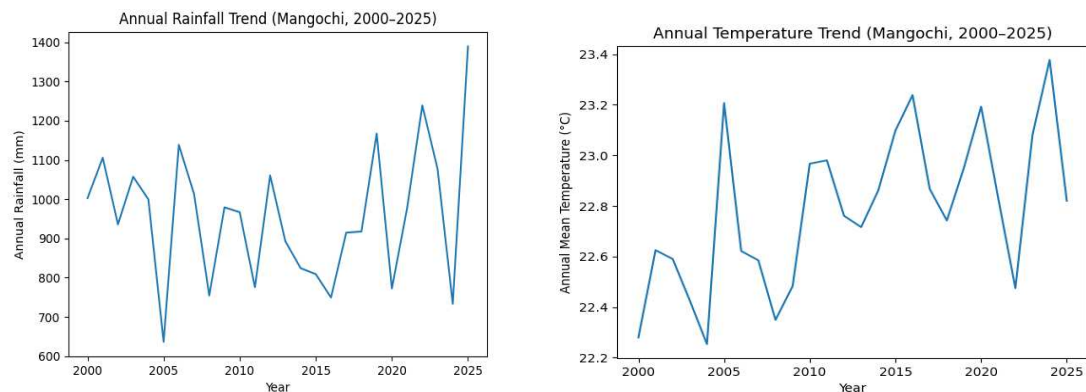


Fig. 2. Annual rainfall variability and mean temperature trends in Mangochi District, Malawi, 2000–2025: **(a)** annual rainfall variability and **(b)** annual mean temperature trends.

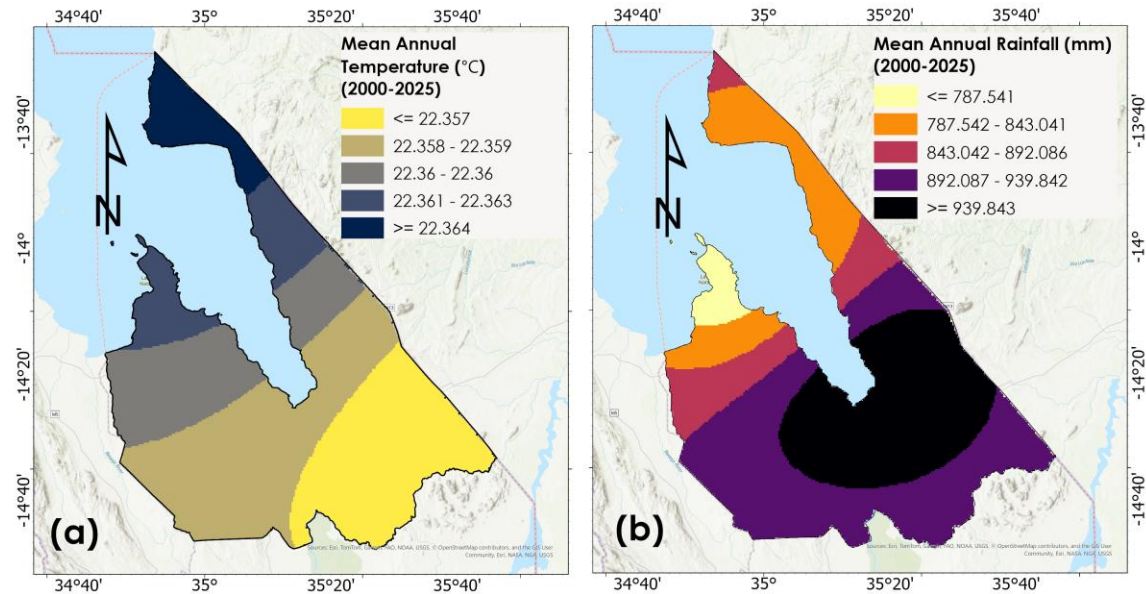


Fig. 3. Spatial distribution of (a) mean annual temperature and (b) mean annual rainfall in Mangochi District, Malawi, for the period 2000–2025.

In contrast, mean annual rainfall displayed a substantially stronger spatial gradient, ranging from approximately 787.5 to 939.8 mm (**Fig. 3b**). The lowest rainfall values were concentrated in the northern and northwestern portions of the district, whereas rainfall generally increased toward the central and southeastern areas. The contrasting spatial patterns indicate that rainfall is substantially more spatially variable than mean annual temperature across the study area, providing an important climatic context for examining spatial differences in land-use dynamics.

4.1.1 Kriging cross-validation results

Cross-validation was used to assess the predictive performance of the ordinary kriging models for mean annual temperature and rainfall. The validation was based on the six observations identified as included in the supplied ArcGIS cross-validation outputs. Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Standardized Error (MSE), and Root Mean Square Standardized Error (RMSSE) were used to assess prediction bias and the magnitude of prediction errors.

Table 3. Cross-validation statistics for the ordinary kriging models

Climate variable	n	ME	MAE	RMSE	Mean standardized error	RMS standardized error
Mean annual temperature	6	0.00024 °C	0.00069 °C	0.00078 °C	0.125	0.775
Mean annual rainfall	6	−4.54 mm	52.98 mm	64.08 mm	0.004	0.832

Note: ME = mean error; MAE = mean absolute error; RMSE = root mean square error; RMS standardized error = root mean square standardized error. Values are calculated from the observations marked as included in the supplied ArcGIS cross-validation results. ME and mean standardized error values close to zero indicate low systematic prediction bias, while RMS standardized error values approaching 1 indicate reasonable agreement between prediction errors and their estimated uncertainties.

Cross-validation of the ordinary kriging models indicated low systematic prediction bias for both climate variables (**Table 3**). The temperature model produced a mean error of 0.00024 °C, with an MAE of 0.00069 °C and RMSE of 0.00078 °C, indicating very small prediction errors. The rainfall model had a mean error of −4.54 mm, suggesting a slight tendency toward underprediction, while its MAE and RMSE were 52.98 and 64.08 mm, respectively. Mean standardized errors were close to zero for both temperature (0.125) and rainfall (0.004), while RMS standardized errors were 0.775 and 0.832, respectively. These results indicate low systematic bias and reasonable agreement between prediction errors and estimated kriging uncertainties, although rainfall predictions exhibited greater error than temperature predictions.

4.1.2 Mann-Kendall test statistics and Sen's Slope estimates

The Mann–Kendall trend test and Sen's slope estimator (**Table 4**) showed contrasting trajectories over 2000–2025. Rainfall had $S = -7$; $Z \approx -0.13$, and a Sen's slope of $-1.2 \text{ mm year}^{-1}$; the trend was not statistically significant, so the small negative slope should not be interpreted evidence of a sustained rainfall decline. Temperature, in contrast, showed a statistically positive trend ($S = 125$; $Z \approx 2.73$), with a Sen's slope of approximately $+0.032 \text{ °C year}^{-1}$.

Table 4. Mann–Kendall test statistics and Sen's slope estimates for annual rainfall and temperature in Mangochi District, Malawi (2000–2025).

Variable	S value	Z value	Sen's slope	Trend direction	Significance
Rainfall	−7	−0.13	−1.2 mm/year	Decreasing	Not significant
Temperature	125	2.73	+0.032 °C/year	Increasing	Significant

These results suggest that while rainfall in Mangochi District is dominated by inter-annual variability without a clear monotonic trend, temperature exhibits a significant warming trend over the study period.

