

Article

Remote Sensing-Based Assessment of Interannual Change of the Ecological Sustainability of Agricultural Landscapes in Northern Benin

Mikhaïl J. D. D. Padonou ^{1,2,*} , Antoine Denis ² , Yvon-Carmen H. Hountondji ³, Bernard Tychon ²  and Gérard N. Gouwakinnou ¹ 

¹ Laboratoire d'Écologie, de Botanique et de Biologie Végétale, Unité de Recherche Biodiversity Conservation at the Interface People, Land Use and Climate Changes, Faculté d'Agronomie, Université de Parakou, Parakou 03 BP 125, Benin; gougerano@gmail.com

² Agro-Ecosystem Sensing for Environmental Sustainability (AgroEcoSEnS), Département des Sciences et Gestion de l'Environnement, Arlon Campus Environnement, Faculté des Sciences, UR SPHERES, Université de Liège, 185 avenue de Longwy, B-6700 Arlon, Belgium; antoine.denis@uliege.be (A.D.); bernard.tychon@uliege.be (B.T.)

³ Laboratoire d'Études et de Recherches Forestières (LERF), Faculté d'Agronomie, Université de Parakou, Parakou 03 BP 123, Benin; yvonhountondji@gmail.com

* Correspondence: dotou.padonou@gmail.com; Tel.: +229-01977-899-58

Abstract

Assessing ecological sustainability in agricultural landscapes requires approaches that integrate land-cover change, its ecological effects, and their spatial determinants. This study analysed changes between 2023 and 2024 across six agricultural landscapes in northern Benin using the Landscape Ecological Sustainability Index (LESI), calculated for 1 km² landscape cells from Human Disturbance Coefficients (HDCs) assigned to satellite-derived land-cover classes. Interannual changes were assessed using Δ LESI, the Wilcoxon signed-rank test, Global Moran's I, and the Local Indicators of Spatial Association (LISA). The contribution of land-cover transitions to HDC change was quantified and a Monte Carlo sensitivity analysis based on classification accuracy was additionally used to assess the robustness of the observed interannual changes to classification uncertainty, and complementary univariate and bivariate regression models examined the relationships between LESI variations and 11 biophysical and geographical variables, including their pairwise interactions. The interannual comparison between 2023 and 2024 showed a decrease in ecological sustainability in four sites, a slight increase in one, and relative stability in another. Significant spatial autocorrelation was detected in all sites (Moran's I = 0.44–0.65; $p < 0.001$). Some spatially limited transitions exerted important effects on HDC change. Sensitivity analysis confirmed that the direction of Δ HDC was robust to classification uncertainty in five of the six landscapes. The low explanatory power of the univariate models ($R^2 \leq 0.081$) indicates that no single variable independently explains the observed changes. The bivariate interaction analyses further showed that some associations were context-dependent, although their explanatory power remained limited, with the best-performing model accounting for only 10.9% of the variation in Δ LESI. This integrated framework provides a reproducible approach for assessing, mapping, and prioritising interannual change of ecological sustainability from remote sensing data to support evidence-based agricultural landscape planning and sustainable land management.



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1. Introduction

By 2100, the global population, estimated at 7.7 billion in 2019, is projected to reach approximately 10.9 billion [1]. Low-income countries in sub-Saharan Africa are expected to account for the largest share of this population growth, owing to persistently high fertility rates (averaging around 4.6 children per woman) and an ongoing demographic transition [2]. Population growth is one of the principal drivers of increasing demand for agricultural commodities, which, in turn, intensifies pressure on agrarian systems [3,4]. Indeed, meeting the food requirements of a global population projected to reach 9.7 billion by 2050 is expected to require an increase in agricultural productivity of approximately 110% [5,6].

The imperative to increase agricultural productivity is transforming cropping systems and driving profound changes in agrarian systems across agricultural landscapes in sub-Saharan Africa. One of the defining characteristics of this transformation is the progressive decline in the amount of cultivable land available per agricultural worker as a consequence of population growth. This reduction has led to increasing agricultural land use intensity, characterised by more frequent and intensive cultivation of farmland, often at the expense of its physical, chemical, and biological quality [7,8]. Such intensification is accompanied by a growing dependence on inorganic external inputs, including mineral fertilisers, pesticides, and herbicides, which are used to enhance productivity but simultaneously contribute to soil degradation, environmental contamination, and biodiversity loss [9–11]. Moreover, the expansion of monoculture systems, driven by the objective of maximising yields and farm income, increases the vulnerability of agrarian systems to pest outbreaks. This vulnerability is reinforced by the homogenisation of agricultural landscapes and the simplification of crop rotation schemes, both of which favour pest proliferation [12,13]. Finally, when productivity gains become insufficient to meet rising demand, agricultural expansion remains the predominant strategy, resulting in the conversion of natural vegetation and the cultivation of marginal lands [14,15].

Although these transformations have supported increases in agricultural production, they have also generated substantial environmental externalities that undermine the long-term sustainability of agrarian systems across sub-Saharan Africa. These impacts include biodiversity loss and the degradation of natural habitats [16,17], together with the contamination of surface water and groundwater through nutrient leaching, sedimentation, and saline drainage processes [18]. Furthermore, these dynamics impair ecosystem services that are fundamental to the functioning of cropping systems, including pollination, natural pest regulation, and the maintenance of soil fertility, thereby weakening the biological foundations of agricultural production [19,20]. In addition, the intensification of agricultural practices and land-cover change contribute to increased greenhouse gas emissions, reinforcing the negative feedbacks between agriculture and climate change [21].

These challenges underscore the urgent need to reconfigure farming systems towards models capable of reconciling increased agricultural production with environmental conservation, notably by reducing the negative environmental externalities associated with agricultural intensification [22,23]. This need has stimulated the emergence of several conceptual frameworks, among which sustainable intensification has become particularly influential [24,25]. Sustainable intensification is founded on the principle of increasing or maintaining agricultural production without expanding cultivated land or causing net environmental degradation [15].

Achieving these two objectives simultaneously, however, cannot rely on standardised approaches. Agrarian systems exhibit considerable heterogeneity in terms of their biophysical and geographical conditions, cropping systems, and socio-economic contexts. Consequently, understanding the ecological dynamics specific to individual agricultural

landscapes is essential for identifying management strategies capable of effectively reconciling agricultural production with environmental conservation in agrarian systems [26].

As in many other tropical regions, the expansion of agricultural land is the primary driver of natural ecosystem degradation [27–29] in the agricultural landscapes of northern Benin, located within the Sudanian zone of West Africa. This region alone accounts for approximately 81% of the country's cultivated agricultural land and constitutes Benin's principal agricultural production basin, making a dominant contribution to the national production of crops such as maize, cotton, cashew, and soybean [30]. The increase in agricultural production observed over recent decades has been driven largely by the expansion of cultivated land rather than by substantial gains in agricultural productivity [30]. This process of agricultural expansion has been accompanied by the progressive degradation of ecosystems and the services they provide, notably through soil erosion, sedimentation, water eutrophication, biodiversity loss, and increased greenhouse gas emissions [31–34]. Moreover, agrarian systems in this region are characterised by an increasing reliance on inorganic inputs, particularly mineral fertilisers, herbicides, and pesticides [35], which contribute to the degradation of both terrestrial and aquatic ecosystems. Consequently, the agrarian systems of northern Benin provide a particularly relevant case study for investigating the trade-offs between agricultural intensification, farmland expansion, and the ecological sustainability of Sudanian agricultural landscapes.

Research on the ecological sustainability of agricultural landscapes generally focuses on three complementary levels of analysis. The first seeks to characterise the spatio-temporal dynamics of landscape ecological condition using Earth observation-derived indicators, composite indices, or spatial analyses conducted at successive time periods [36–38]. The second relates these ecological changes to land-cover dynamics by examining land-cover change and landscape trajectories [39]. The third aims to identify the biophysical and geographical factors associated with these dynamics using statistical or machine learning models, thereby explaining the observed spatio-temporal patterns of change [40]. Although these approaches are well established in the literature, they are generally applied independently, limiting the ability to establish explicit relationships between observed spatiotemporal changes in ecological sustainability, the land-cover transitions associated with these changes, and the biophysical and geographical factors associated with their spatial variability. Integrating these complementary dimensions within a single analytical framework could therefore provide a more comprehensive understanding of ecological sustainability changes in agricultural landscapes and strengthen the evidence base for landscape planning and sustainable land management.

Against this background, this chapter addresses the following research questions:

- (1) How has the ecological sustainability of agricultural landscapes in northern Benin changed over space and time?
- (2) Which land-cover transitions are associated with the observed changes in ecological sustainability?
- (3) Which biophysical and geographical factors are associated with the spatial variation in interannual ecological sustainability changes in the agricultural landscapes of northern Benin?

2. Materials and Methods

2.1. Study Area

The study area is located between 8.45–11.68° N and 1.35–3.85° E (Figure 1). It covers 65,926 km², representing approximately 57% of the total land area of Benin, a country situated in West Africa [41]. The six study sites (Bagou, Ouenou, Parakou, Soadoudou, Awanla, and Gbanlin) were named after the principal settlements located within each site.

They are distributed across four agroecological zones (AEZs) within the northern Benin agricultural basin (Table 1): the North Cotton Zone (AEZ II), the South Borgou Food Crop Zone (AEZ III), the West Atacora Zone (AEZ IV), and the Central Benin Cotton Zone (AEZ V).

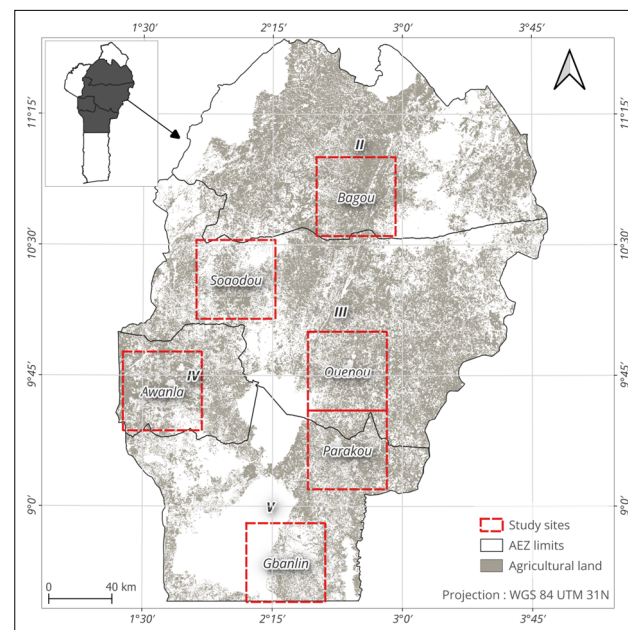


Figure 1. Study area (II: North cotton zone; III: South Borgou crop zone; IV: West Atacora zone; V: Central Benin cotton zone).

