

SPATIOTEMPORAL PATTERNS AND ASSOCIATIVE STRUCTURE BETWEEN NDVI AND BARE SOIL IN KENYAN COUNTIES (2024–2025)

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ABSTRACT: Environmental planning requires a systemic reading of territories where vegetation vigor and exposed soil are treated as complementary indicators of ecological condition and land vulnerability, since approaches based on isolated variables limit both interpretation and action. Guided by this perspective, we evaluated statistical and spatial patterns in vegetation vigor and exposed soil across Kenya's 47 counties for 2024 and 2025 using Moderate Resolution Imaging Spectroradiometer (MODIS) composites processed in Google Earth Engine. Normalized Difference Vegetation Index (NDVI) from MOD13Q1 and a Bare Soil Index from MCD43A4 were summarized as county means, then examined using Bayesian paired t tests, Bayesian correlations, Bayesian model averaging, random forest clustering, Local Moran's I, and Besag-York-Mollié 2 model (BYM2) spatial models fitted with INLA. Results show a modest decline in mean NDVI from 0.568 in 2024 to 0.542 in 2025, alongside a shift in mean BSI from -0.023 to -0.007, with Bayes factor evidence for change in both indicators. County rankings were persistent over time for NDVI and BSI, while cross indicator associations were strongly negative, indicating consistent opposition between vegetation cover and soil exposure. Clustering identified three environmental regimes, with a dominant regime characterized by low NDVI and higher exposed soil. Local indicators revealed contiguous clusters of change for both indices, and BYM2 estimates indicated that most latent variance was spatially structured (ϕ about 0.88 to 0.90). The workflow yields county typologies and maps to guide monitoring and planning, and it establishes a baseline for linking regimes to climate variability and land use trajectories.

Keywords: Vegetation vigour; Land degradation; Spatial analysis; Environmental planning; Territorial typologies

PADRÕES ESPAÇO-TEMPORAIS E ESTRUTURA ASSOCIATIVA ENTRE NDVI E SOLO EXPOSTO EM CONDADOS QUENIANOS (2024–2025)

RESUMO: O planejamento ambiental exige uma leitura sistêmica dos territórios, onde o vigor da vegetação e o solo exposto são tratados como indicadores complementares da condição ecológica e da vulnerabilidade da terra, uma vez que abordagens baseadas em variáveis isoladas limitam tanto a interpretação quanto a ação. Guiados por essa perspectiva, avaliamos padrões estatísticos e espaciais no vigor da vegetação e no solo exposto nos 47 condados do Quênia para 2024 e 2025, utilizando composições do Espectrorradiômetro de Imagem de Resolução Moderada (MODIS) processadas no Google Earth Engine. O Índice de Vegetação por Diferença Normalizada (NDVI) do MOD13Q1 e um Índice de Solo Exposto do MCD43A4 foram resumidos como médias por condado e, em seguida, examinados utilizando testes t pareados Bayesianos, correlações Bayesianas, média de modelos Bayesianos, agrupamento por floresta aleatória, I de Moran Local e modelos espaciais do modelo Besag-York-Mollié 2 (BYM2) ajustados com o INLA. Os resultados mostram um declínio moderado no NDVI médio, de 0,568 em 2024 para 0,542 em 2025, juntamente com uma mudança no BSI médio de -0,023 para -0,007, com evidências do fator Bayesiano para mudança em ambos os indicadores. A classificação dos condados permaneceu consistente ao longo do tempo para NDVI e BSI, enquanto as associações entre os indicadores foram fortemente negativas, indicando uma oposição consistente entre a cobertura vegetal e a exposição do solo. A análise de agrupamento identificou três regimes ambientais, com um regime dominante caracterizado por baixo NDVI e maior exposição do solo. Os indicadores locais revelaram agrupamentos contíguos de mudança para ambos os índices, e as

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estimativas do BYM2 indicaram que a maior parte da variância latente era espacialmente estruturada (ϕ entre 0,88 e 0,90). O fluxo de trabalho gera tipologias e mapas de condados para orientar o monitoramento e o planejamento, e estabelece uma base para vincular os regimes à variabilidade climática e às trajetórias de uso da terra.

Palavras-chave: Vigor da vegetação; Degradação da terra; Análise espacial; Planejamento ambiental; Tipologias territoriais

PATRONES ESPACIO-TEMPORALES Y ESTRUCTURA ASOCIATIVA ENTRE EL NDVI Y EL SUELO EXPUESTO EN LOS CONDADOS DE KENIA (2024-2025)