Taken together, the trend and anomaly analyses indicate contrasting forms of climate variability: temperature exhibited a directional and statically detectable warming trend, whereas rainfall was characterized mainly by episodic interannual variability without

a detectable monotonic trend. This distinction is important because substantial rainfall variability can affect land and water use even when the long-term trend is statistically non-significant,

4.1.3 Rainfall anomalies/SRAI

Rainfall anomaly results (**Fig. 4; Table 5**) revealed substantial interannual variability during the 2000–2025 study period. Selected years exhibited both negative and positive departures from the long-term mean, with percentage anomalies ranging from –33.51% in 2005 to +45.13% in 2025. The SRAI further characterized these variations in terms of standardized rainfall severity. 2005 was classified as very dry (SRAI = –1.84), while 2020 was moderately dry (SRAI = –1.06). In contrast, 2025 was classified as extremely wet (SRAI = +2.48). The years 2000 (SRAI = +0.26), 2010 (SRAI = +0.06), and 2015 (SRAI = –0.85) were classified as near-normal conditions, although 2000 and 2010 were slightly wetter than the long-term mean and 2015 was below average. Overall, the results demonstrate pronounced year-to-year fluctuations in rainfall, including episodes of severe dryness and extreme wetness, despite the absence of a statistically significant long-term rainfall trend. This variability indicates that land-use changes during the study period occurred under substantially different moisture conditions, potentially influencing the spatial and temporal dynamics of land-use responses to climate variability.

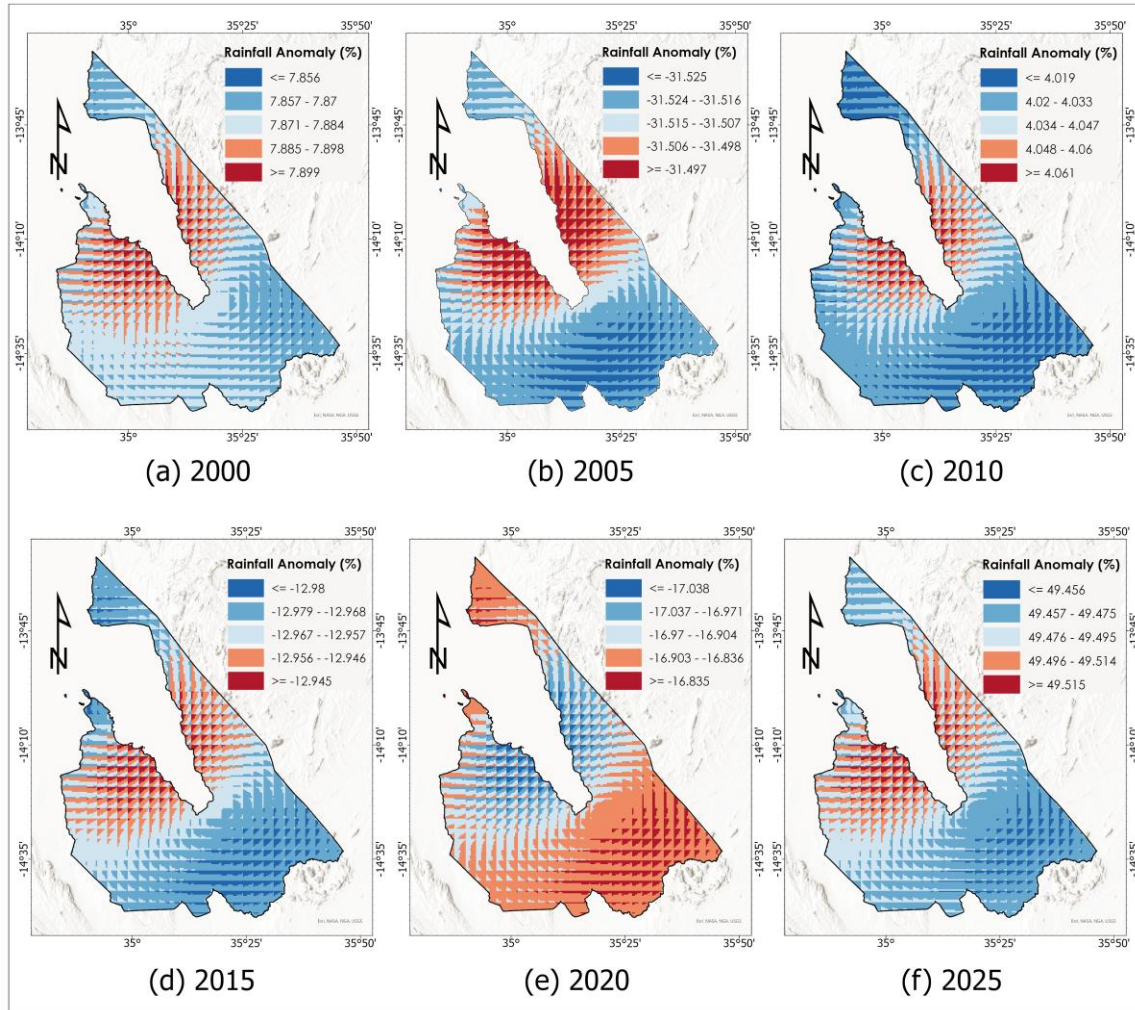


Fig. 4. Spatial distribution of rainfall anomalies in Mangochi District, Malawi, for selected years between 2000 and 2025: (a) 2000, (b) 2005, (c) 2010, (d) 2015, (e) 2020, and (f) 2025.

Table 5. Selected annual rainfall anomalies and standardized rainfall anomaly index (SRAI), 2000–2025

Year	Annual rainfall (mm)	Rainfall anomaly (%)	SRAI	SRAI category	Interpretation
2000	934.17	+4.74	+0.26	Near normal	Slightly wetter than average
2005	593.08	−33.51	−1.84	Very dry	Strongly below average
2010	900.87	+1.00	+0.06	Near normal	Close to average
2015	753.68	−15.50	−0.85	Near normal	Below average, but within normal variability
2020	719.72	−19.31	−1.06	Moderately dry	Moderately below average
2025	1294.45	+45.13	+2.48	Extremely wet	Exceptionally above average

Note: Annual rainfall represents the arithmetic mean of rainfall recorded at the six meteorological stations used in the study. Rainfall anomaly (%) represents the percentage departure of annual rainfall from the 2000–2025 mean. The Standardized Rainfall Anomaly Index (SRAI) was calculated as $SRAI_i = (P_i - \bar{P}) / \sigma$, where P_i is annual rainfall in year i , $\bar{P}$ is the 2000–2025 mean annual rainfall, and σ is the standard deviation of annual rainfall over the reference period. Positive SRAI values indicate wetter-than-average conditions, whereas negative values indicate drier-than-average conditions. SRAI categories (**Appendix 1**) indicate the relative severity of wet and dry conditions.

4.2 Land -use and land-cover classification and temporal changes

4.2.1 Classification accuracy - confusion matrices

Results for the overall classification accuracy and Kappa coefficients for the LULC maps are shown in **Table 6**. Overall accuracy increased from 59.14% in 2000 to 64.20% in 2020, while Kappa increased from 0.513 to 0.557, indicating a modest improvement in classification agreement over the study period.