Table 1. Main biophysical and agricultural characteristics of the AEZs represented in the study.

AEZ	Climate	Annual Pre- cipitation (mm)	Dominant Soils	Main Crops	Chemical Fertilisers (%)	Chemical Herbicides (%)	Chemical Insecticides (%)	Study Sites
II	Sudanian, with Sudano-Sahelian influence in the northern part	800–1200	Ferruginous soils (Lixisols)	Cotton	60	70	51	Bagou
III	Sudanian	1100–1200	Ferruginous soils (Lixisols)	Yam, cotton, maize and cashew	71	81	70	Ouenou and Soadou
IV	Sudanian, with strong spatial variability in mean precipitation due to mountainous terrain	800–1000	Concretionary ferruginous soils (Leptosols)	Yam, cotton, maize, and cashew	87	75	66	Awanla
V	Sudano-Guinean	600–1400	Leached tropical ferruginous soils (Leptosols and Luvisols)	Tubers, legumes, and cotton	50	70	51	Gbanlin and Parakou

Across these four agroecological zones, the natural vegetation is dominated by wooded savannas characterised by species such as *Adansonia digitata*, *Parkia biglobosa*, *Vitellaria paradoxa*, *Ceiba pentandra*, and *Blighia sapida* [42]. The region experiences Sudanian to Sudano-Guinean climatic conditions, with mean annual rainfall ranging from 600 to 1400 mm [43]. The dominant soil types are ferruginous soils, mainly classified as Lixisols, Leptosols, and Luvisols [43]. The principal crops cultivated in the region include cotton, root and tuber crops, legumes, maize, yam, and cashew [44]. Agricultural production is highly dependent

on chemical inputs: 50–71% of farmers apply mineral fertilisers, 70–81% use herbicides, and 51–70% apply insecticides [35].

2.2. Global Methodological Framework

The methodological framework comprises five interconnected components (Figure 2). First, the input data include the 2023 and 2024 land-cover maps, auxiliary spatial data, and biophysical and geographical variables used at different stages of the analysis. Second, ecological sustainability was assessed within 1×1 km landscape cells by combining the proportional area of each land-cover class with its Human Disturbance Coefficient (HDC) to calculate LESI for each year and the resulting interannual change (Δ LESI). Third, cross-tabulation of the two land-cover maps was used to quantify individual land-cover transitions and their contributions to changes in HDC. Fourth, global and local spatial autocorrelation analyses were applied to characterise the spatial patterns of Δ LESI. Finally, the biophysical and geographical factors associated with the spatial variability of Δ LESI were investigated using complementary univariate and bivariate regression analyses. The univariate models characterised the individual relationships between Δ LESI and each of the 11 explanatory variables, while the bivariate analysis systematically examined all 55 possible pairwise combinations, including their interaction terms. The explanatory performance of these models and the statistical relevance of the interactions were assessed using adjusted R^2 and interaction significance, respectively.

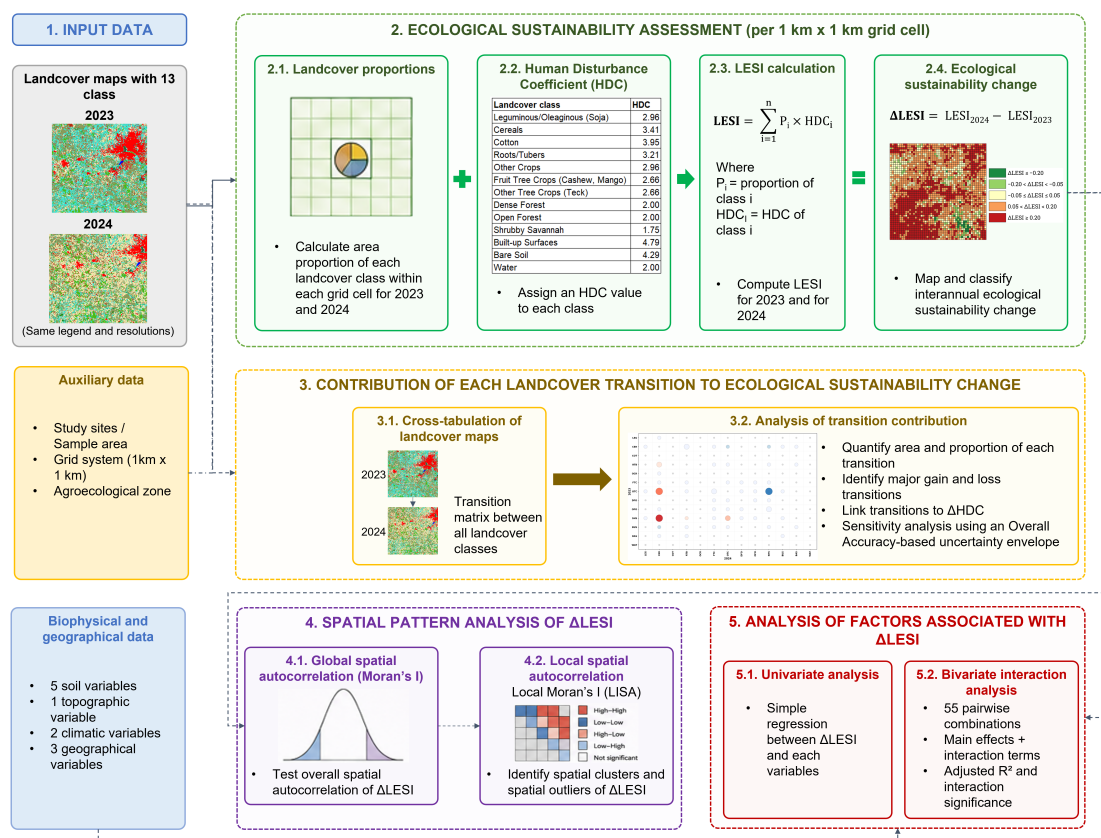


Figure 2. Overall methodological framework for assessing interannual changes in agricultural landscape ecological sustainability and their associated factors.

2.3. Description of Land-Cover Maps

This study is based on a time series of 12-class land-cover maps available for the six study sites for the years 2023 and 2024. These maps were produced by CIRAD as part of the OBSYDYA research project (Figure 2).

The LULC maps used in this study were generated using the automated Moringa processing chain [45]. This workflow integrates several complementary remote sensing data sources (Table 2), including very high spatial resolution SPOT 6/7 imagery (1.6 m), Sentinel-2 Level-2A multispectral image time series (10–20 m spatial resolution), and a 30-m Digital Elevation Model (DEM) derived from the Shuttle Radar Topography Mission (SRTM).

Table 2. Description of remote sensing images used for the production of the land cover maps used in this study.

Data Type	Spatial Resolution (m)	Collection Time
SPOT 6/7	1.5 m	10/2023 and 10/2024
Sentinel-2	10 m	Time series from 01/2023 to 12/2023 and 01/2024 to 12/2024
SRTM	30 m	2000

The Moringa classification workflow is based on the Random Forest machine learning algorithm implemented through Orfeo ToolBox 9.1.0 (OTB) functions, operationalised using Python 3.13.0 scripts, and complemented by intermediate processing steps carried out in QGIS 3.44 LTR. The first stage of the workflow consists of segmenting the very high-resolution imagery to delineate spectrally homogeneous image objects. These objects are subsequently classified using a Random Forest model trained and validated with a reference dataset compiled from field surveys and photo-interpretation.

Field reference data were collected using the QField 3.4 mobile application installed on tablet devices, initially as georeferenced point observations. These points were subsequently converted into training polygons by digitising the corresponding object boundaries visible on the SPOT 6/7 imagery. Table 3 summarises the classification accuracy metrics obtained for the land-cover maps generated using the Moringa processing chain. Detailed classification assessment reports are provided in the Supplementary Material S1 for each study site and observation year. These reports include the overall map accuracy, Cohen’s Kappa coefficient, class-specific F1-scores, and the results of the five-fold cross-validation, including confusion matrices and class-specific precision, recall, F1-score, and support values. This Supplementary Material S1 provides a more detailed assessment of classification performance and class-specific uncertainties underlying the land-cover maps used in the subsequent analyses. Overall classification performance remained high across all study sites for both years, with overall accuracies ranging from 0.79 to 0.90 and Cohen’s Kappa coefficients ranging from 0.66 to 0.88. Compared with the 2023 classifications, the 2024 results showed a decline in classification performance across all sites. This decrease was particularly pronounced at Bagou, where overall accuracy declined from 0.90 to 0.82 and the Kappa coefficient from 0.86 to 0.66, and at Soaodou, where overall accuracy decreased from 0.88 to 0.79 and the Kappa coefficient from 0.82 to 0.73.

Table 3. Overall classification accuracy of the land-cover maps.

Sites	Overall Map Accuracy		Cohen’s Kappa	
	2023	2024	2023	2024
Bagou	0.90 ± 0.01	0.82 ± 0.02	0.86 ± 0.01	0.66 ± 0.03
Ouenou	0.88 ± 0.02	0.84 ± 0.01	0.84 ± 0.02	0.80 ± 0.01
Parakou	0.86 ± 0.03	0.84 ± 0.03	0.83 ± 0.04	0.81 ± 0.04
Soaodou	0.88 ± 0.03	0.79 ± 0.02	0.82 ± 0.04	0.73 ± 0.03
Awanla	0.90 ± 0.02	0.84 ± 0.01	0.88 ± 0.03	0.80 ± 0.01
Gbanli	0.90 ± 0.02	0.88 ± 0.01	0.86 ± 0.03	0.83 ± 0.01

The minimum size of the features mapped is approximately 20 m², providing the land-cover maps with a high level of spatial detail (Figure 3).