RESUMEN: La planificación ambiental requiere una lectura sistémica de los territorios, donde el vigor de la vegetación y el suelo expuesto se consideran indicadores complementarios del estado ecológico y la vulnerabilidad de la tierra, ya que los enfoques basados en variables aisladas limitan tanto la interpretación como la acción. Guiados por esta perspectiva, evaluamos los patrones estadísticos y espaciales del vigor de la vegetación y el suelo expuesto en los 47 condados de Kenia para 2024 y 2025, utilizando imágenes compuestas del espectrorradiómetro de imágenes de resolución moderada (MODIS) procesadas en Google Earth Engine. El Índice de Vegetación de Diferencia Normalizada (NDVI) de MOD13Q1 y un Índice de Suelo Expuesto de MCD43A4 se resumieron como promedios de condado y luego se examinaron usando pruebas t pareadas bayesianas, correlaciones bayesianas, promedio de modelos bayesianos, agrupamiento de bosques aleatorios, I de Moran local y modelos espaciales del modelo Besag-York-Mollié 2 (BYM2) ajustado con INLA. Los resultados muestran una disminución moderada en el NDVI medio, de 0,568 en 2024 a 0,542 en 2025, junto con un cambio en el BSI medio de -0,023 a -0,007, con evidencia del factor bayesiano para el cambio en ambos indicadores. La clasificación de los condados se mantuvo consistente a lo largo del tiempo para NDVI y BSI, mientras que las asociaciones entre los indicadores fueron fuertemente negativas, lo que indica una oposición consistente entre la cobertura vegetal y la exposición del suelo. El análisis de conglomerados identificó tres regímenes ambientales, con un régimen dominante caracterizado por un NDVI bajo y una mayor exposición del suelo. Los indicadores locales revelaron agrupaciones contiguas de cambios para ambos índices, y las estimaciones de BYM2 indicaron que la mayor parte de la varianza latente estaba estructurada espacialmente (ϕ entre 0,88 y 0,90). El flujo de trabajo genera tipologías y mapas de condados para orientar el monitoreo y la planificación, y establece una base para vincular los regímenes con la variabilidad climática y las trayectorias del uso del suelo.

Palabras clave: Vigor de la vegetación; Degradación del suelo; Análisis espacial; Planificación ambiental; Tipologías territoriales.

Introduction

Environmental planning deals with interacting ecological, spatial, and social processes that rarely operate in isolation (Ramírez & Lizarazo, 2024). For that reason, analytical approaches that focus on a single variable or sector often miss the way land systems function across scales. Recent work on landscape approaches and territorial sustainability has placed strong emphasis on integrated, cross sector, and spatially explicit analysis as a basis for sound land management and public decision making (Shiri et al., 2025).

Within this perspective, it becomes necessary to apprehend territories through their statistical and spatial patterns, since territorial processes are expressed unevenly across space and through interactions among environmental and human drivers (Ramírez & Lizarazo, 2024). A territorial reading is not limited to physical form alone. It also considers the ways ecological conditions, land use practices, governance arrangements, and lived geographies intersect within place-based systems (Albizua, 2025). Recent geographical scholarship has continued to treat territory as a relational and socio ecological construct, while applied planning studies have shown that spatially differentiated analysis improves the ability to connect landscape evidence with territorial management (Ramírez & Lizarazo, 2024).

Among the available analytical pathways, vegetation cover deserves a prominent place in environmental planning because it captures the cumulative imprint of climatic conditions, hydrology, topography, land use, and ecological disturbance (Parracciani et al., 2023). Recent reviews of vegetation index research note that remotely sensed vegetation metrics remain widely used for monitoring vegetation condition, change detection, and ecosystem response across diverse environments (Yan et al., 2025). In Kenya, vegetation dynamics are already being used to interpret climate related stress, drought conditions, and longer-term shifts in ecological zones, which makes vegetation vigor a practical indicator for territorially grounded planning (Parracciani et al., 2023; Kipkemoi, 2026; Ogembo et al., 2026).

Treating the vegetational dimension as secondary can weaken environmental assessment because vegetation loss is commonly linked with land degradation, reduced ecosystem functioning, and rising vulnerability to drought and heat stress (Parracciani et al., 2023). In parallel, exposed soil is an informative indicator of territorial vulnerability because it is associated with erosion risk, degradation processes, and, in many settings, higher land surface temperature (Albizua, 2025). Recent soil remote sensing literature shows that soil spectral indices are useful for characterising bare ground and monitoring surface conditions, although careful index selection and interpretation remain necessary (Chen et al., 2025). Reviews and applied studies also show that bare soil exposure and erosion related processes are now central concerns in remote sensing-based land monitoring, including across sub Saharan African grassland systems and in studies where bare soil indices covary positively with surface temperature (Mubonderi et al., 2025; Thepvongsa & Butar Butar, 2025).

This joint reading of vegetation vigor and exposed soil is especially relevant in Kenya, where strong climatic gradients, recurrent drought, land use change, and pressure on dryland systems produce marked territorial contrasts (Ogembo et al., 2026). Recent Kenya based studies show that vegetation and drought patterns are spatially structured across counties, while land use and land cover change in arid and semi-arid settings continues to affect ecosystem functioning, erosion processes, and land management needs (Kipkulei et al., 2025). Spatially explicit analysis is therefore not just a methodological preference (Njoroge et al., 2024). It is a practical route for identifying territorial regimes, locating vulnerable areas, and informing differentiated planning responses (Parracciani et al., 2023).

However, previous Kenya-based studies have mostly emphasized vegetation dynamics, drought indicators, land-use change, or isolated spatial patterns, while fewer studies have jointly examined vegetation vigor and exposed soil as complementary indicators within an integrated county-level spatial framework. As a result, there remains a need for approaches that combine temporal comparison, associative statistical modeling, environmental typology, local spatial autocorrelation, and Bayesian spatial inference to identify territorially differentiated regimes of vegetation–soil exposure.