Overall classification accuracy was 59.14% in 2000, 61.54% in 2010, and 64.20% in 2020, with Kappa coefficients of 0.513, 0.533, and 0.557, respectively. these values indicate moderate, rather than high, classification performance. Water and woodland classes generally exhibited stronger classification performance, whereas built-up areas, marshes, and wetland cultivation showed greater classification uncertainty. Consequently, the LULC results are most defensible for identifying broad landscape patterns; exact class areas and transition magnitudes, particularly for spectrally similar classes, should be interpreted cautiously.

Table 6. Classification accuracy and Kappa coefficients for the LULC maps, 2000–2020

Year	Overall Accuracy	Kappa coefficient
2000	59.14%	0.513
2010	61.54%	0.533
2020	64.20%	0.557

Note: Overall accuracy represents the proportion of correctly classified validation samples, while the Kappa coefficient measures agreement between the classified and reference datasets beyond chance.

The spatial distribution of land-use and land-cover classes in Mangochi District for 2000, 2010, and 2020 illustrated in **Figure 5**, highlight progressive expansion of agricultural land and reduction in natural vegetation.

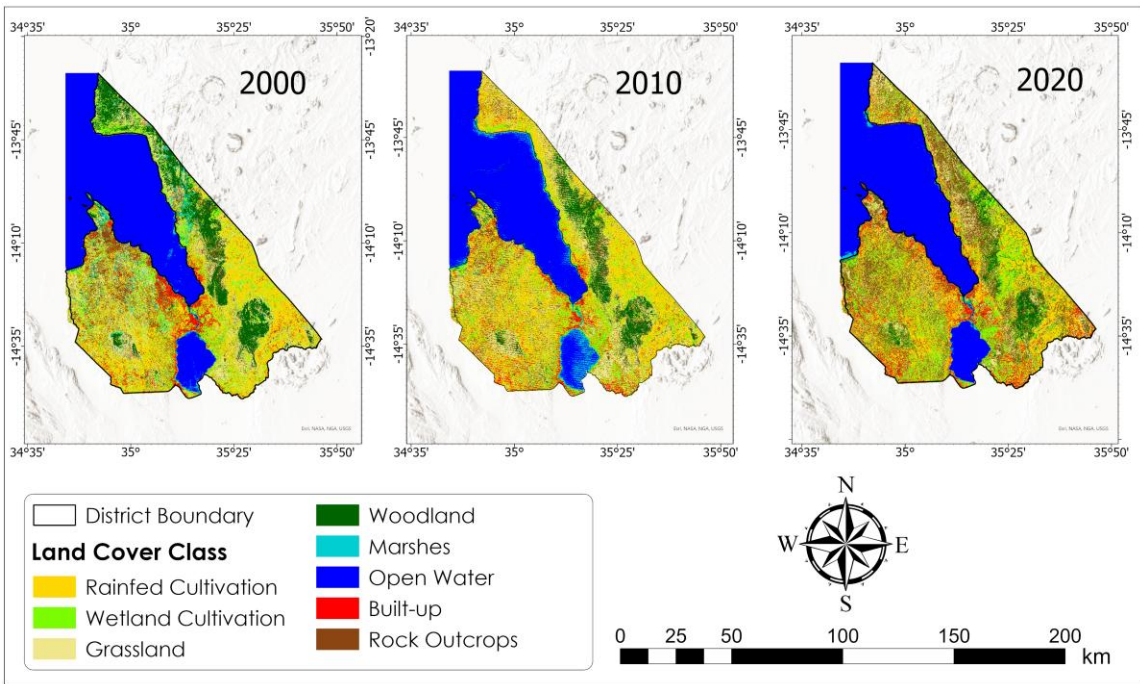


Fig. 5. Spatial distribution of LULC classification maps in Mangochi District for 2000, 2010, and 2020.

The LULC classification for 2020 depicts a heterogeneous landscape of agricultural, natural, water-related, and exposed-surface classes (**Fig. 5**; **Table 7**). The largest mapped classes were rock outcrops (25.12%), wetland cultivation (23.62%), and rainfed cultivation (19.97%), whereas woodland represented 4.60% of the district. Given the moderate overall classification accuracy, these proportions should be treated as mapped estimates rather than exact inventories, particularly for classes susceptible to spectral confusion.

Table 7. LULC area estimates for Mangochi District in 2020 based on supervised classification.

Class Code	LULC Class	Area (km ²)	Percentage (%)
0	Rainfed Cultivation	1,332.71	19.97
1	Wetland Cultivation	1,576.38	23.62
2	Grassland	884.10	13.25
3	Woodland	306.90	4.60
4	Marshes	37.23	0.56
5	Open Water	326.38	4.89
6	Built-up	533.19	7.99
7	Rock Outcrops	1,676.32	25.12
	Total	6,673.20	100.00

Wetland cultivation and marshes were concentrated mainly in low-lying and moisture-available areas. Built-up land represented 7.99% of the 202 classification, while rock outcrops represented 25.12%. The comparatively large mapped extent of rock outcrops, together with its large apparent increase through time, warrants particular caution because confusion with other sparsely vegetated or exposed-surfaces classes could inflate estimated change. The classification results highlight the spatial complexity of land-use systems in Mangochi District and provide a baseline for assessing temporal changes.

4.2.2 Spatiotemporal land-use change (2000–2020)

The mapped LULC comparison between 2000 and 2020 indicates significant transformations across several land-use classes (Table 8). This is because these estimates are derived from classifications with moderate overall accuracy, the magnitude of change is interpreted as approximate, with greatest confidence placed on large and spatially coherent patterns,

The LULC analysis indicates substantial changes in the composition of Mangochi District between 2000 and 2020. Rainfed cultivation decreased from 1,611.44 km² in 2000 to 1,332.71 km² in 2020, representing a net loss of 278.73 km² (17.30%). However, the class increased substantially between 2000 and 2010, reaching 2,118.42 km², before declining by 2020. This temporal fluctuation indicates that rainfed cultivation did not follow a simple linear trend and may reflect changing environmental and socioeconomic conditions during the study period.

Wetland cultivation expanded from 1,174.19 km² in 2000 to 1,576.38 km² in 2020, a mapped increase of 402.19 km² (34.25%). This pattern is consistent with increasing use of wetter or low-lying land for cultivation, but the remote-sensing analysis alone cannot determine whether the expansion represents an intentional farmer adaptation to rainfall variability. That interpretation therefore remains a plausible mechanism to be evaluated with household, irrigation, and soil-moisture data.

Table 8. LULC area changes in Mangochi District between 2000 and 2020, arranged according to the LULC classification scheme

Class Code	LULC Class	2000 (km ²)	2010 (km ²)	2020 (km ²)	Change 2000–2020 (km ²)	% Change
0	Rainfed Cultivation	1,611.44	2,118.42	1,332.71	–278.73	–17.30%
1	Wetland Cultivation	1,174.19	1,155.86	1,576.38	+402.19	+34.25%
2	Grassland	1,324.42	1,329.25	884.10	–440.33	–33.25%
3	Woodland	890.19	560.70	306.90	–583.29	–65.52%
4	Marshes	227.00	154.79	37.23	–189.77	–83.60%
5	Open Water	307.54	203.26	326.38	+18.85	+6.13%
6	Built-up Areas	325.85	363.23	533.19	+207.33	+63.63%
7	Rock Outcrops	812.57	779.12	1,676.32	+863.75	+106.30%

Grasslands experienced a substantial decline, decreasing from 1,324.42 km² in 2000 to 884.10 km² in 2020, corresponding to a loss of 440.33 km² (33.25%). This reduction indicates considerable transformation of grassland areas during the study period and may reflect conversion to cultivation or other land uses.