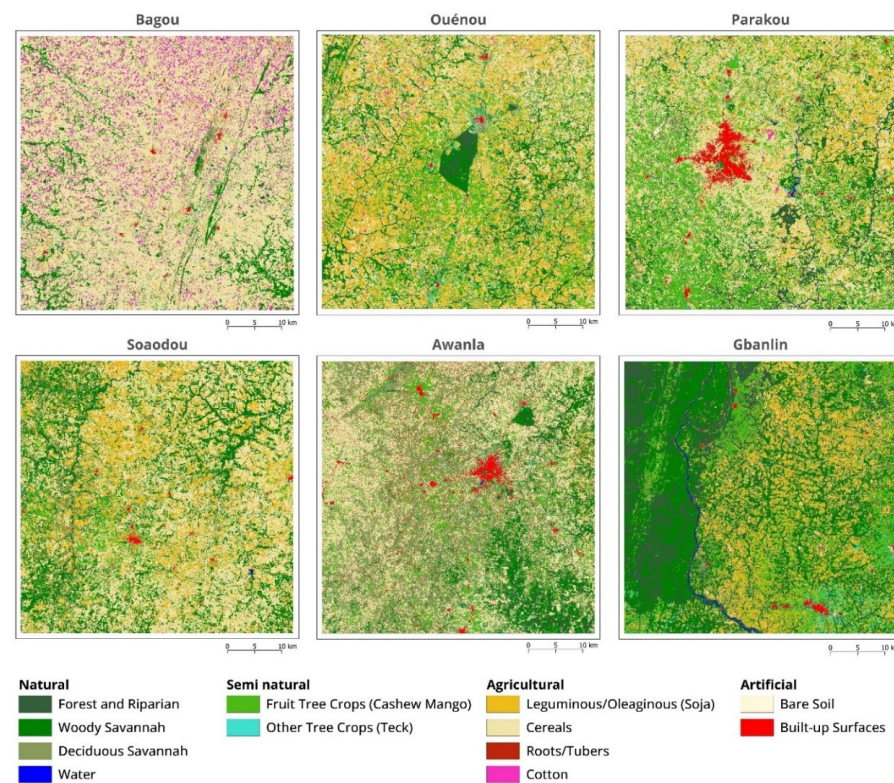


Figure 3. Types of land cover in the 6 study sites.

2.4. Unit of Analysis

The spatial unit of analysis adopted for the spatio-temporal assessment of the ecological sustainability of agricultural landscapes in northern Benin was the regular landscape cell [46], defined as a square grid cell of fixed dimensions forming a regular lattice covering the entire study area.

The use of a regular landscape grid offers several methodological advantages. First, it provides a uniform level of cartographic detail, thereby standardising the spatial framework and facilitating the handling of complex geographical information. This approach also avoids the ambiguities associated with reference units of variable size, such as administrative boundaries [47]. Furthermore, regular grids facilitate spatio-temporal comparisons by ensuring that the units of analysis remain constant across both space and time. They provide a common spatial reference framework and enable straightforward aggregation to broader spatial scales without being constrained by administrative divisions [48].

In this study, a 1 km × 1 km landscape cell was selected as the landscape-level unit of analysis rather than as a resampling resolution for the original fine-resolution land-cover maps. For each grid cell, the spatial information contained in the original land-cover maps was retained by calculating the proportional area occupied by each land-cover class. LESI was subsequently calculated as the area-weighted combination of these proportions and their corresponding HDC values. Thus, the aggregation procedure did not assign a single dominant land-cover class to each 1 km² cell but instead summarised its internal land-cover composition. The 1 km² analytical unit was selected as an operational compromise between capturing within-landscape heterogeneity, maintaining a consistent analytical unit across the six study sites, ensuring sufficient spatial discrimination of ecological sustainability patterns, and providing an adequate number of spatial units for subsequent spatial and statistical analyses.

2.5. Temporal Change in the Ecological Sustainability of Agricultural Landscapes

The temporal changes of ecological sustainability were assessed by analysing changes in the Landscape Ecological Sustainability Index (LESI) [49] between the two reference years (2023 and 2024). The Landscape Ecological Sustainability Index (LESI) is an indicator specifically developed to assess the ecological sustainability of agricultural landscapes and is based on the Human Disturbance Coefficient (HDC). The HDC quantifies the intensity of anthropogenic disturbance associated with each land-cover class. It is founded on the principle that different land-cover types exert varying levels of pressure on the major environmental systems, namely, the hydrosphere, pedosphere, atmosphere, and biosphere. HDC values range from 1 to 7, with higher values assigned to land-cover classes generating the greatest anthropogenic disturbance and lower values assigned to land-cover types that remain close to their natural condition and exert only limited pressure on ecosystems. The LESI is subsequently calculated as the area-weighted aggregation of the HDC values associated with the different land-cover classes occurring within each landscape cell.

For each landscape cell, the temporal change in ecological sustainability (ΔLESI) was calculated as the difference between the LESI value in 2024 and that in 2023, according to Equation (1).

$$\Delta\text{LESI} = \text{LESI}_{2024} - \text{LESI}_{2023} \quad (1)$$

This equation was used to assign each landscape cell to an ecological sustainability trajectory. Cells exhibiting a decrease in LESI between 2023 and 2024 ($\Delta\text{LESI} < 0$) were classified as showing an improvement in ecological sustainability, those with no change ($\Delta\text{LESI} = 0$) were considered stable, and cells with an increase in LESI ($\Delta\text{LESI} > 0$) were classified as undergoing ecological degradation. To facilitate comparison of the magnitude of ecological sustainability changes, ΔLESI values were grouped into five standardised classes applied consistently across the six study sites. A symmetric interval of -0.05 to $+0.05$ around zero was used as an operational stability class to avoid interpreting very small numerical variations in LESI as meaningful improvement or degradation. Values outside this interval were further divided into two levels of change intensity (moderate and high). Accordingly, cells with $\Delta\text{LESI} \leq -0.20$ were classified as exhibiting high improvement, those with values between -0.20 and -0.05 as moderate improvement, values between -0.05 and 0.05 as stable, values between 0.05 and 0.20 as moderate degradation, and those with $\Delta\text{LESI} \geq 0.20$ as high degradation. These thresholds were adopted for comparative and cartographic interpretation within this study and should not be interpreted as empirically established ecological thresholds.

For each study site, the proportion of landscape cells associated with improvement, stability, and degradation concerning interannual change was calculated. The median and interquartile range (IQR) of ΔLESI were also computed to summarise, respectively, the central tendency and variability of the observed changes. The distributions of ΔLESI were subsequently visualised using violin plots, enabling comparisons of the magnitude, dispersion, and skewness of interannual change in ecological sustainability among the six study sites.

The statistical significance of the observed changes was then assessed using the Wilcoxon signed-rank test, applied to paired LESI values (2023–2024) for each landscape cell. This non-parametric test was selected because of the non-normal distribution of the data and the paired nature of the observations. It assesses whether the median of the paired differences differs significantly from zero, thereby indicating the presence of a significant temporal change in ecological sustainability across the six study sites.

2.6. Spatial Patterns of Changes in the Ecological Sustainability of Agricultural Landscapes

To characterise the spatial dynamics of ecological sustainability, a global spatial autocorrelation analysis was first performed using Moran's Index [50], calculated separately for each study site from the Δ LESI values of the landscape cells. Moran's Index measures the degree of similarity between the Δ LESI value of a given landscape cell and those of its neighbouring cells by comparing the observed spatial covariance with that expected under the assumption of complete spatial randomness. The objective of this analysis was to determine whether the spatial distribution of Δ LESI values exhibited significant spatial organisation, that is, whether geographically proximate cells tended to display similar values or whether the observed pattern was randomly distributed across space.

For each study site, Moran's Index produces a single statistic theoretically ranging from -1 to 1 . A value close to 0 indicates the absence of spatial autocorrelation, implying that Δ LESI values are randomly distributed. Conversely, a positive and statistically significant Moran's Index indicates positive spatial autocorrelation, meaning that neighbouring landscape cells tend to exhibit similar Δ LESI values, thereby revealing the presence of spatially homogeneous areas. In contrast, a negative Moran's Index would indicate a checkerboard pattern, characterised by an alternation of contrasting Δ LESI values between adjacent cells.

In the second step, local spatial autocorrelation was investigated using the Local Indicators of Spatial Association (LISA) proposed by Anselin [51]. LISA identifies, for each landscape cell, whether its Δ LESI value is significantly associated with those of its neighbouring cells. The analysis was performed using a first-order Queen contiguity neighbourhood, whereby each landscape cell was considered adjacent to the eight surrounding cells sharing either a side or a corner. The local statistic compares the standardised z-score of the Δ LESI value of each landscape cell with the weighted mean of the standardised Δ LESI values observed within its neighbourhood.

The statistical significance of local spatial associations was assessed using a random permutation test. This test involves randomly permuting the Δ LESI values among landscape cells 999 times to generate a reference distribution representing the null hypothesis of no spatial structure. The observed Local Moran's I value is then compared with this simulated distribution to estimate the probability (p -value) that the observed spatial association occurred by chance. Only associations significant at the 5% significance level ($p < 0.05$) were retained for mapping spatial clusters. Four types of statistically significant spatial configurations were distinguished:

- High–High (HH): A landscape cell with the Δ LESI value above the site mean, surrounded by neighbouring cells that also exhibit above-average Δ LESI values. This configuration represents a cluster of high Δ LESI values, indicating a spatial concentration of areas experiencing relatively low ecological sustainability.
- Low–Low (LL): A landscape cell with the Δ LESI value below the site mean, surrounded by neighbouring cells that also display below-average Δ LESI values. This configuration represents a cluster of low Δ LESI values, identifying areas characterised by relatively higher ecological sustainability.
- High–Low (HL): A landscape cell with an above-average Δ LESI value surrounded by neighbouring cells with below-average values. This pattern represents a positive spatial outlier, indicating a locally more disturbed landscape cell embedded within a relatively more sustainable surrounding landscape.
- Low–High (LH): A landscape cell with a below-average Δ LESI value surrounded by neighbouring cells exhibiting above-average values. This configuration represents a negative spatial outlier, identifying a locally more ecologically sustainable landscape cell within a comparatively less sustainable neighbourhood.

Landscape cells classified as non-significant correspond to situations in which the observed local spatial association did not differ significantly from that expected under a random spatial distribution of ΔLESI values ($p \geq 0.05$). Consequently, these cells do not exhibit sufficiently pronounced local spatial structure to be attributed to processes of spatial clustering or spatial contrast.

2.7. Identification of Land-Cover Changes Associated with the Spatio-Temporal Variation in the Interannual Ecological Sustainability of Agricultural Landscapes

To identify the land-cover dynamics underlying the spatio-temporal changes in the ecological sustainability of agricultural landscapes, the adopted approach was based on the analysis of land-cover transition matrices between 2023 and 2024. This approach linked changes in land-cover classes to variations in the Human Disturbance Coefficient (HDC) and, consequently, changes in LESI.

The analyses were conducted separately for each of the 6 study sites using the land-cover maps produced for 2023 and 2024. For each site, a transition matrix was generated by overlaying the two land-cover maps and comparing the land-cover class assigned to each pixel in 2023 with that in 2024. The resulting matrices therefore quantified both stable land-cover classes and conversions between different land-cover categories. Transition matrices were initially expressed as the number of pixels and subsequently converted into surface areas to quantify the spatial extent of each land-cover transition.