Accordingly, this article evaluates the statistical, associative, and spatial patterns between NDVI, as an indicator of vegetation vigor and photosynthetic activity, and Bare Soil Index, as an indicator of exposed soil conditions, across Kenya's 47 counties in 2024 and 2025. The 2024–2025 window was adopted as a recent short-term monitoring interval, suitable for detecting interannual changes and establishing a reproducible baseline for future temporal extensions. The county scale was selected because counties constitute Kenya's main subnational territorial units for planning, allowing remote-sensing evidence to be linked to administratively meaningful spatial units.

The research contributes by integrating Bayesian paired testing, Bayesian correlation, Bayesian Model Averaging, Random Forest Clustering, Local Moran's I, and BYM2 spatial modeling into a single territorial workflow. This framework allows the identification of county-level environmental regimes, spatial clusters of change, and latent spatial effects that can support territorially differentiated environmental planning.

Materials and Methods

Environmental variables were extracted in Google Earth Engine (GEE) using Kenya's 47 counties as the territorial units of analysis. Annual composites were generated separately for 2024 and 2025 using all available observations within each calendar year. For NDVI (MOD13Q1 Collection 6.1), quality-controlled observations were retained according to the product quality information provided by MODIS, minimizing the influence of clouds and low-quality pixels. Annual values were aggregated using mean composites to represent average vegetation conditions throughout the year rather than short-term seasonal fluctuations. For BSI estimation, annual mean reflectance composites derived from MCD43A4 were adopted following the same temporal aggregation logic.

The Normalized Difference Vegetation Index was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13Q1 product (Collection 6.1), which has an approximate spatial resolution of 250 m and a temporal frequency of 16 days. For each year analyzed, an annual mean NDVI was computed. In this sense, NDVI represents a synthetic indicator of average vegetation cover at the subnational scale and does not imply causality; rather, it provides an associative measure of vegetation vigor and photosynthetic activity (Didan, 2021; Pettorelli et al., 2005).

Exposed soil conditions were estimated through the Bare Soil Index (BSI), derived from MODIS MCD43A4 Collection 6.1 surface reflectance data (~500 m). The index was computed from Red, NIR, Blue and SWIR1 bands and aggregated into annual mean values. Because NDVI and BSI originate from products with different native spatial resolutions (~250 m and ~500 m, respectively), harmonization was performed during county-level aggregation by summarizing both indices at the administrative unit level. Thus, the final analytical unit consisted of county averages rather than pixel-to-pixel comparison, reducing the influence of spatial resolution differences on subsequent statistical analyses (Schaaf et al., 2002; Rikimaru et al., 2002).

The temporal window (2024–2025) was intentionally selected to provide a recent interannual assessment capable of identifying short-term territorial changes while establishing a reproducible baseline for future temporal extensions. Although MODIS offers longer historical records, the present research prioritizes recent environmental conditions and exploratory evaluation of current spatial organization rather than long-term trend reconstruction.

Initially, descriptive statistics were computed for the variables under investigation. Subsequently, to assess whether a substantive change occurred in the mean level of each variable between the two years analyzed, explicitly accounting for uncertainty, a Bayesian Paired Samples *t*-Test was applied. This approach enabled further investigation of the associative structure of the system, and, in line with this objective, a Bayesian correlation analysis was conducted to identify consistent relationships among the variables (Rouder et al., 2009; Ly et al., 2016).

Bayesian Model Averaging (BMA) was subsequently applied considering BSI_2025 as the response variable and NDVI_2024, NDVI_2025 and BSI_2024 as explanatory variables, with the objective of identifying which environmental dimensions exhibited stronger associative evidence while explicitly accounting for model uncertainty. (Hoeting et al., 1999; Breiman, 2001).

Following this step, Random Forest Clustering (RFC) was employed to identify county typologies with similar multivariate environmental profiles. RFC was selected instead of traditional clustering approaches (e.g., *k*-means or hierarchical clustering) because it better accommodates non-linear relationships and interactions among variables while reducing sensitivity to assumptions regarding cluster geometry and variable distribution.

These statistical analyses provided the basis for interpreting the spatial patterns observed. In this regard, a thematic map was produced based on the RFC results, alongside a Local Moran's *I* (LISA) map of temporal variation, capturing the spatial organization of

changes in the variables between 2024 and 2025 (Anselin, 1995). In addition, BYM2 maps were estimated to identify latent spatial tendencies associated with each variable, distinguishing structured territorial dependence from local heterogeneity. The spatial maps were estimated in the R environment (R Core Team, 2024) using the BYM2 model fitted via INLA, adopting the Bayesian inference framework for latent Gaussian models proposed by Rue et al. (2009) and the penalized complexity-based reparameterization developed by Simpson et al. (2017).

Results

Descriptive statistics indicated that NDVI exhibited relatively high mean values in both years, with a modest decrease from 0.568 in 2024 to 0.542 in 2025. NDVI variability increased in 2025, as evidenced by the rise in the standard deviation from 0.136 in 2024 to 0.147.

In turn, BSI presented negative mean values in both years, with -0.023 in 2024 and -0.007 in 2025. The range between minimum and maximum BSI values showed a higher maximum in 2025 (0.243), suggesting the presence of localized areas with greater soil exposure. Table 01 reports the results of the Bayesian Paired Samples *t*-Test.

Table 01 - Bayesian Paired Samples T-Test

		BF ₁₀
NDVI_2024	- NDVI_2025	4.282
		0.846
		5.064
BSI_2024	- BSI_2025	4.975
		0.813
		6.120

Source: Google Earth Engine (GEE); authors' elaboration.