The most pronounced decline among the natural vegetation classes occurred in woodlands, which decreased from 890.19 km² to 306.90 km², representing a loss of 583.29 km² (65.52%). This substantial reduction suggests considerable pressure on woodland resources and widespread transformation of wooded areas during the study period. Marshes also declined markedly, from 227.00 km² in 2000 to 37.23 km² in 2020, representing a reduction of 189.77 km² (83.60%). The substantial decline in both woodland and marsh areas indicate a broader contraction of important natural ecosystems.

In contrast, built-up areas increased considerably, from 325.85 km² in 2000 to 533.19 km² in 2020, representing a 207.33 km² (63.63%) increase. Rock outcrops showed the largest absolute increase, increasing from 812.57 km² to 1,676.32 km², equivalent to an increase of 863.75 km² (106.30%). The substantial increase in mapped rock outcrop area should, however, be interpreted cautiously because it may partly reflect differences in classification performance and spectral confusion between land-cover classes. This is particularly relevant given the moderate classification accuracies reported for the LULC maps.

Open water remained comparatively stable, increasing from 307.54 km² in 2000 to 326.38 km² in 2020, representing a modest net increase of 18.85 km² (6.13%).

Overall, the results indicate a marked transformation of natural and agricultural landscapes between 2000 and 2020, characterized in particular by substantial declines in woodland, marshes, and grassland, alongside increases in wetland cultivation and built-up areas. Rainfed cultivation exhibited considerable temporal variability, increasing strongly between 2000 and 2010 before declining by 2020. These changes may reflect increasing pressure and transformation of natural land resources, while the expansion of wetland cultivation may represent an important land-use response to changing environmental and climatic conditions. The observed patterns provide an important basis for subsequently examining whether spatial variations in climate variables are associated with differences in LULC change across the 11 EPAs.

4.3 Land-use land transition dynamics

The LULC transition analysis revealed substantial persistence of existing land-use/land-cover classes alongside extensive inter-class conversions across Mangochi District (**Fig. 6; Table 9**). During 2000–2010, rainfed cultivation showed the largest persistence, with 859.10 km² remaining in the same class. Nevertheless, substantial transitions occurred between cultivated and natural land-cover classes. Rainfed cultivation transitioned to wetland cultivation (305.84 km²) and grassland (213.38 km²), while grassland transitioned to rainfed cultivation (355.37 km²) and woodland (203.22 km²). Woodland also showed considerable persistence (364.96 km²) but experienced transitions to grassland (203.22 km²) and rainfed cultivation (114.08 km²). These patterns indicate considerable reorganization of agricultural and natural land-cover classes during the first decade.

During 2010–2020, the transition dynamics became more pronounced for several agricultural and natural vegetation classes. Rainfed cultivation remained relatively persistent (784.62 km²), but substantial areas transitioned to wetland cultivation (481.61 km²), grassland (260.45 km²), and rock outcrops (398.70 km²). Grassland exhibited considerable transitions to wetland cultivation (370.90 km²) and rock outcrops (488.52 km²), while its persistence declined to 253.05 km². Woodland persistence also declined to 164.22 km², accompanied by transitions to rock outcrops (203.36 km²), wetland cultivation (96.59 km²), and grassland (77.48 km²). These patterns indicate increasing turnover among cultivated land, grassland, woodland, and rock-outcrop classes during the latter period.

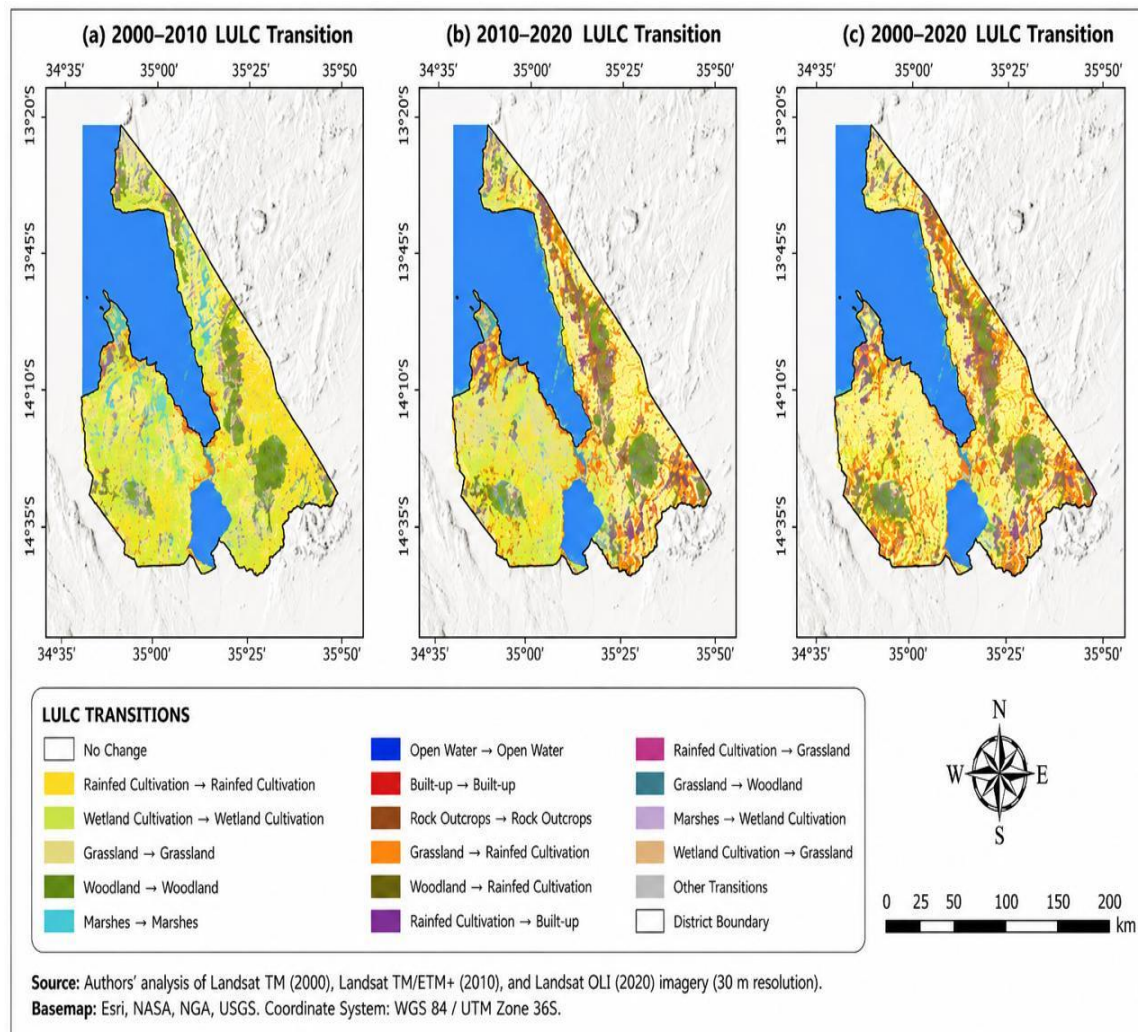


Fig. 6. Spatial patterns of land-use/land-cover (LULC) transitions in Mangochi District, Malawi: (a) 2000–2010, (b) 2010–2020, and (c) cumulative 2000–2020 transitions. Transitions represent changes from the initial to the final LULC class within each analysis period. Persistent areas indicate locations where the LULC class remained unchanged.