To evaluate the influence of these transitions on ecological sustainability, the transition matrices were subsequently converted into HDC change contribution matrices for each study site. This transformation was based on the HDC values assigned to each land-cover class. For every transition from class i in 2023 to class j in 2024, the contribution to the overall change in the site's HDC was calculated as the product of the proportion of the area affected by the transition and the difference in the HDC values of the two classes (ΔHDC), as expressed in Equation (2):

$$\text{Contribution}_{i \rightarrow j} = \frac{\text{Surface}_{i \rightarrow j}}{\text{Surface}_{\text{total}}} \times (\text{HDC}_j - \text{HDC}_i) \quad (2)$$

where

$\text{Contribution}_{i \rightarrow j}$ represents the contribution of the transition from class i (2023) to class j (2024) to the overall change in the site's HDC;

$\text{Surface}_{i \rightarrow j}$ is the area that changed from class i in 2023 to class j in 2024;

$\text{Surface}_{\text{total}}$ is the total area of the study site;

HDC_i and HDC_j are the Human Disturbance Coefficients assigned to the initial and final land-cover classes, respectively.

This equation estimates the specific contribution of each land-cover transition to the overall change in the site's HDC.

The ΔHDC contribution matrices were displayed as matrix tables in which the rows represent the land-cover classes at the initial date and the columns represent those observed at the final date. Each matrix cell indicates the contribution of the corresponding land-cover transition to the overall change in the site's HDC. To facilitate visual interpretation, the contribution values were represented using a colour gradient, with colour intensity proportional to the relative contribution of each land-cover transition to the overall ΔHDC . This contribution depends both on the spatial extent of the transition and on the difference in anthropogenic disturbance between the initial and final land-cover classes. Circle size was scaled according to the area affected by each transition, expressed as a percentage of the total study-site area, thereby distinguishing extensive transitions from more localised ones. This dual representation makes it possible to differentiate the spatial extent of land-

cover transitions from their effective contribution to changes in anthropogenic disturbance. Particular attention was paid to identifying the transitions exhibiting the largest positive and negative contributions, thereby distinguishing the principal processes associated with the degradation and improvement of interannual ecological sustainability.

2.8. Assessment of Sensitivity of Land-Cover Transitions to Classification Uncertainty

To assess whether the estimated interannual changes were sensitive to classification uncertainty, a complementary sensitivity analysis was performed using the Overall Map Accuracy (OA) of the independently classified 2023 and 2024 maps. For each site, a site-specific uncertainty envelope was defined as $U = 1 - (OA_{2023} \times OA_{2024})$, representing a conservative approximation of the uncertainty potentially affecting the comparison between the two classifications under the simplifying assumption of independent errors between years. In each of 10,000 Monte Carlo simulations, a random perturbation within $\pm U$ was applied separately to each off-diagonal land-cover transition using a uniform distribution. Transition contributions to ΔHDC were then recalculated relative to the fixed observed total area of the corresponding site. Thus, the perturbations represented uncertainty in the estimated extent of individual transitions, while the reference area used to express their contribution remained constant across simulations. For each simulation, site-level ΔHDC was recomputed. Robustness was assessed from the 95% simulation-based sensitivity interval and the proportion of simulations retaining the direction of the observed ΔHDC .

2.9. Biophysical and Geographical Factors Associated with the Spatio-Temporal Changes in the Ecological Sustainability of Agricultural Landscapes

To investigate the relationships between biophysical and geographical factors and changes in the ecological sustainability of agricultural landscapes, as measured by ΔLESI , the analytical approach focused on examining the functional relationships between each explanatory variable and ΔLESI , without assuming a priori that these relationships were strictly linear.

The analyses were conducted using all 1 km² landscape cells across the six study sites. For each landscape cell, a set of 11 biophysical and geographical variables (Table 4) was extracted and aggregated. Quantitative variables were represented by their mean value within each landscape cell, whereas qualitative variables were represented by their dominant category.

These variables were selected because of their potential influence on both land-cover change and the ecological sustainability of agricultural landscapes. They comprised:

- Five soil variables derived from the Soil Property Maps of Africa, produced at a spatial resolution of 250 m [52]:

Depth to bedrock: Depth to bedrock influences several key soil properties, including rooting depth, plant-available water capacity, and nutrient availability. Deep soils generally provide more favourable conditions for agricultural production and are therefore more likely to be converted to cultivation or subjected to agricultural intensification than shallow soils or areas with exposed bedrock. This greater agricultural suitability may promote land-cover change and, consequently, influence the interannual change in the ecological sustainability of agricultural landscapes. Conversely, shallow soils are generally less suitable for intensive agriculture and are therefore more likely to maintain stable land cover over time.

Soil drainage: Soil drainage describes the ability of soils to remove excess water and therefore directly controls soil moisture conditions. Poorly drained soils, which are prone to frequent or prolonged waterlogging, may constrain agricultural activities and reduce the suitability of land for cultivation. In contrast, moderately to well-drained soils generally provide more favourable conditions for crop development and are consequently

more susceptible to agricultural conversion or intensification. Soil drainage may therefore influence land-cover dynamics and, ultimately, the interannual change in the ecological sustainability of agricultural landscapes.

Table 4. Biophysical and geographical variables aggregated at the landscape-cell level.

Variable	Code	Category	Unit	Aggregation Method	Description
Depth to bedrock	BDRICM	Biophysical	cm	Mean	Soil depth to bedrock, indicating the volume of soil available for crop root development.
Soil drainage	DRAINFAO		Unitless	Dominant class	Soil capacity to remove excess water according to the FAO drainage classification.
Soil texture	TEXMHT		Unitless	Dominant class	Dominant soil texture (clay, sand, or silt), influencing water retention and soil fertility.
Cation exchange capacity	CEC		Cmol (+)/kg	Mean	Soil capacity to retain and exchange essential plant nutrients.
Available water-holding capacity	GYGA		%	Mean	Amount of water available for plant uptake within the soil profile.
Terrain Ruggedness Index	IR		Unitless	Mean	Measure of terrain heterogeneity and topographic complexity.
Precipitation	PRECIP		mm	Mean	Mean annual precipitation.
Aridity	ARIDITY	Geographical	Unitless	Dominant class	Dominant aridity class.
Distance to urban areas	DURB		km	Mean	Distance to major urban centres, used as a proxy for anthropogenic pressure and accessibility.
Distance to roads	ROAD		km	Mean	Distance to the principal road network.
Distance to water bodies	DEAU		km	Mean	Distance to surface water resources.

Soil texture: Soil texture determines water-holding capacity, nutrient availability, permeability, and susceptibility to erosion. Sandy and sandy loam soils, characterised by limited water and nutrient retention, are generally less favourable for intensive agriculture and may therefore restrict certain land-cover conversions. Conversely, silty, clay loam, and clay soils usually possess greater water storage capacity and higher natural fertility, making them more attractive for agricultural production. This increased agricultural suitability may encourage cropland expansion or intensification and consequently influence land-cover change. Soil texture is therefore expected to affect interannual change in ecological sustainability indirectly through its influence on the agricultural potential of the land.

Cation exchange capacity (CEC): Cation exchange capacity is a widely recognised indicator of soil fertility and reflects the capacity of soils to retain and supply nutrients to plants. Soils with high CEC values generally provide more favourable conditions for crop production and may therefore be more attractive for agricultural development. This attractiveness may promote the expansion or intensification of agricultural land use, with potential implications for land-cover dynamics and the ecological sustainability of agricultural landscapes. Conversely, soils with low CEC are generally less productive and may therefore experience lower pressure for agricultural conversion or intensification.

Soil water-holding capacity: Soil water-holding capacity refers to the amount of water that a soil can retain and make available to plants after gravitational water has

drained away. Unlike soil drainage, which describes the capacity of a soil to remove excess water, this variable reflects the volume of water available for plant uptake. Soils with a high water-holding capacity generally provide more favourable conditions for crop growth, particularly during dry periods, thereby increasing their suitability for agricultural production. Conversely, soils with a low water-holding capacity are more susceptible to water stress and may be less suitable for certain crops. Consequently, this variable is expected to influence land-cover change and, indirectly, the interannual change in the ecological sustainability of agricultural landscapes.

Terrain Ruggedness Index (TRI): This topographic variable was derived from a 30 m Digital Elevation Model (DEM) [53] and describes the topographic heterogeneity of the landscape. Areas with greater terrain ruggedness generally exhibit lower accessibility and greater constraints on agricultural expansion, thereby favouring the persistence of natural vegetation. Conversely, relatively flat landscapes are typically more suitable for agricultural intensification. Terrain ruggedness is therefore expected to influence both land-cover dynamics and the ecological sustainability of agricultural landscapes.

- Two climatic variables, comprising:

Precipitation: This variable was obtained through Inverse Distance Weighting (IDW) interpolation of rainfall records collected between 1980 and 2009 from 43 meteorological stations across Benin, producing a continuous precipitation surface at a 10 m spatial resolution. Precipitation is a major determinant of water availability for both agricultural crops and natural ecosystems. It influences vegetation productivity, the regenerative capacity of plant communities, and the suitability of land for rainfed agriculture. In northern Benin, areas receiving higher rainfall are generally more attractive for agricultural expansion or intensification, which may promote land-cover change and alter levels of anthropogenic disturbance. Conversely, higher rainfall may also support the maintenance of vegetation cover and enhance ecosystem resilience. Precipitation is therefore expected to influence the interannual change in the ecological sustainability of agricultural landscapes.

Aridity: This variable was derived from the Global Aridity Index dataset at a 1 km spatial resolution [54]. Aridity characterises the degree of hydroclimatic stress experienced by ecosystems. Unlike precipitation, which quantifies only water inputs, the aridity index integrates the balance between water availability and atmospheric evaporative demand. More arid areas generally experience greater water deficits, which may constrain vegetation productivity, reduce ecosystem regeneration capacity, and increase land susceptibility to degradation. These hydroclimatic constraints are likely to influence land-cover decisions, agricultural management practices, and, consequently, the interannual change in the ecological sustainability of agricultural landscapes.

- Three geographical variables, comprising:

Distance to urban areas: This variable corresponds to the Euclidean distance between each landscape cell and the main urban areas, characterised by a high concentration of population, economic activities, and infrastructure. Urban areas were delineated using the GRID3 Settlement Extents v3 (2024) dataset produced by the Center for International Earth Science Information Network (CIESIN). Only features classified as “Built-up area” were retained, while the “Village” and “Hamlet” categories were excluded to ensure that only the principal urban centres likely to exert substantial influence on land-cover dynamics were represented. Proximity to urban areas may increase demand for agricultural land, natural resources, and built-up space, thereby promoting land-cover change and land-cover intensification. Conversely, landscapes located farther from major urban centres are generally less exposed to the direct pressures associated with urban expansion and market accessibility. Distance to urban areas is therefore expected to influence the interannual

change in the ecological sustainability of agricultural landscapes through its effects on land-cover change.