Based on the results presented in Table 01, the test revealed moderate to strong evidence in favor of the existence of temporal differences for both NDVI and BSI between 2024 and 2025. For NDVI, a BF₁₀ value of 4.282 indicates that the observed data are approximately four times more likely under the hypothesis of temporal change than under the null hypothesis of no difference, thereby corroborating the interpretation suggested by the descriptive statistics. Similarly, BSI yielded a BF₁₀ of 4.975, indicating comparable evidence of temporal change with respect to exposed soil conditions.

Table 02 summarizes the associative relationships among NDVI and BSI across years.

Table 02 – Bayesian Correlation

		Kendall's tau B	BF ₁₀
NDVI_2024	- NDVI_2025	0.924	$5.739 \times 10^{+16}$
NDVI_2024	- BSI_2025	-0.780	$6.834 \times 10^{+11}$
NDVI_2024	- BSI_2024	-0.791	$1.544 \times 10^{+12}$
NDVI_2025	- BSI_2025	-0.808	$5.346 \times 10^{+12}$
NDVI_2025	- BSI_2024	-0.785	$1.026 \times 10^{+12}$
BSI_2025	- BSI_2024	0.922	$4.917 \times 10^{+16}$

Source: Google Earth Engine (GEE); authors' elaboration.

The results of the Bayesian correlations (Kendall's tau-b) revealed a territorially coherent system over time. A very strong and positive association was observed between NDVI_2024 and NDVI_2025 ($\tau = 0.924$; $BF_{10} \approx 10^{16}$), indicating temporal and spatial persistence in vegetation vigor.

Similarly, a strong correlation was identified between BSI_2024 and BSI_2025 ($\tau = 0.922$; $BF_{10} \approx 10^{16}$), pointing to territorial persistence in exposed soil patterns. In contrast, the correlations between NDVI (2024 and 2025) and BSI (2024 and 2025) were strongly negative (τ ranging from -0.78 to -0.81), robustly evidencing the structural opposition between vegetation cover and soil exposure across the analyzed territories. This pattern suggests that counties with greater biomass and photosynthetic activity tend to exhibit lower reflectance associated with bare surfaces, whereas areas with higher soil exposure indicate reduced vegetation cover due to natural conditions, agricultural management practices, or other anthropogenic activities.

Table 03 presents the associative hierarchy estimated by BMA.

Table 03 – Bayesian Model Averaging

Coefficient	P(incl)	P(excl)	P(incl data)	P(excl data)	BF _{inclusion}	Mean	SD	95% Credible Interval	
								Lower	Upper
Intercept	1.000	0.000	1.000	0.000	1.000	-0.007	0.001	-0.009	0.005
BSI_2024	0.500	0.500	1.000	0.000	$1.687 \times 10^{+30}$	0.965	0.027	0.916	1.014
NDVI_2024	0.500	0.500	1.000	2.408×10^{-13}	$4.153 \times 10^{+12}$	0.806	0.062	0.692	0.918
NDVI_2025	0.500	0.500	1.000	2.131×10^{-13}	$4.694 \times 10^{+12}$	-0.829	0.061	-0.941	-0.720

Source: Google Earth Engine (GEE); authors' elaboration.

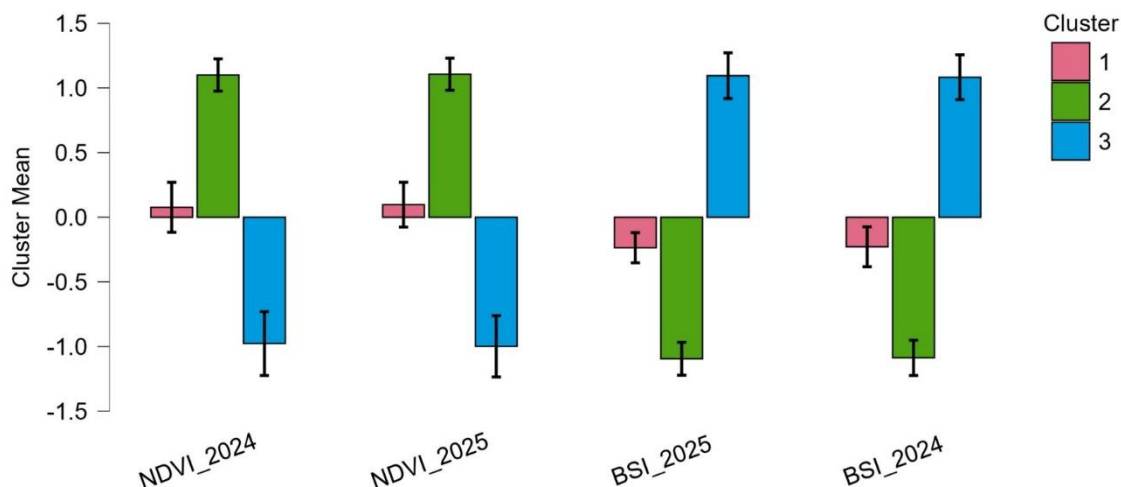
The BMA results indicate strong evidence for the inclusion of all explanatory variables considered, with posterior inclusion probabilities equal to 1.0 and very large Bayes Factors. Among these, BSI_2024 exhibits the highest associative weight (Mean = 0.965), suggesting that soil conditions retain a strong imprint of past dynamics. Likewise, NDVI_2024 shows a relevant associative contribution (Mean = 0.806), indicating that prior levels of vegetation vigor play an important role in the explanatory structure of the system under analysis.