Over the full 2000–2020 period, the transition matrix indicates substantial LULC transformation while also showing persistence within several classes (**Table 9**). Rainfed cultivation persisted across 640.25 km², while 388.79 km² transitioned to wetland cultivation, 153.09 km² to grassland, and 288.23 km² to rock outcrops. Wetland cultivation showed 368.27 km² of persistence and substantial transitions to rainfed cultivation (259.94 km²), grassland (153.65 km²), and rock outcrops (254.90 km²). Grassland exhibited 243.03 km² of persistence, with substantial transitions to wetland cultivation (387.78 km²), rock outcrops (422.89 km²), and rainfed cultivation (168.46 km²). Woodland persistence was 198.34 km², while 168.72 km² transitioned to wetland cultivation, 160.56 km² to grassland, and 307.50 km² to rock outcrops.

Table 9. Land-use/land-cover (LULC) transition matrix for Mangochi District, Malawi, 2000–2020: Transition area (km^2)

Initial LULC class ↓ / Final LULC class →	Rainfed Cultivati on	Wetland Cultivati on	Grassla nd	Woodla nd	Marsh es	Ope n Wate r	Built -up Area s	Rock Outcro ps
Rainfed Cultivati on	640.25	388.79	153.09	5.71	0.48	0.13	162.18	288.23
Wetland Cultivati on	259.94	368.27	153.65	20.90	4.98	0.39	128.04	254.90
Grasslan d	168.46	387.78	243.03	42.93	2.18	0.08	77.26	422.89
Woodlan d	30.96	168.72	160.56	198.34	8.80	0.51	19.88	307.50
Marshes	9.88	38.29	42.21	14.78	13.78	22.22	6.88	81.30
Open Water	0.02	0.14	0.08	0.32	4.25	293.74	0.09	0.10
Built-up Areas	108.66	43.10	22.30	0.87	0.30	0.07	93.31	62.49
Rock Outcrops	130.56	198.67	121.91	24.65	1.88	0.24	58.22	283.60

Note: Values represent transition areas in km^2 derived from pixel-level comparison of the classified 2000 and 2020 LULC rasters using the supplied Mangochi District boundary as the spatial mask. Diagonal values represent LULC persistence, whereas off-diagonal values represent transitions between classes. Lake Malawi pixels outside the district boundary were excluded.

Overall, the transition analysis demonstrates that LULC change in Mangochi District was characterized by both class persistence and substantial bidirectional conversion, particularly among rainfed cultivation, wetland cultivation, grassland, woodland, and rock outcrops. The transition patterns also indicate that land-use transformation was spatially heterogeneous rather than uniformly distributed across the district (Figure 5). These findings provide a spatial basis for subsequently examining whether climate variability was associated with differences in LULC change across the district using the OLS and GWR models.

4.4 Climate–land use relationships

The combined climate and LULC results indicate that land-use dynamics in Mangochi District occurred under conditions of significant warming and pronounced interannual rainfall variability. Temperature exhibited a significant increasing trend over the study period, whereas rainfall showed substantial year-to-year variability without a significant long-term trend. Over the same period, major changes occurred among agricultural and natural land-cover classes, including changes in rainfed and wetland cultivation and declines in grassland and woodland.

The contrasting trajectories of rainfed and wetland cultivation suggest spatial and temporal differences in agricultural land-use responses under varying moisture conditions. However, these descriptive patterns alone do not establish the strength or direction of climate–LULC relationships. Therefore, the relationships between mean annual rainfall, mean annual temperature, and LULC change were subsequently evaluated using OLS and GWR. The OLS provided a global assessment of the relationships, while GWR was used to identify spatial variation in the magnitude and direction of these relationships across the district.

4.4.1 Ordinary least squares regression results

The OLS regression identified statistically significant climate associations for several LULC responses, but the models explained only a modest proportion of spatial variation overall (**Table 10**). The results therefore quantify partial associations with rainfall and temperature rather than comprehensive explanations of land-use change.

The rainfed-cultivation model had the highest explanatory power ($R^2 = 0.261$; adjusted $R^2 = 0.255$), with significant positive and negative associations with mean temperature ($\beta = 2.7343$, $p < 0.001$) and mean rainfall ($\beta = -0.0171$, $p < 0.001$), respectively. Wetland cultivation was negatively associated with temperature ($\beta = -2.1890$, $p < 0.001$), whereas rainfall was not. Grassland change showed a significant positive association with temperature ($\beta = 1.8193$, $p < 0.001$), whereas rainfall showed no significant association. Woodland change was positively associated with rainfall ($\beta = 0.0235$, $p < 0.001$), whereas the relationship with temperature was not statistically significant ($p = 0.070$). *VIF* values of approximately 1.06 across all models indicated no evidence of multicollinearity between the climate predictors.

Table 10. Global Ordinary Least Squares (OLS) regression results for climate–LULC relationships in Mangochi District

LULC change	Predictor	Coefficient (β)	Robust p-value	VIF	R ²	Adj. R ²	Overall model p-value	Koenker BP p-value	AICc
Rainfed cultivation	Rainfall	−0.0171	<0.001	1.065	0.261	0.255	<0.001	0.0038	1332.96
	Temperature	+2.7343	<0.001	1.065					
Wetland cultivation	Rainfall	+0.0041	0.107	1.065	0.122	0.116	<0.001	0.935	1289.84
	Temperature	−2.1890	<0.001	1.065					
Grassland	Rainfall	−0.0010	0.705	1.065	0.072	0.065	<0.001	0.0051	1309.78
	Temperature	+1.8193	<0.001	1.065					
Woodland	Rainfall	+0.0235	<0.001	1.065	0.133	0.126	<0.001	<0.001	1494.81
	Temperature	−0.6732	0.070	1.065					