Distance to roads: This variable represents the Euclidean distance from each landscape cell to the paved roads constituting the principal transport corridors within the study area. Transport infrastructure improves access to agricultural land, markets, and natural resources, thereby facilitating human mobility and the establishment of economic activities. Agricultural landscapes located in close proximity to roads are generally more exposed to agricultural expansion, land-cover intensification, natural resource exploitation, and infrastructure development. Conversely, more remote areas often benefit from a degree of isolation that may reduce the intensity of anthropogenic transformations. Distance to roads is therefore expected to influence land-cover change and, consequently, the interannual change in the ecological sustainability of agricultural landscapes.

Distance to water bodies: This variable corresponds to the Euclidean distance between each landscape cell and permanent and seasonal watercourses derived from a 30 m Digital Elevation Model (DEM) [53]. Proximity to water resources may influence interannual change in ecological sustainability through several potentially contrasting mechanisms. On the one hand, riparian areas generally benefit from greater water availability, relatively fertile soils, and the persistence of vegetation associated with aquatic ecosystems, all of which can enhance the ecological resilience of agricultural landscapes. On the other hand, these favourable conditions also make such areas particularly attractive for agriculture, livestock production, and other human activities, potentially leading to land-cover intensification, degradation of riparian vegetation, and increased anthropogenic disturbance. Consequently, distance to water bodies is expected to influence land-cover dynamics and, ultimately, the interannual change in the ecological sustainability of agricultural landscapes.

A series of univariate regression models were fitted to descriptively characterise the relationships between ΔLESI and each of the 11 biophysical and geographical variables. For the continuous variables, six alternative functional forms were evaluated: linear, quadratic, cubic, logarithmic, exponential, and power models. For the categorical variables, Ordinary Least Squares (OLS) regression models were fitted after transforming the categorical predictors using one-hot encoding, whereby each category of a qualitative variable is converted into a binary variable, taking the value 1 when the category is present and 0 otherwise [55].

The performance of the competing regression models was evaluated using the coefficient of determination (R^2), adjusted coefficient of determination (adjusted R^2), root mean square error (RMSE), relative root mean square error (RRMSE), mean absolute error (MAE), and the Akaike Information Criterion (AIC). These models were used as descriptive and exploratory tools to characterise the relationships observed across the complete set of landscape cells within the six study sites. Model interpretation therefore focused on the direction and strength of the observed relationships and on their explanatory performance.

To complement the univariate analyses and assess whether the associations between biophysical and geographical factors and ΔLESI depended on interactions between factors, systematic bivariate interaction analyses were performed. All 55 possible pairwise combinations among the 11 explanatory variables were examined, thereby avoiding an a priori selection of candidate interactions. For each pair of variables, a bivariate regression model including both main effects and their interaction term was fitted ($\Delta\text{LESI} \sim X_1 + X_2 + X_1 \times X_2$). Continuous predictors were standardised before modelling, whereas categorical variables were dummy-coded.

The descriptive performance of the bivariate models was primarily assessed using adjusted R^2 , which accounts for differences in model complexity. For each pair of variables, the change in adjusted R^2 ($\Delta\text{adjusted } R^2$) between the interaction and corresponding additive model was calculated to assess whether including the interaction improved the description

of the observed variability in Δ LESI. AIC was additionally used to compare the relative fit of the additive and interaction models, with lower values indicating a better balance between model fit and complexity. The interaction analyses were therefore interpreted in terms of improvement in descriptive model performance and context-dependent associations.

Then, given the spatial nature of the landscape-cell data, the regression analyses were used for descriptive and exploratory purposes rather than for statistical inference.

3. Results

3.1. Spatio-Temporal Changes in the Ecological Sustainability of Agricultural Landscapes

The LESI maps reveal interannual changes in the spatial distribution of ecological sustainability between 2023 and 2024 across all six study sites, although the magnitude of these changes varied among landscape cells (Figure 4). Furthermore, the Δ LESI maps show that interannual changes in ecological sustainability affected the majority of landscape cells. These interannual changes were spatially heterogeneous, resulting in a mosaic of cells undergoing degradation (Δ LESI > 0) and improvement (Δ LESI < 0). The predominance of degrading cells in Awanla, Bagou, Ouenou, and Soaodou indicates a widespread increase in LESI and, consequently, an overall decline in interannual ecological sustainability. By contrast, Gbanlin exhibited a higher proportion of improving cells, reflecting an increase in interannual ecological sustainability between 2023 and 2024. Parakou displayed an intermediate pattern, with interannual improving and degrading cells occurring in relatively balanced proportions.

These spatial patterns are corroborated by the descriptive statistics of Δ LESI (Table 5). Median Δ LESI values were positive in Awanla (0.152), Bagou (0.081), Ouenou (0.135), and Soaodou (0.227), indicating an overall trend towards interannual declining ecological sustainability. Soaodou emerged as the most interannual degraded site, exhibiting both the highest median Δ LESI and the largest proportion of degrading cells (91.24%). In contrast, Gbanlin was the only site with a negative median (−0.018), indicating a slight overall improvement in interannual ecological sustainability, with 55.60% of landscape cells showing a decrease in interannual LESI between the two years. Parakou recorded a median Δ LESI close to zero (0.003), reflecting overall stability in interannual ecological sustainability at the site scale despite the coexistence of improving (48.04%) and degrading (51.32%) landscape cells.

Table 5. Wilcoxon signed-rank test.

Site	Δ LESI Median	IQR Δ LESI	% Δ LESI > 0	% Δ LESI < 0	% Δ LESI = 0	W	r
Awanla	0.152	0.186	88.92%	10.92%	0.16%	151,724.0 *	0.782 **
Bagou	0.081	0.124	85.24%	14.56%	0.20%	203,477.0 *	0.753 **
Gbanlin	−0.018	0.177	42.68%	55.60%	1.72%	1,201,249.0 *	0.177 *
Ouenou	0.135	0.195	89.24%	9.00%	1.76%	105,278.0 *	0.806 **
Parakou	0.003	0.133	51.32%	48.04%	0.64%	1,396,562.5 ^{ns}	0.082 ^{ns}
Soaodou	0.227	0.250	91.24%	8.64%	0.12%	104,215.0 *	0.808 **

IQR = interquartile range; * indicates statistical significance (*p*-value) at the 1% level for the Wilcoxon signed-rank test, while effect size (*r*) is interpreted as weak (*), strong (**), or not significant (ns).

Furthermore, the violin plots (Figure 5) reveal marked spatial heterogeneity in interannual change in ecological sustainability within each study site. Although the median values indicate the dominant interannual trend, the wide spread of the distributions demonstrates that processes of interannual ecological improvement and degradation coexisted locally across all six sites. The distributions are predominantly shifted towards positive interannual Δ LESI values in Awanla, Ouenou, and Soaodou, reflecting the predominance of degradation processes. In contrast, Gbanlin exhibits a slight predominance of negative interannual Δ LESI values, whereas Parakou appears broadly stable, with a median close to

zero. Bagou also displays a slightly positive median, indicating a modest overall tendency towards interannual ecological degradation. Ouenou and Soaodou recorded the largest interquartile ranges (IQRs) (0.195 and 0.250, respectively), indicating greater diversity in local interannual ecological sustainability. By contrast, Bagou exhibited the smallest IQR (0.124), suggesting a more homogeneous pattern of interannual ecological change across the site.

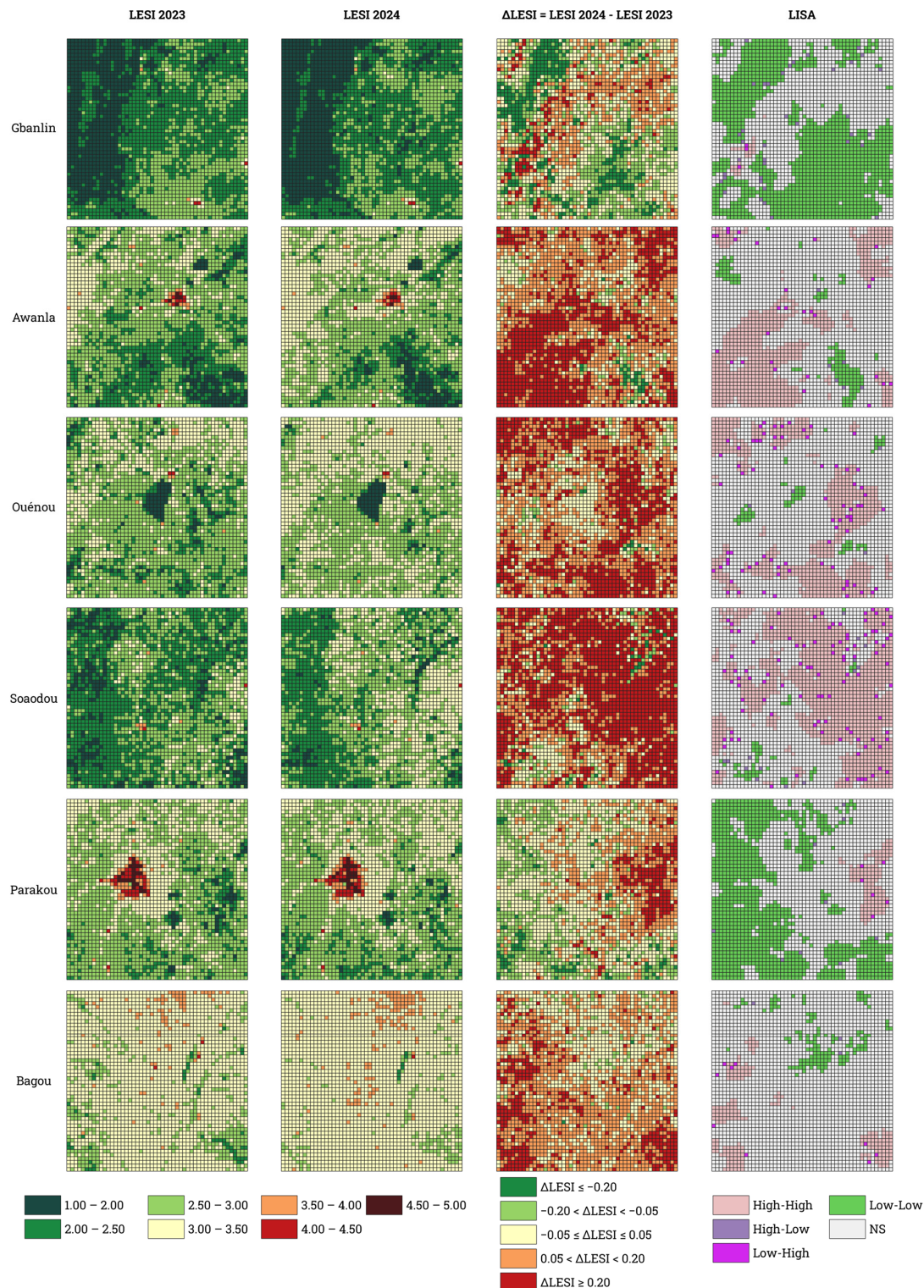


Figure 4. Spatial distribution of the LESI in 2023 and 2024, interannual change (ΔLESI), and local spatial autocorrelation patterns of the Landscape Ecological Sustainability Index (LESI) across the six study sites.