In contrast, NDVI_2025 presents a negative mean coefficient (Mean = -0.829), reflecting the structural opposition between vegetation vigor and photosynthetic activity in relation to Bare Soil, that is, exposed soil conditions.

Collectively, the results indicate persistence in exposed soil conditions and an inverse association between vegetation vigor and exposed soil.

Figure 01 presents the environmental regimes identified across Kenyan counties.

Figure 1: Cluster Mean Plot

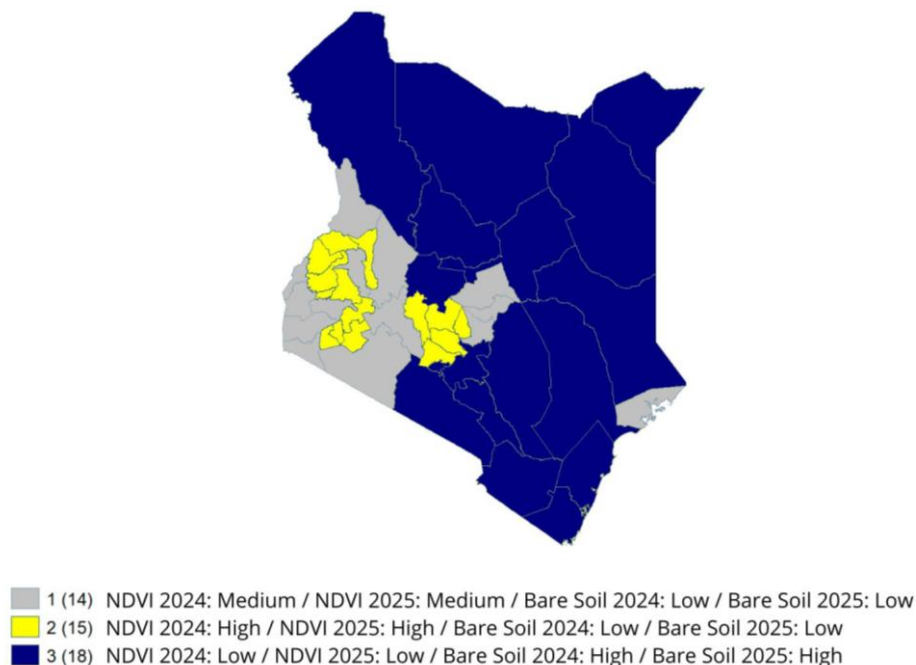


Source: Google Earth Engine (GEE); authors' elaboration.

Based on the analysis of Figure 01, the clusters can be classified as follows: Cluster 01 is characterized by medium NDVI_2024, medium NDVI_2025, low Bare Soil_2024 and low Bare Soil_2025; Cluster 02 by high NDVI_2024, high NDVI_2025, low Bare Soil_2024 and low Bare Soil_2025; and Cluster 03 by low NDVI_2024, low NDVI_2025, high Bare Soil_2024 and high Bare Soil_2025.

Cluster 02 concentrated higher vegetation vigor and lower exposed soil, whereas Cluster 03 showed the opposite configuration.

Figure 02: Spatial Visualization of RFC Clusters in Kenya (2024 and 2025)



Source: Google Earth Engine (GEE); authors' elaboration.

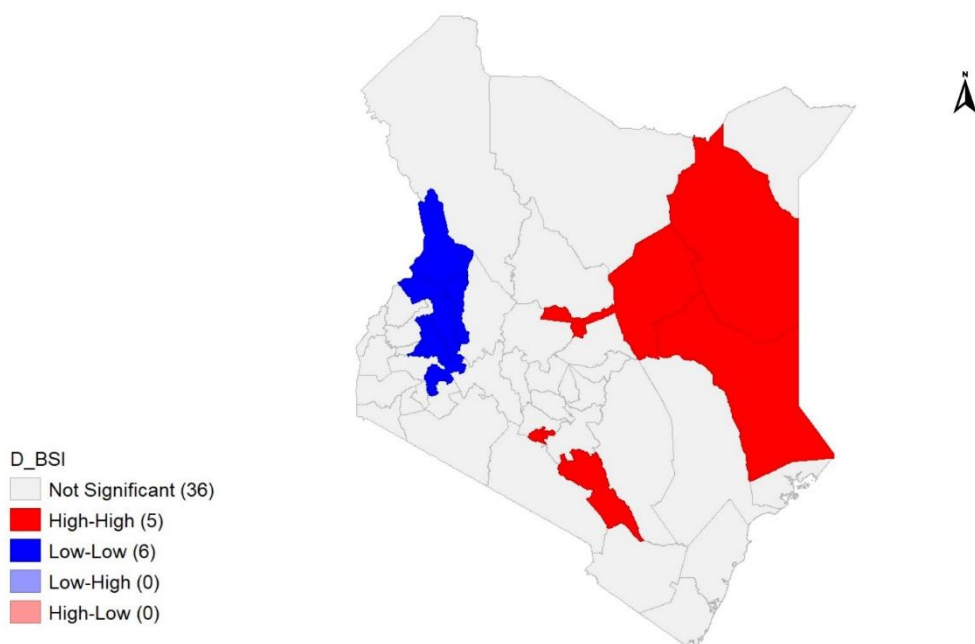
As shown in Figure 02, Cluster 03 (blue) predominates across Kenyan territories and is associated with counties exhibiting low NDVI values in both 2024 and 2025, alongside

elevated levels of exposed soil in both years. From a statistical and territorial standpoint, this cluster represents an environmental regime characterized by soil exposure, thereby indicating areas that warrant particular attention in environmental planning.