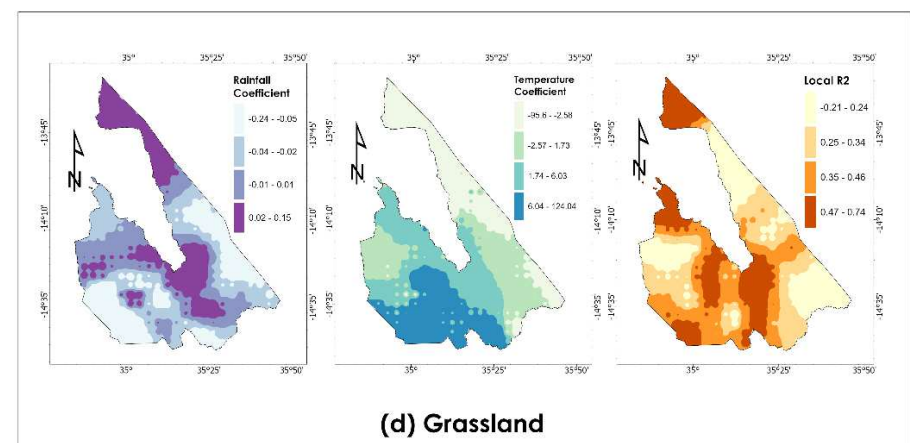
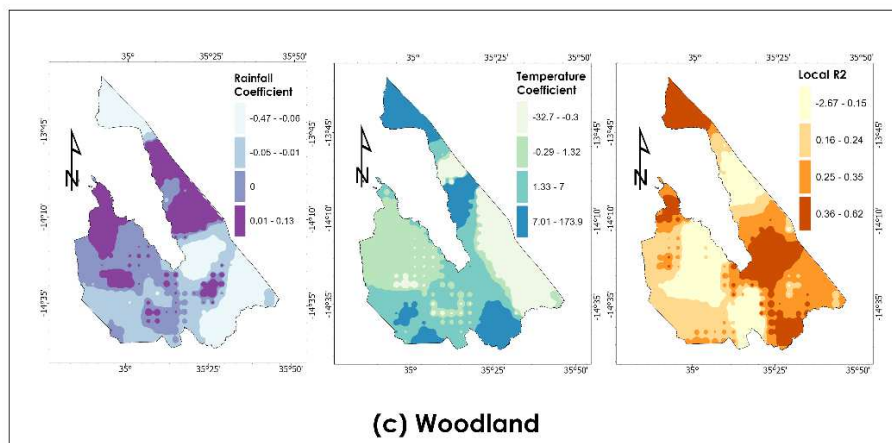
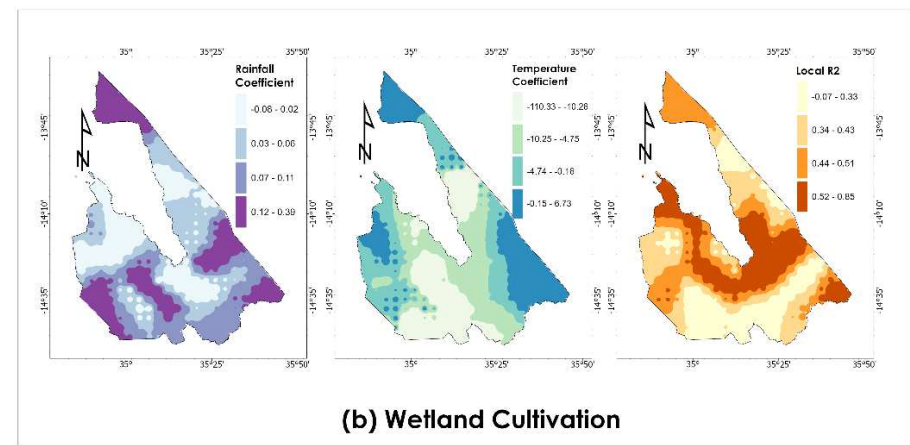
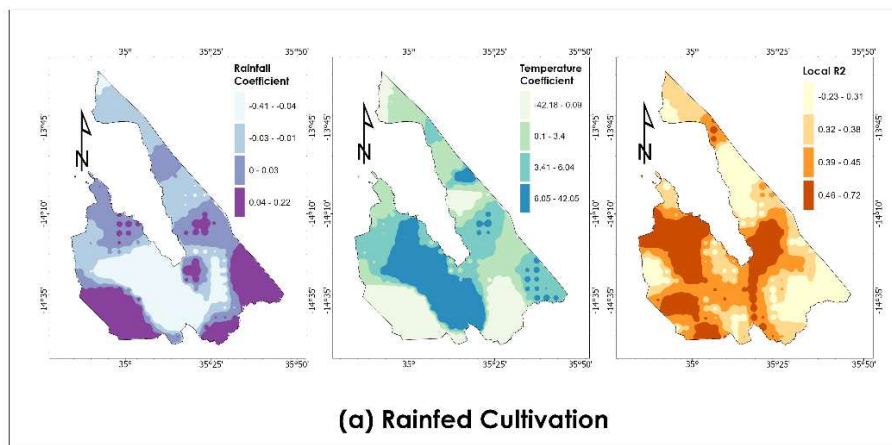
Note: $n = 273$ spatial grid cells. Because the Koenker (BP) test was significant for Rainfed cultivation, Grassland, and Woodland, the robust probabilities are used to assess individual coefficient significance for those models. For Wetland cultivation, the Koenker test was not significant, so the conventional probabilities are appropriate. VIF values were 1.065 for both explanatory variables in all models, indicating no problematic multicollinearity.

Across the OLS models, statistical significance was interpreted alongside effect direction, model fit, and diagnostics. The rainfed-cultivation model had the strongest fit ($R^2 = 0.261$), but approximately 73.9% of its spatial variation remained unexplained by rainfall and temperature; the other models had even lower R^2 values. Thus, small p-values indicate evidence that a coefficient differs from zero under the fitted model, not that the predictor explains a large share of LULC change. The significant Koenker tests and Moran's I results further show that global coefficient estimates should be interpreted cautiously because heteroskedasticity/non-stationarity and residual spatial dependence remain present.

4.4.2 Geographically weighted regression results

The GWR estimates showed marked spatial variation in the direction and magnitude of climate-LULC coefficients across Mangochi District (**Fig. 7; Table 11**). However, statistically significant local relationships occurred only about 16-30% of the 272 grid cells, depending on the predictor and LULC class. The coefficient surfaces therefore demonstrate spatial heterogeneity in estimated relationships, but they should not be interpreted as evidence that rainfall or temperature exerted a strong or statistical reliable influence at every location.

For rainfed cultivation, rainfall coefficients ranged from -0.434 to $+0.222$, with a median coefficient of -0.006 , with statistically significant rainfall association at 56 of the 273 locations (20.5%). Temperature coefficients showed considerably greater spatial variation, ranging from -43.039 to $+43.222$, with a median of $+2.973$. Temperature was significant at 83 locations (30.4%), representing the highest proportion of significant temperature relationships among the four LULC models. The median local R^2 was 0.367, indicating that local fit was stronger in some areas than suggested by the global OLS model, but the limited share of significant location cautions against generalizing the positive median temperature association to the entire district.



725
726 **Fig. 7.** Spatial variation in GWR results for climate–LULC relationships in Mangochi District, Malawi. Local R^2 and spatially varying
727 regression coefficients for rainfall and temperature are presented for (1) rainfed cultivation, (2) wetland cultivation, (3) grassland, and
728 (4) woodland change. Panels a, b, and c show local R^2 , rainfall coefficients, and temperature coefficients, respectively. Positive
729 coefficients (red) indicate positive relationships, while negative coefficients (blue) indicate negative relationships.

730 **Table 11.** Summary of GWR results for climate–LULC relationships

LULC change	Predictor	Local coefficient range	Median coefficient	Significant locations, n (%)	Median local (R^2)
Rainfed cultivation	Rainfall	−0.434 to +0.222	−0.006	56 (20.5%)	0.367
	Temperature	−43.039 to +43.222	+2.973	83 (30.4%)	
Wetland cultivation	Rainfall	−0.086 to +0.389	+0.057	74 (27.1%)	0.444
	Temperature	−112.499 to +7.447	−4.011	55 (20.1%)	
Grassland	Rainfall	−0.246 to +0.150	−0.018	47 (17.2%)	0.335
	Temperature	−95.606 to +124.037	+1.349	44 (16.1%)	
Woodland	Rainfall	−0.481 to +0.131	−0.004	44 (16.1%)	0.269
	Temperature	−32.706 to +173.902	+0.730	45 (16.5%)	

731 *Note:* Significant locations are those identified by the GWR significance indicator in the output.
732 Local coefficient ranges represent the minimum and maximum coefficients across the 273 grid-cell
733 locations. The GWR models used 31 nearest neighbors for each local regression.