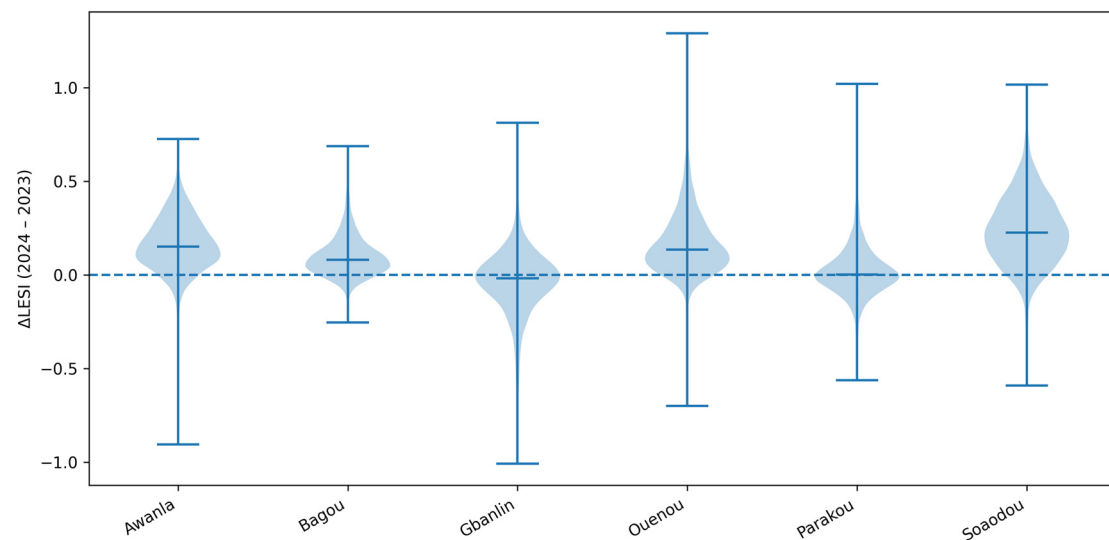


Figure 5. Violin plots showing the distribution of Δ LESI values across the six study sites between 2023 and 2024. The light-blue violins represent the probability density of Δ LESI values, with wider sections indicating a higher concentration of landscape cells. The horizontal blue bar inside each violin corresponds to the median Δ LESI, while the vertical whiskers indicate the minimum and maximum observed values. The dashed horizontal line represents Δ LESI = 0, separating cells that experienced an improvement (Δ LESI < 0) from those that experienced a degradation (Δ LESI > 0).

The Wilcoxon signed-rank test (Table 5) confirms the patterns described above. A significant increase in LESI was observed in Awanla, Bagou, Ouenou, and Soaodou ($p < 0.01$), where the vast majority of landscape cells (85.24–91.24%) exhibited a decline in interannual ecological sustainability. In contrast, Gbanlin showed a significant improvement ($p < 0.01$), with a higher proportion of improving cells (55.60%) than interannual degrading cells (42.68%). By comparison, no significant difference was detected in Parakou ($p > 0.05$), where the proportions of degrading (51.32%) and improving (48.04%) landscape cells remained nearly balanced.

The global Moran's I results (Table 6) further revealed a positive and highly significant spatial autocorrelation across all study sites (Moran's I = 0.44–0.65; $p < 0.001$), indicating that the observed changes were not randomly distributed in space. Instead, neighbouring landscape cells tended to exhibit similar interannual ecological conditions.

Table 6. Moran's I test results.

Site	n	Moran's I	p-Value	z-Score
Awanla	2500	0.58	0.001	59.40
Bagou	2500	0.53	0.001	51.64
Gbanlin	2500	0.57	0.001	55.87
Ouenou	2500	0.47	0.001	45.09
Parakou	2500	0.65	0.001	61.64
Soaodou	2500	0.44	0.001	42.12
Global	15,000	0.65	0.001	154.78

This spatial organisation is further confirmed by the LISA maps (Figure 4), which reveal statistically significant spatial clusters. Low–Low clusters, representing landscape cells with low Δ LESI values surrounded by neighbouring cells exhibiting similarly low values, are particularly prevalent in Gbanlin and Parakou, indicating the presence of localised areas of improving interannual ecological sustainability. Conversely, High–High clusters, characterised by high Δ LESI values and therefore reflecting ecological degradation,

are more frequently observed in Awanla, Ouenou, and Soadoudou. Transitional clusters (High–Low and Low–High) are comparatively uncommon, suggesting that changes in interannual ecological sustainability are predominantly organised into coherent spatial patterns rather than occurring as isolated events.

Overall, these findings indicate that interannual changes in ecological sustainability between 2023 and 2024 were characterised by an overall trend towards degradation in four of the six study sites, whereas Gbanlin experienced a slight improvement and Parakou remained broadly stable. They further demonstrate that these changes exhibit significant spatial organisation, reflecting the influence of localised landscape processes on the interannual ecological sustainability of agricultural landscapes.

3.2. Land-Cover Changes Associated with the Spatio-Temporal Variation in the Interannual Ecological Sustainability of Agricultural Landscapes

Figure 6 highlights the land-cover transitions that contributed most to changes in the Human Disturbance Coefficient (ΔHDC) across the six study sites. Positive contributions (red) represent transitions that increase anthropogenic disturbance and therefore contribute to the degradation of interannual ecological sustainability, whereas negative contributions (blue) correspond to transitions that reduce anthropogenic disturbance and consequently promote improvements in interannual ecological sustainability.

Across study sites, transitions involving the conversion of natural and semi-natural vegetation into agricultural land emerged as the principal factors associated with interannual ecological degradation. The positive contributions were generally associated with the conversion of shrub savannas (SHS) into cereal crops (CER), tree crop plantations (OTC), or other agricultural land-cover classes. This transition constituted the dominant contributor in Awanla, Bagou, Gbanlin, and Soadoudou, where it accounted for a substantial proportion of the increase in ΔHDC observed between 2023 and 2024.

Transitions involving tree crop plantations also represented a major factor associated with agricultural landscape transformation. In Awanla, Bagou, Ouenou, and Parakou, the conversion of tree crop plantations (OTC) (predominantly teak plantations) to cereal crops (CER) ranked among the principal positive contributors to ΔHDC . This pattern reflects the progressive anthropogenic transformation of agricultural landscapes through the expansion of commercial forest plantations.

Conversely, several land-cover transitions contributed to reducing the overall level of anthropogenic disturbance. These negative contributions were primarily associated with the reconversion of cultivated land to more natural or semi-natural vegetation. In Gbanlin, where the overall ΔHDC remained close to zero and an improvement in LESI was observed, several transitions involving the reversion of agricultural land and plantations to shrub savannas (SHS) made substantial negative contributions to the reduction of anthropogenic disturbance. These restorative transitions largely explain why Gbanlin was the only study site to exhibit a clear improvement in interannual ecological sustainability.

The magnitude of these contributions also varied among the study sites. Soadoudou recorded the highest ΔHDC (0.257), characterised by a marked predominance of positive contributions associated with agricultural expansion at the expense of shrub savannas. In contrast, Gbanlin exhibited the lowest ΔHDC (0.003), reflecting a near balance between positive and negative contributions. Awanla ($\Delta\text{HDC} = 0.163$), Bagou ($\Delta\text{HDC} = 0.111$), and Ouenou ($\Delta\text{HDC} = 0.095$) occupied an intermediate position, where the conversion of natural and semi-natural vegetation to agricultural land remained more influential than processes of ecological restoration and natural regeneration.

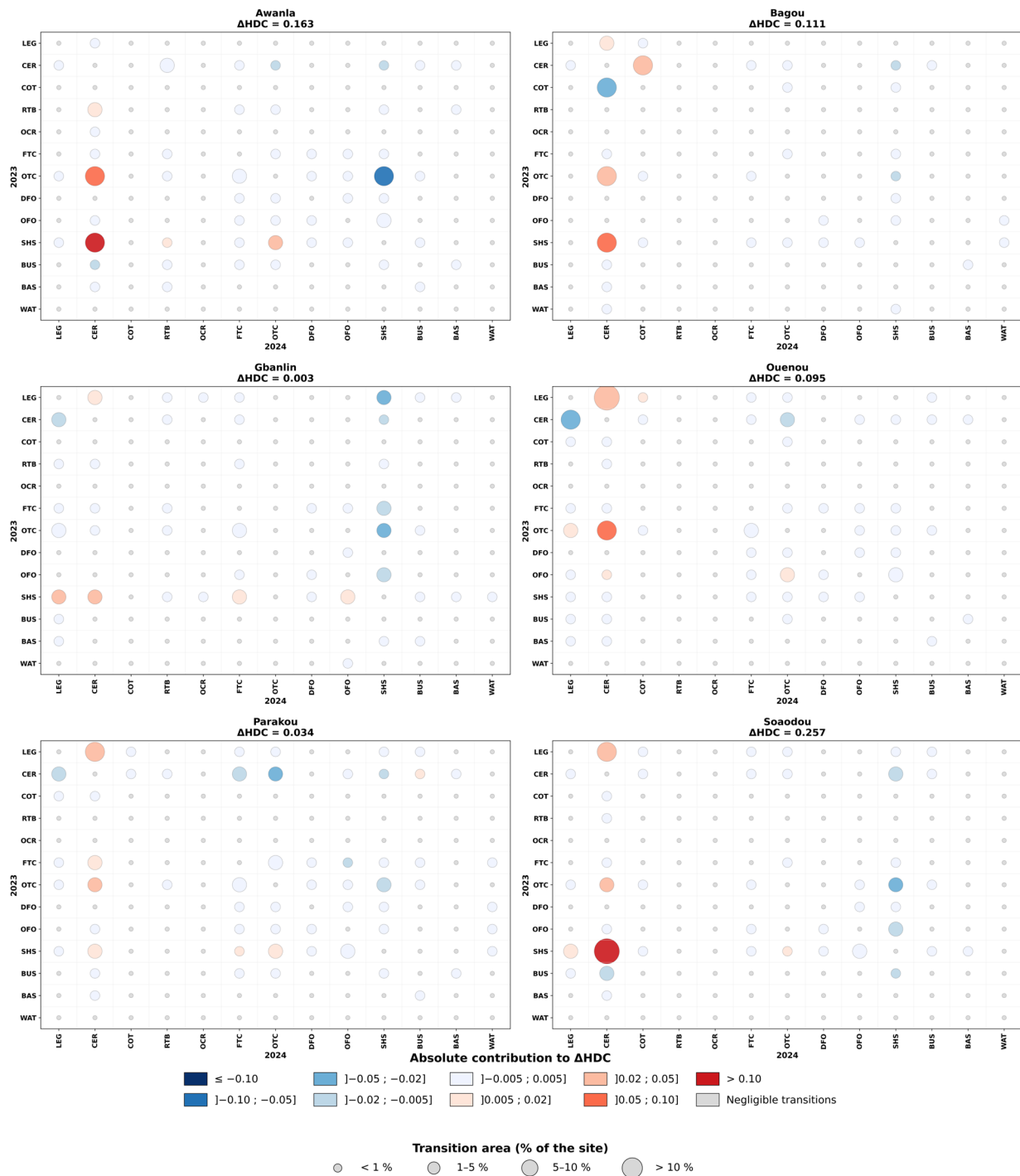


Figure 6. Absolute contribution of land-cover transitions to changes in the global variation of Human Disturbance Coefficient (ΔHDC) across the six study sites. LEG: Leguminous/Oleaginous (Soja); CER: Cereals; COT: Cotton; RTB: Roots/Tubers; OCR: Other Crops; FTC: Fruit Tree Crops (Cashew, Mango); OTC: Other Tree Crops (Teak); DFO: Dense Forest; OFO: Open Forest; SHS: Shrubby Savannah; BUS: Built-up Surfaces; BAS: Bare Soil; WAT: Water.