Clusters 01 (gray) and 02 (yellow) form more localized and spatially heterogeneous patterns. From an ecological perspective, Cluster 02 encompasses counties or areas with high and stable NDVI values across both years, coupled with low levels of exposed soil, thus characterizing a regime of greater environmental protection and persistent photosynthetic activity. Cluster 01, in turn, occupies an intermediate position, with moderate NDVI and low soil exposure, suggesting territories in a state of relative balance. Overall, the RFC-derived map enabled the identification of distinct types of environmental territories when NDVI and exposed soil are jointly considered across both years, rather than examining each variable in isolation.

Accordingly, based on the identification of multivariate environmental regimes provided by the RFC, a Local Moran's I (LISA) map of the percentage change in exposed soil was produced. This approach allowed the investigation of whether recent changes in this indicator exhibit significant spatial organization and the identification of local patterns of concentration within and across these territorial regimes. Figure 03 presents the resulting map.

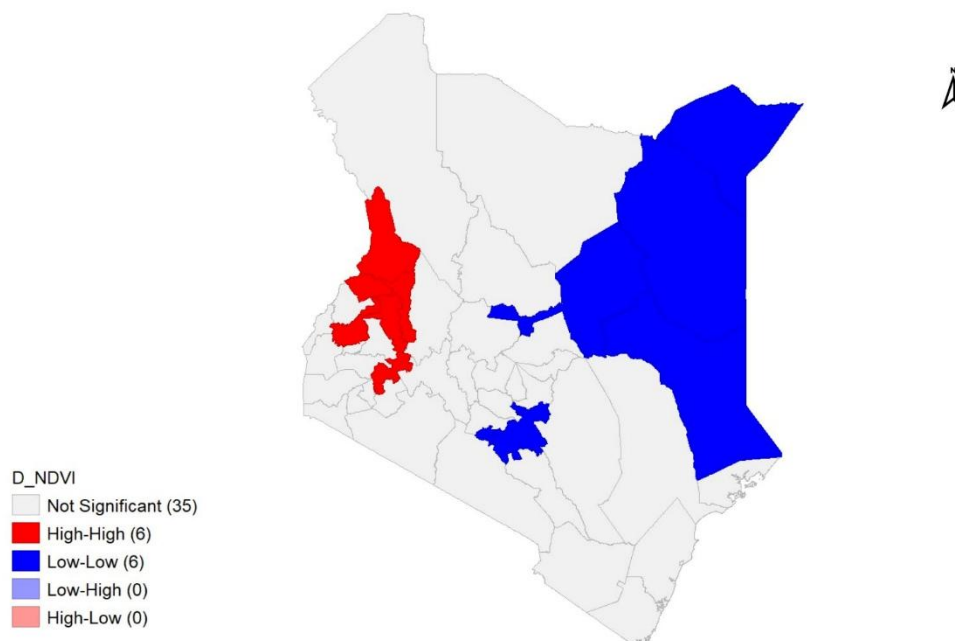
Figure 03: Local Moran's I (LISA) of the Percentage Change in BSI in Kenya (2024–2025)



Source: Google Earth Engine (GEE); authors' elaboration.

High–High clusters indicate groupings of counties where the relative increase in exposed soil between 2024 and 2025 was both high and spatially concentrated, suggesting the presence of shared environmental processes. In contrast, Low–Low clusters highlight areas where changes in exposed soil were minimal, forming pockets of territorial stability. The absence of High–Low or Low–High patterns suggests that BSI dynamics tend to organize into continuous spatial regimes. This finding is consistent with the regimes identified by the RFC and illustrated in Figures 01 and 02, further reinforcing the relevance of the present analysis grounded in multivariate structures and local spatial dependence. Figure 04 presents the Local Moran's I results for the NDVI variable.

Figure 04: Local Moran's I (LISA) of the Percentage Change in NDVI in Kenya (2024–2025)