734 Wetland cultivation had the highest median local R^2 (0.444), but fit ans coefficient
735 direction varied considerably across space. Rainfall coefficients ranged from −0.086 to
736 +0.389 (median + 0.057), with significant rainfall relationships at 74 locations (27.1%).
737 Temperature coefficients ranged from −112.499 to +7.447 (median −4.011) and were
738 significant at 55 locations (20.1%). Thus, the negative median temperature coefficient
739 describes the center of the local coefficient distribution, not a district-wide negative effect;
740 statistically reliable temperature relationships were confined to a minority of locations.

741 For grassland, rainfall coefficients ranged from −0.246 to +0.150 (median −0.018),
742 with significant associations at 47 locations (17.2%). Temperature coefficients ranged from
743 −95.606 to +124.037 (median +1.349) and were significant at 44 locations (16.1%). The
744 median local R^2 was 0.335. The broad coefficient ranges, together with relatively few
745 significant locations, indicate heterogeneous and locally uncertain climate-grassland
746 relationships rather than a uniform response across the district.

747 The woodland model had the lowest median local R^2 (0.269). Rainfall coefficients
748 ranged from −0.481 to +0.131 (median −0.004), with significant rainfall associations at 44
749 locations (16.1%). Temperature coefficients ranged from −32.706 to +173.902 (median
750 +0.730) with significant associations at 45 locations (16.5%). The extreme local
751 coefficients are especially sensitive to location and should be interpreted cautiously rather
752 than as stable local effect sizes.

Overall, GWR showed that a single district-wide coefficient can mask spatial variation in climate-LULC associations. Nevertheless, spatial variability in coefficient estimates is not synonymous with explanatory importance: most grid cells did not show statistically significant local coefficients, and model fit varied substantially. The GWR results are therefore strongest as evidence of spatial non-uniformity and as a guide to locations requiring further investigations, rather than a proof of climate-driven land-use change throughout Mangochi District.

4.5 Spatial diagnostics of the regression models

Spatial diagnostics were conducted to assess whether the regression models adequately accounted for the spatial structure of the climate–LULC relationships across Mangochi District. Because spatial dependence in model residuals can indicate that important spatially structured variation remains unexplained, residual spatial autocorrelation was evaluated following the OLS and GWR analyses. Global Moran's I was used to determine whether model residuals were significantly clustered or spatially dispersed across the study area. The results of the residual spatial autocorrelation analysis are presented in the following subsection.

4.5.1 Moran's I residual spatial autocorrelation

Table 12. Spatial autocorrelation of OLS residuals for climate–LULC models

LULC change	R ²	Adj. R ²	Koenker BP p	Moran's I	Moran's I p
Rainfed cultivation	0.261	0.255	0.0038	0.5508	<0.001
Wetland cultivation	0.122	0.116	0.935	0.4276	<0.001
Grassland	0.072	0.065	0.0051	0.4637	<0.001
Woodland	0.133	0.126	<0.001	0.6639	<0.001

The OLS residuals showed significant positive spatial autocorrelation across all four LULC models (Moran's I = 0.428–0.664; $p < 0.001$; **Table 12.**) This indicates that residuals were spatially clustered rather than independent, with the strongest clustering for woodland change. The result is an important model-specification warning: rainfall and temperature did not capture all spatially structured variation, so coefficient interference from the global models must be interpreted together with the robust probabilities and spatial diagnostics.

The OLS models produced class-specific climate associations, but explanatory power remained modest: R² was 0.261 for rainfed-cultivations, 0.133 for woodland, 0.122 for wetland cultivation, and 0.072 for grassland. Signification Koenker BP statistics for

rainfed cultivations, grassland, and woodland further indicated heteroskedasticity and/or non-stationarity. Accordingly, statically significant coefficients should not be equated with high explanatory importance, and the combination of low-to-moderate R^2 and residual spatial autocorrections provided a clear rationale for examining geographically varying relationships.

Furthermore, Moran's I tests indicated significant positive spatial autocorrelation in the residuals of all four models ($p < 0.001$), demonstrating that substantial spatial structure remained unexplained by the global OLS specifications.

4.5.2 Geographically weighted regression model diagnostics

Table 13. GWR model performance and residual spatial diagnostics

LULC change	Median local R^2	Local R^2 range	Moran's I	z-score	p-value
Rainfed cultivation	0.367	-0.254–0.722	0.0859	2.699	0.00695
Wetland cultivation	0.444	-0.095–0.865	0.1492	4.606	<0.001
Grassland	0.335	-0.217–0.737	-0.0124	-0.262	0.793
Woodland	0.269	-2.681–0.618	0.0853	2.698	0.00698

GWR local fit varied widely among and within the four LULC-change responses (**Table 13**). Median local R^2 was 0.444 for wetland cultivation, 0.367 for rainfed cultivation, 0.335 for grassland, and 0.269 for woodland. Importantly, local R^2 values were negative at some locations, including a minimum of -2.681 for woodland. These negative values indicate locations where the local model performed worse than a baseline without the climate predictors; they should therefore be interpreted as evidence of poor local specification rather than as 'negative explained variance'. The medians consequently mask areas in which the local models had little to no explanatory value.

Residual spatial diagnostics showed GWR reduced, but did not eliminate, spatial dependence for most responses. Significant positive residual spatial autocorrelation remained for rainfed cultivation (Moran's $I=0.0859$, $z=2.699$, $p=0.00695$), wetland cultivation ($I=0.1492$, $z=4.606$, $p<0.001$), and woodland ($I=0.0853$, $z=2.698$, $p=0.00698$). The persistence of clustered residuals despite improved local fit indicated that spatially structured drivers beyond rainfall and temperature remain unmodelled.

Grassland was the exception: its GWR residuals were not significantly spatially autocorrelated ($I=-0.0124$, $z=-0.262$, $p=0.793$), suggesting that the local specification captured the dominant spatial structure evident in the residuals. For the other three LULC responses, however, significant residual clustering means that the GWR should be viewed as an improvement over global OLS rather than a fully specified explanation of land-use change.

5. Discussion

This study demonstrates that LULC transformations in Mangochi District occurred within a climatic context of statistically significant warming and pronounced interannual rainfall

variability. The Sen's slope of approximately $0.032\text{ }^{\circ}\text{C year}^{-1}$ implied a substantial warming signal over the 2000-2025 period, while rainfall showed no statistically detectable monotonic trend. At the same time, standardized rainfall anomalies identified very dry, moderately dry, and extremely wet years. The key interpretation is therefore not that rainfall was stable, but that rainfall variability was episodic rather than directional monotonic. This distinction is important in a district where rainfed agriculture is highly sensitive to the timing and reliability of moisture availability (Ngongondo et al. 2011; Koseki and Mooney 2019; Emediegwu et al. 2022; Kavwenje et al. 2024).

The LULC results demonstrate substantial transformation of both agricultural and natural land systems between 2000 and 2020. These contrasting trajectories indicate that landscape change was characterized by substantial redistribution among LULC classes rather than simply a uniform expansion of agriculture. Similar LULC transformations have been documented in Malawi, where agricultural expansion, settlement growth, and changes in natural vegetation have interacted with environmental and socioeconomic pressures (Manda et al. 2023; Mungai et al. 2025).