Finally, the analysis of the contributions of land-cover transitions to ΔHDC (Figure 7) shows that the differences observed among the study sites were driven primarily by a limited number of dominant transitions. In Awanla, the conversion of shrub savanna to cereal crops (SHS $\rightarrow$ CER) accounted for only 7.8% of the site's total area but alone explained 36.0% of the overall ΔHDC dynamics. Similarly, the transition OTC $\rightarrow$ CER occupied 9.8% of the site while contributing 20.6% of the total ΔHDC dynamics.

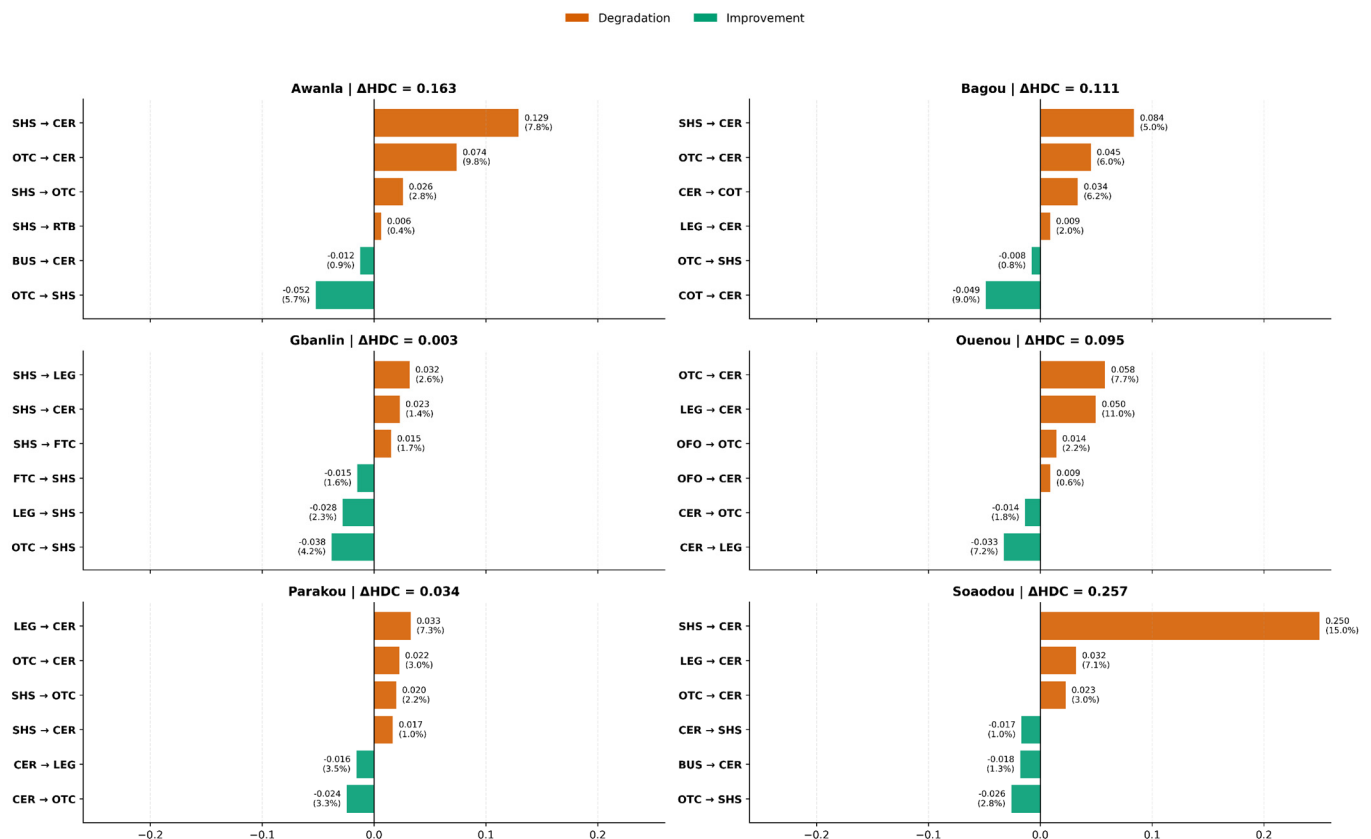


Figure 7. Main land-cover transitions associated with changes in the Human Disturbance Coefficient (ΔHDC) across the six sites between 2023 and 2024. LEG: Leguminous/Oleaginous (Soja); CER: Cereals; COT: Cotton; RTB: Roots/Tubers; OCR: Other Crops; FTC: Fruit Tree Crops (Cashew, Mango); OTC: Other Tree Crops (Teak); DFO: Dense Forest; OFO: Open Forest; SHS: Shrubby Savannah; BUS: Built-up Surfaces; BAS: Bare Soil; WAT: Water. Positive (orange) bars represent land-cover transitions contributing to an increase in anthropogenic disturbance (degradation), whereas negative (green) bars represent transitions contributing to a decrease in disturbance (improvement). Values indicate the absolute contribution of each land-cover transition to the overall change in the Human Disturbance Coefficient (ΔHDC). Values in parentheses correspond to the percentage of the site area occupied by each transition. Only the six most influential transitions are shown for each site.

A similar pattern was observed in the other study sites. In Bagou, the transition SHS → CER covered only 5.0% of the landscape yet accounted for 31.4% of the site's overall ΔHDC dynamics. In Ouenou, the transitions OTC → CER and LEG → CER occupied 7.7% and 11.0% of the site, respectively, while contributing 24.0% and 20.6% of the total ΔHDC dynamics. Soaodou, which recorded the highest ΔHDC (0.257), provides the most striking example: although the conversion SHS → CER affected only 15.0% of the site's area, it alone explained 57.4% of the site's ΔHDC, highlighting its pivotal role in the observed ecological degradation.

Conversely, the largest contributions to improving interannual ecological sustainability were associated with transitions towards semi-natural vegetation. In Gbanlin, the transitions OTC → SHS, LEG → SHS, and FTC → SHS occupied 4.2%, 2.3%, and 1.6% of the landscape, respectively, but accounted for 17.7%, 13.0%, and 6.9% of the site's ΔHDC. These restorative transitions almost entirely offset the degradation processes occurring within the site, thereby explaining both its very low ΔHDC (0.003) and the overall improvement in LESI.

Overall, these findings demonstrate that changes in the interannual ecological sustainability of agricultural landscapes depend on both the nature of land-cover transitions and their spatial extent. Relatively limited transitions can exert a major influence on ΔHDC

dynamics when they involve substantial changes in anthropogenic disturbance, whereas more extensive transitions may contribute comparatively little to the overall evolution of landscape interannual ecological sustainability.

3.3. Sensitivity of Land-Cover Transitions to Classification Uncertainty

The sensitivity analysis showed that the direction of site-level ΔHDC was highly robust to the classification uncertainty considered in five of the six agricultural landscapes (Figure 8). Detailed results of the sensitivity analysis for all land-cover transitions across the six study sites are provided in Supplementary Material S2. Despite site-specific uncertainty envelopes ranging from 20.80% in Gbanlin to 30.48% in Soadoudou, the direction of ΔHDC was retained in 100% of the 10,000 simulations for Awanla, Bagou, Ouenou, Soadoudou, and Parakou. Their 95% simulation-based sensitivity intervals remained entirely above zero, supporting the robustness of the observed increase in human disturbance. Gbanlin differed from the other sites: its observed ΔHDC was close to zero (0.0027), its sensitivity interval crossed zero (-0.0131 to 0.0184). Thus, the sensitivity analysis provides no robust evidence of either an increase or a decrease in disturbance at Gbanlin, supporting its characterisation as relatively stable between 2023 and 2024.