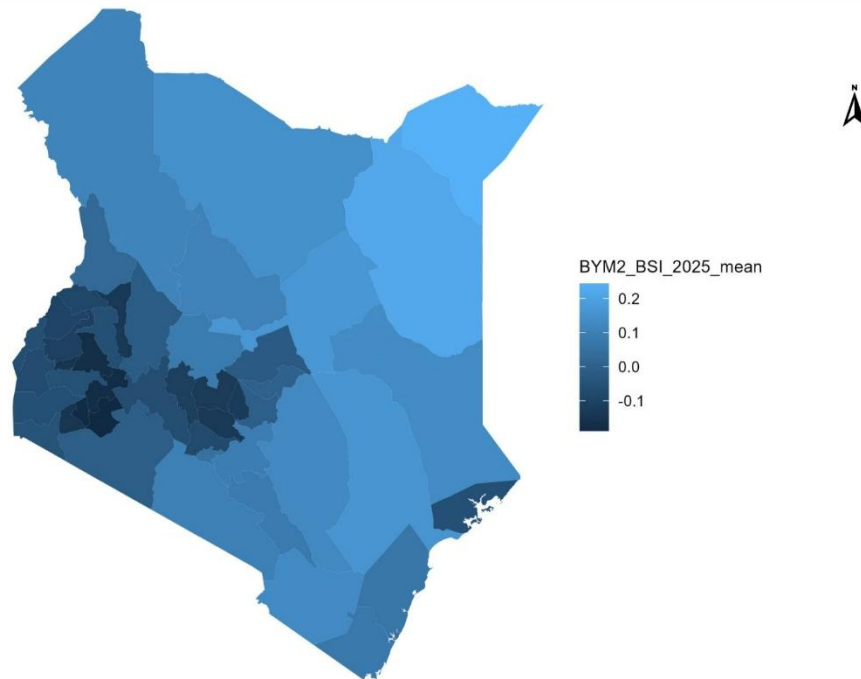
Source: Google Earth Engine (GEE); authors' elaboration.

The map presented in Figure 04, depicting the Local Moran's I (LISA), illustrates the percentage variation in NDVI and the associated temporal changes in photosynthetic activity, revealing statistically significant spatial organization across the territories. High–High (red) clusters indicate areas of relative NDVI increase, suggesting gains in vegetation vigor among neighboring counties. Conversely, Low–Low (blue) clusters identify regions characterized by reduction or stagnation in this variable. As observed in Figure 03, the absence of High–Low or Low–High clusters further reinforce the interpretation that temporal NDVI dynamics manifest through continuous spatial regimes rather than isolated or contrasting local patterns.

When interpreted in conjunction with the results obtained for BSI in Figure 03, these findings provide a territorially complementary understanding. Areas classified as High–High in the percentage change of BSI largely correspond to Low–Low clusters of NDVI, indicating an inverse spatial relationship between increases in exposed soil and reductions in vegetation vigor.

Similarly, areas characterized by stability or reduction in BSI more frequently exhibit gains in NDVI. These patterns are not random; rather, they reflect shared territorial processes in which the dynamics between vegetation cover and soil exposure are spatially interrelated. This reinforces the need for systemic and integrated analytical approaches. Figure 05 presents the BYM2 mapping for the BSI variable in 2025.

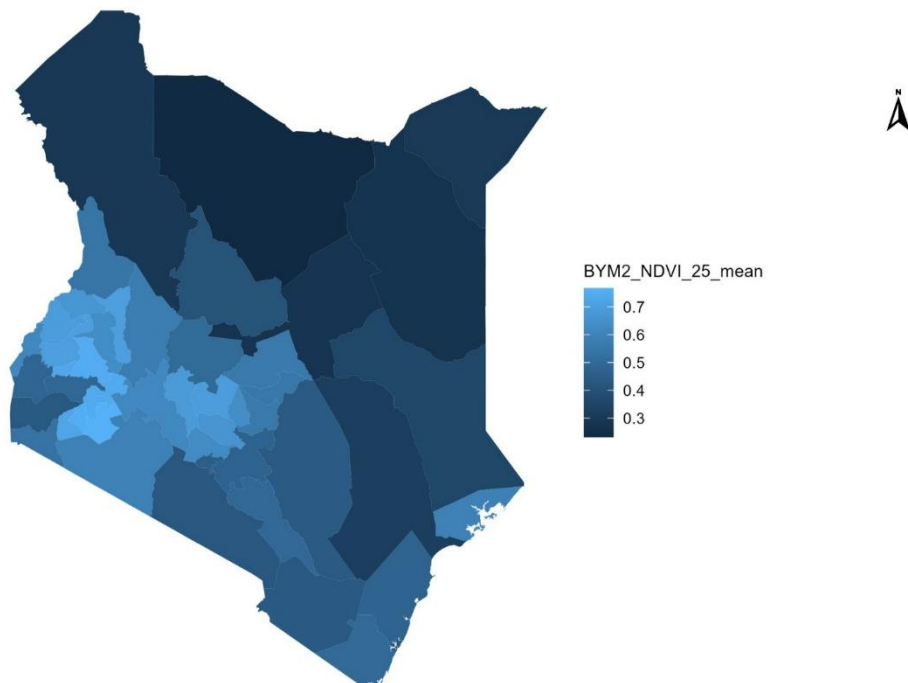
Figure 05: BYM2 sobre variável BSI – Kenya (2025)



Source: Google Earth Engine (GEE); authors' elaboration.

Figure 06 presents the BYM2 results for the NDVI variable.

Figure 06: BYM2 map of the NDVI variable – Kenya (2025)



Source: Google Earth Engine (GEE); authors' elaboration.

The map shown in Figure 06 highlights, based on the BYM2 model, the territories that tend to favor or attenuate the NDVI variable in 2025. Lighter blue tones indicate a

positive spatial effect, whereas darker tones indicate lower spatial effects, suggesting reduced territorial support for NDVI. Figure 06 shows comparable spatial organization for NDVI.

The parameter ϕ (phi) in the BYM2 model expresses the proportion of the total variance attributed to the spatially structured component, ranging from 0 to 1. High ϕ values, such as those observed for both NDVI_25 and BSI_2025 ($\approx 0.88-0.90$), indicate that most of the latent variability of the phenomenon is explained by spatial dependence among municipalities rather than by random local heterogeneity. High ϕ values indicate predominance of structured spatial dependence.