The transition analysis reinforces the interpretation of a dynamic agricultural-natural land-use interface than a simple, one-directional expansion of cropland. The movement between rainfed cultivation wetland cultivation, grassland, woodland, and exposed-surface classes suggests repeated redistribution of land uses through time. Expansion of wetland cultivation is consistent with the possibility that areas offering more reliable moisture become increasingly important under variable rainfall conditions (Nalivata et al. 2017). However, the analysis cannot establish farmer motivation, and the adaptation interpretation should therefore remain a hypothesis rather than a demonstrated behavioral response.

The OLS results further show why statistical significance and explanatory importance must be distinguished. The rainfed-cultivation model had the highest R^2 (0.261), meaning that rainfall and temperature together accounted for only about one quarter of the observed spatial variation. The remaining LULC models explained still less. Significant coefficients therefore identify partial associations after controlling for other climate predictor, they do not imply that climate was the dominant driver of land-use change. The contrasting signs for rainfed and wetland cultivation are nevertheless consistent with the expectation that agricultural systems respond differently to moisture availability and heat exposure (Emediegwu et al. 2022; Kavwenje et al. 2024).

The pronounced mapped declines in grassland, woodland, and marshes point to substantial pressure on natural land systems, but the regression results indicate that climate variables alone provided only a limited explanation. For grassland, the OLS model explained 7.2% of spatial variation, for woodland, it explained, 13.3%. This weak-to-modest explanatory power, together with significant spatially clustered residuals, is more consistent with a multi-driven process in which climate interacts with agricultural demand, population pressure, accessibility, settlement expansion, topography, and the other land-use determinants (Mungai et al. 2025). Climate should therefore be treated as one component of landscape change rather than the sole determinant.

GWR adds an important spatial qualification to the global results, but it also limits how strongly the climate relationships can be generalized. Local coefficients varied widely in sign and magnitude, while statistically significant associations were restricted to a minority of grid cells. In addition, some local R^2 values were negative, especially for

woodland, indicating locations where the climate-only local model performed poorly. These findings support the use of spatially explicit modeling because average OLS coefficients conceal geographic variation, but they also show that GWR does not by itself establish local casual effects. Differences in water access, soils, topography, settlement patterns, accessibility, and agricultural practices remain plausible explanations for the observed spatial heterogeneity (Verburg et al. 2015; Mungai et al. 2025; Yeboah et al. 2025).

The residual diagnostics are central to the interpretations. GWR removed statistically significant residual spatial autocorrelation only for grassland; clustered residuals remained for rainfed cultivation, wetland cultivation, and woodland. The wetland model is particularly instructive: it had the highest median local R^2 but also retained the strongest residual autocorrelation. Higher local fit therefore did not mean that the model had captured the full spatial process. The remaining clustering strongly suggests omitted spatially structured variables, including socioeconomic conditions, topography, market and road access, population pressure, water availability, and land-management practices (Mungai et al., 2025).

The policy implications should consequently be framed around risk management rather than assumed farmer responses. The observed expansion of wetland cultivation may indicate increasing dependence on moisture-retaining landscapes, but this study does not demonstrate that farmers deliberately shifted cultivation as an adaptation strategy. Even so, the pattern raises an important planning concern: greater agricultural use of wetlands can improve short-term access to moisture while increasing pressure on hydrological and ecological functions. Adaptation policy should therefore prioritize climate-resilient productivity on existing agricultural lands, protection and sustainable management of wetland and natural vegetation, and locally differentiated planning informed by climate, water, ecological, and socioeconomic conditions (Verburg et al. 2015; Yeboah et al. 2025).

Several limitations materially affect interpretation. First, climate predictors were mean annual rainfall and mean annual temperature; they do not represent rainfall onset and cessation, dry-spell duration, seasonal distribution, extreme rainfall, heat extremes, or growing-season moisture conditions that may be more directly relevant to agricultural decisions. Second, the kiring surfaces were cross-validated with only six station observations, so the very small temperature errors and the rainfall error statistics should be interpreted as internal cross-validation of a sparse network rather than proof of fine-scale predictive accuracy. Third, LULC overall accuracy was moderate (59.14%-64.20%), creating uncertainty in class areas and transition estimates, particularly for spectrally similar classes and the unusually large mapped change in rock outcrops. Fourth, the use of a 2020 global reference product within a multi-temporal classification introduces potential temporal-transfer uncertainty for historical maps. Fifth, the climate series extends to 2025 whereas the LULC change analysis ends in 2020; the longer climate series strengthens climatic characterization but should not be interpreted as contemporaneous land-use evidence after 2020. Finally, the regression models are ecological, spatially aggregated analyses and omit several plausible drivers; significant coefficients therefore represent conditional associations, not causal effects at household or farm level.

Despite these limitations, the integration of climate trends, standardized rainfall anomalies, LULC change, transition analysis, OLS, GWR and residual spatial diagnostics provides a useful multi-method framework for examining climate–land-use relationships in Mangochi District. The strongest conclusion is not that climate variability independently caused the observed LULC transformations, but that land-use change occurred in a warming and rainfall-variable environment and that the statistical associations with climate were class-specific, spatially heterogeneous, and incomplete. Further work should combine seasonal and extreme-climate indicators with socioeconomic, hydrological, topographic, soil, accessibility, and land-management data, supported by stronger historical reference data and field validation, to identify the mechanisms underlying LULC change and to improve targeting of climate-adaptation and sustainable land-management interventions in Mangochi District.

6. Conclusion

This study demonstrates that substantial LULC transformation in Mangochi District occurred alongside a statistically significant warming trend and pronounced interannual rainfall variability. Temperature showed a significant upward trend, while rainfall remained highly variable with no significant long-term monotonic trend. Over the 2000–2020 period, rainfed cultivation declined, whereas wetland cultivation expanded, alongside marked reductions in grassland and woodland. As classification accuracy was moderate, these LULC estimates are best interpreted as broad patterns rather than exact measurements of change.

OLS and GWR analyses demonstrated that class-specific and spatially heterogeneous association between climate variables and LULC change, but overall explanatory power was modest and significant residual autocorrection remained for several models. The findings therefore support climate variability as one relevant component of land-use dynamics while also demonstrating that additional environmental and socioeconomic drivers are needed to explain the observed spatial patterns.

To this end, the study supports the use of integrated climate and spatial LULC analysis for adaptation planning, while emphasizing the need for cautious casual interpretation, improved historical classification accuracy, and locally differentiated land-management responses. The results are important for identifying areas and relationships that warrant targeted field investigation and for informing climate-resilient agricultural planning, wetland protection, and conservation of natural vegetation in Mangochi District and other climate-vulnerable regions of Malawi. This evidence can support climate adaptation planning, sustainable agricultural land management, and protection of wetlands, grasslands, and woodlands.

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Data availability The data supporting the findings of this study were derived from meteorological records, publicly available climate datasets, satellite imagery, and geospatial data. Derived data supporting the results are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate Not applicable. This study did not involve human participants or animals and was based on climatic, remotely sensed, and geospatial data.

Consent for publication Not applicable.

Conflict of interest The authors declare that they have no competing interests

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1040 Appendix

1041 Appendix 1: SRAI classification

SRAI Category	
$\geq +2.00$	Extremely wet
+1.50 to +1.99	Very wet
+1.00 to +1.49	Moderately wet
−0.99 to +0.99	Near normal
−1.00 to −1.49	Moderately dry
−1.50 to −1.99	Very dry
≤ -2.00	Extremely dry