Discussion

The study identifies measurable change in vegetation vigor and exposed soil between 2024 and 2025, alongside clear spatial organization across Kenyan counties. The paired Bayesian tests and the county level summaries point to a modest decline in mean NDVI with a concurrent shift in bare soil conditions. Work on Kenyan drylands and rangelands using MODIS NDVI similarly reports that vegetation condition varies systematically through time and space, in patterns that align with climatic variability and land use pressure, which is consistent with the presence of structured change rather than random fluctuation (Ndungu et al., 2019). Newer Kenya focused drought mapping that relies on NDVI derived vegetation condition metrics also reports spatially coherent drought patterns, which aligns with the idea that county level vegetation indicators tend to cluster geographically due to shared regional drivers (Ogembo et al., 2026).

A central result is the strong opposition between vegetation cover and exposed soil, shown through the negative associations between NDVI and BSI and reinforced through the model-based hierarchy. This aligns with Chen et al. (2025) who treat vegetation indices and soil exposure or bare ground signals as complementary descriptors of land where loss of cover increases exposure and erosion susceptibility. Global work on cropland soil exposure also reports inverse relationships between soil exposure duration and indicators of growing period and cover persistence, consistent with the broad pattern that longer or larger exposure tends to coincide with reduced vegetative cover (Feng et al., 2025). Methods research on bare ground mapping and bare soil indices supports the use of multi band indices for separating soil from vegetated surfaces, which supports the interpretive framing of BSI patterns as meaningful signals of exposure rather than noise (Nguyen et al., 2021; Becker et al., 2025).

The clustering results separate counties into regimes that range from high and stable NDVI with low exposed soil to the converse pattern where NDVI remains low and soil exposure remains high. Comparable Kenya studies that use spatial diagnostics and machine learning workflows in agricultural and land surface applications also report that spatial dependence and heterogeneity are common and that grouping areas with similar profiles can reveal management relevant patterns that are not visible in purely descriptive summaries (Njoroge et al., 2024). Correlation results extend this by showing that changes in NDVI and exposed soil form contiguous clusters rather than scattered outliers. This is consistent with broader spatial analysis practice where Local Moran's I frequently identifies geographically continuous hot spots and cold spots in land surface indicators, especially when neighboring areas share rainfall regimes, land management systems and soils (Anselin, 1995).

The spatial modeling results show that a high share of variance attributed to the structured spatial component indicate broad territorial processes rather than isolated local variation. This aligns with the rationale for Bayesian spatial models implemented through INLA frameworks in environmental mapping, where smoothing and separation of structured and unstructured component role of geography in shaping observed patterns (Rue et al., 2009; Simpson et al., 2017). In Kenyan contexts, recent work detecting vegetation stress and breakpoints from MODIS time series in protected landscapes and spatially grounded

dynamics. This is consistent with the interpretation that vegetation condition is conditioned by place specific ecological and anthropogenic contexts (Kipkemai, 2026).

Some contrasts emerge when this short period change is compared with longer horizon studies. Focusin on the Horn of Africa, Measho et al. (2021) report greening in some zones over multi decade windows alongside localized browning in others. This indicates mixed trajectories that depend on ecozone, rainfall trends, land use and disturbance regimes. Kenya focused projections and assessments of climate change impacts on vegetation similarly emphasize heterogeneous responses, including shifts that differ between protected and semi protected areas and across climate scenarios (Parracciani et al., 2023). The present results show a modest decline in mean NDVI from 2024 to 2025. A one-year window can diverge from long run trends because annual means are sensitive to short term rainfall anomalies, timing of the growing season and episodic disturbance, so apparent divergence from long horizon greening studies does not imply disagreement on process. Instead, it points to scale and period dependence, where interannual variability can temporarily offset multiyear trajectories.

The combined evidence from temporal testing, associative structure, clustering, local spatial autocorrelation and Bayesian spatial effects supports an integrated interpretation of Kenya's soil vegetation dynamics as spatially patterned and historically conditioned. This is consistent with peer reviewed work in Kenya and the wider region that treats NDVI based monitoring as a useful lens on land condition and drought response, while also showing that bare ground or soil exposure metrics strengthen interpretation when paired with vegetation indicators (Ndungu et al., 2019; Ogembo et al., 2026; Measho et al., 2021).

Conclusions

The results indicate that vegetation vigor and exposed soil across Kenyan counties are not randomly distributed but organized into territorially differentiated environmental regimes. Between 2024 and 2025, a modest reduction in vegetation vigor coincided with shifts in exposed soil conditions, suggesting short-term environmental reorganization across parts of the country.

The combined statistical and spatial evidence consistently revealed an inverse territorial relationship between vegetation vigor and soil exposure, together with strong temporal persistence and marked spatial structuring.

From an environmental planning perspective, the identification of persistent environmental regimes and spatial clusters provides an operational basis for differentiated territorial monitoring and prioritization strategies. Counties characterized by persistent soil exposure may require distinct management approaches compared with territories showing stable vegetation conditions.

Although restricted to a recent two-year window, the research establishes a reproducible territorial assessment framework that can be expanded through longer MODIS series and incorporation of climatic and land-use variables. Future studies may evaluate whether the identified regimes represent short-term fluctuations or persistent environmental trajectories.

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