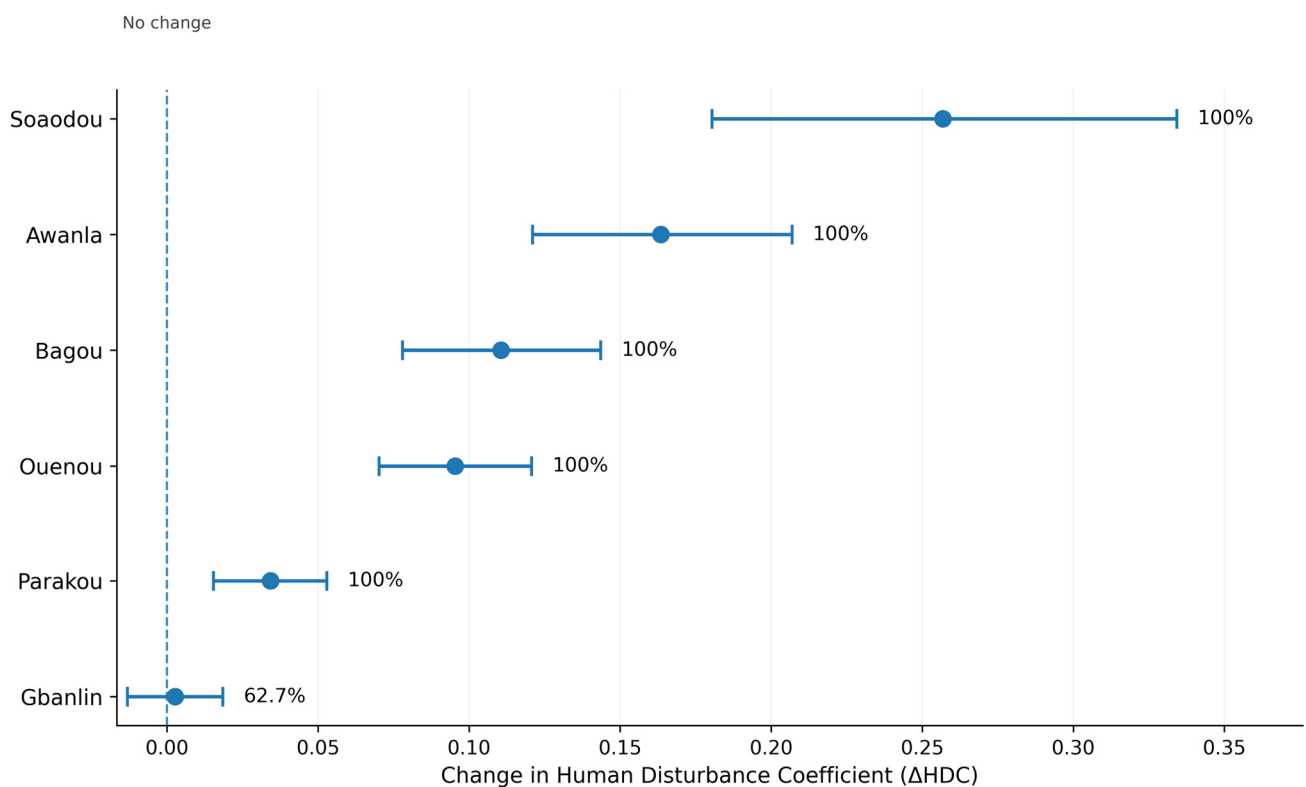


Figure 8. Robustness of site-level changes in the Human Disturbance Coefficient (ΔHDC) to classification uncertainty. Points represent observed ΔHDC values, while horizontal bars show the 95% simulation-based sensitivity intervals obtained from 10,000 simulations using site-specific uncertainty envelopes derived from the Overall Map Accuracy of the 2023 and 2024 classifications. Percentages indicate the proportion of simulations retaining the observed direction of ΔHDC .

3.4. Biophysical and Geographical Factors Associated with the Spatio-Temporal Changes in the ΔLESI

Table 7 presents the best-fitting univariate regression models describing the individual relationships between ΔLESI and the biophysical and geographical variables. Overall, the best-performing models exhibited limited explanatory power, with R^2 values ranging from 0.0004 to 0.0814. Depth to bedrock (BDRICM) showed the highest explanatory performance

($R^2 = 0.0814$), followed by distance to urban areas (DURB; $R^2 = 0.0785$), cation exchange capacity (CEC; $R^2 = 0.0752$), and the Terrain Ruggedness Index (IR; $R^2 = 0.0586$).

Table 7. Best-fitting univariate regression models describing the relationship between Δ LESI and the biophysical and geographical variables.

Variable	Model	R^2	Adj. R^2	RMSE	RRMSE	MAE
BDRICM	Cubic	0.0814	0.08	0.18	164.81	0.13
DURB	Cubic	0.0785	0.08	0.18	165.07	0.13
CEC	Cubic	0.0752	0.08	0.18	165.34	0.13
IR	Cubic	0.0586	0.06	0.18	166.11	0.13
GYGA	Cubic	0.0217	0.02	0.18	170.39	0.13
PRECIP	Quadratic	0.0212	0.02	0.18	170.12	0.13
ARIDITY	OLS	0.0137	0.01	0.18	170.77	0.14
DRAINFAO	OLS	0.0136	0.01	0.18	170.78	0.14
DROAD	Power	0.0099	0.01	0.18	171.10	0.14
DEAU	Linear	0.0019	0.00	0.19	171.79	0.14
TEXMHT	OLS	0.0004	0.00	0.19	171.92	0.14

Variable codes: see Table 4. R^2 : coefficient of determination; Adj. R^2 : adjusted coefficient of determination; RMSE: root mean square error; RRMSE: relative root mean square error; MAE: mean absolute error.

These results indicate that no individual biophysical or geographical variable accounts for a substantial proportion of the observed variation in the interannual ecological sustainability of agricultural landscapes. Moreover, the predominance of cubic models among the best-fitting regressions indicates that several of the observed relationships were better described by non-linear than by simple linear functions.

Figure 9 illustrates the best-fitting univariate relationships between Δ LESI and the biophysical and geographical variables. The fitted regression curves indicate that several continuous variables were better described by non-linear functional forms. The categorical variables likewise exhibit only modest differences among their respective classes. Specifically, the humid climatic zone displays slightly higher median Δ LESI values than the dry sub-humid and semi-arid zones, whereas differences among soil drainage classes remain limited, despite a slight tendency for poorly drained soils (Low) to be associated with higher Δ LESI values. Similarly, soil texture (TEXMHT) shows virtually no variation among its categories, consistent with its very low explanatory performance in the univariate analysis ($R^2 = 0.0004$). Overall, the scatterplots reveal substantial dispersion of landscape cells around the fitted regression curves, consistent with the generally low R^2 values of the univariate models. Thus, each variable considered individually accounts for only a small proportion of the observed variability in Δ LESI.

The bivariate interaction models showed generally limited explanatory performance, with adjusted R^2 values ranging from approximately 0.002 to 0.109 (Figure 10). The highest performance was obtained for the model combining CEC and distance to urban areas (DURB), including their interaction (adjusted $R^2 = 0.109$). Importantly, the contribution of the interaction term varied substantially among variable pairs. For CEC $\times$ DURB, inclusion of the interaction term increased the adjusted R^2 from 0.001 in the corresponding linear additive model to 0.109 in the interaction model (Δ adjusted $R^2 = +0.109$), representing the largest improvement among all pairwise combinations. Other notable improvements were observed for DURB $\times$ TEXMHT (Δ adjusted $R^2 = +0.061$), CEC $\times$ DROAD (+0.048), CEC $\times$ TEXMHT (+0.040), IR $\times$ DRAINFAO (+0.032), and DROAD $\times$ DURB (+0.031). Conversely, some models with comparatively higher overall explanatory performance showed little additional improvement after inclusion of the interaction term; for example, BDRICM $\times$ IR reached an adjusted R^2 of 0.069 but showed no increase relative to the additive

model. Overall, although pairwise interactions improved the descriptive performance of several models, adjusted R^2 remained below 0.11 across all combinations, indicating that the observed variation in ΔLESI was only partially accounted for by simple pairwise relationships among the biophysical and geographical variables considered.

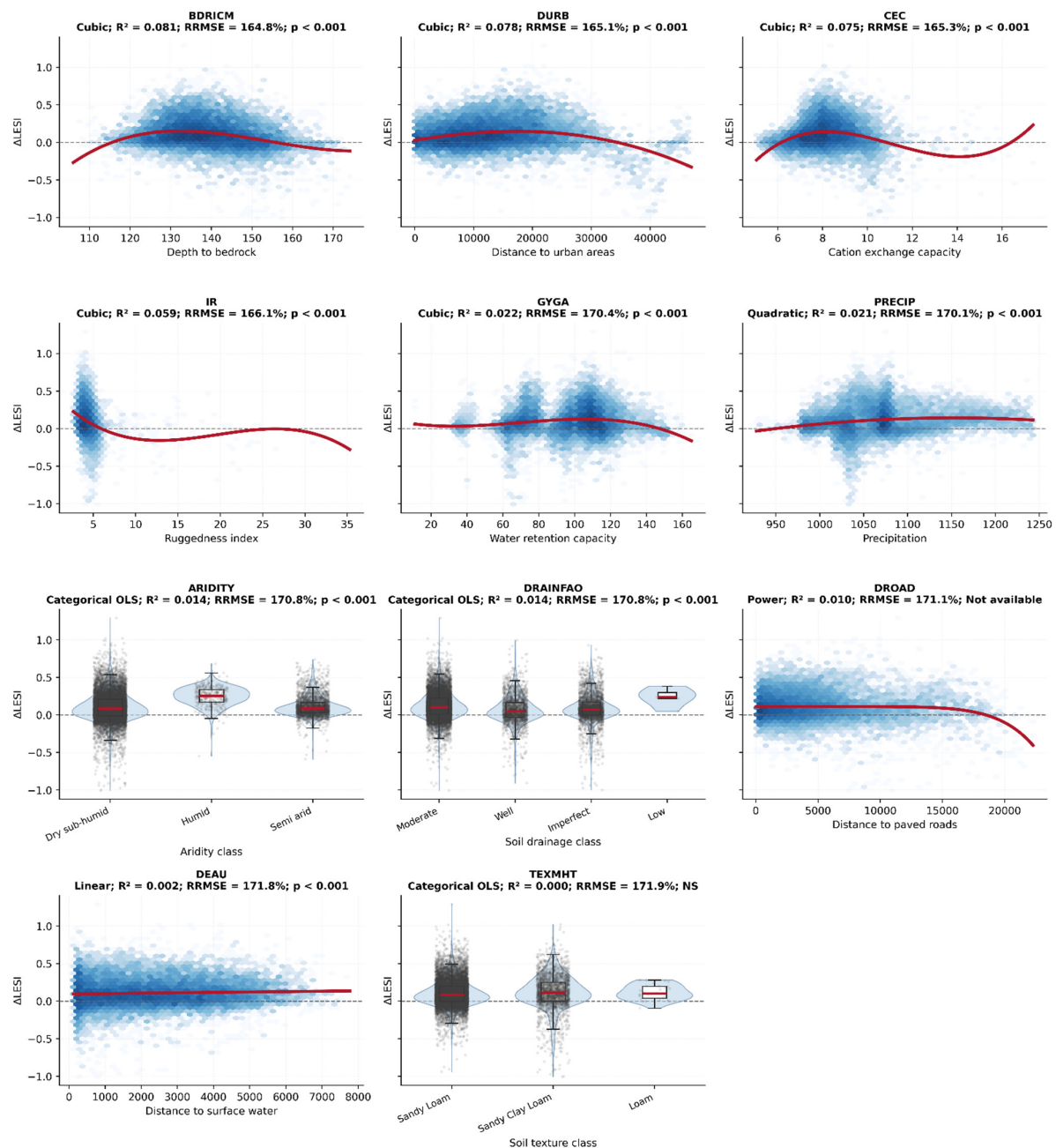


Figure 9. Best adjusted univariate relationships between ΔLESI and the biophysical and geographical variables. For numerical variables, hexagon shading indicates the density of landscape cells on a logarithmic scale, and the contrasting line represents the best-fitted model. For categorical variables, violins show the distribution density, boxes show the median and interquartile range, and jittered points represent individual landscape cells.

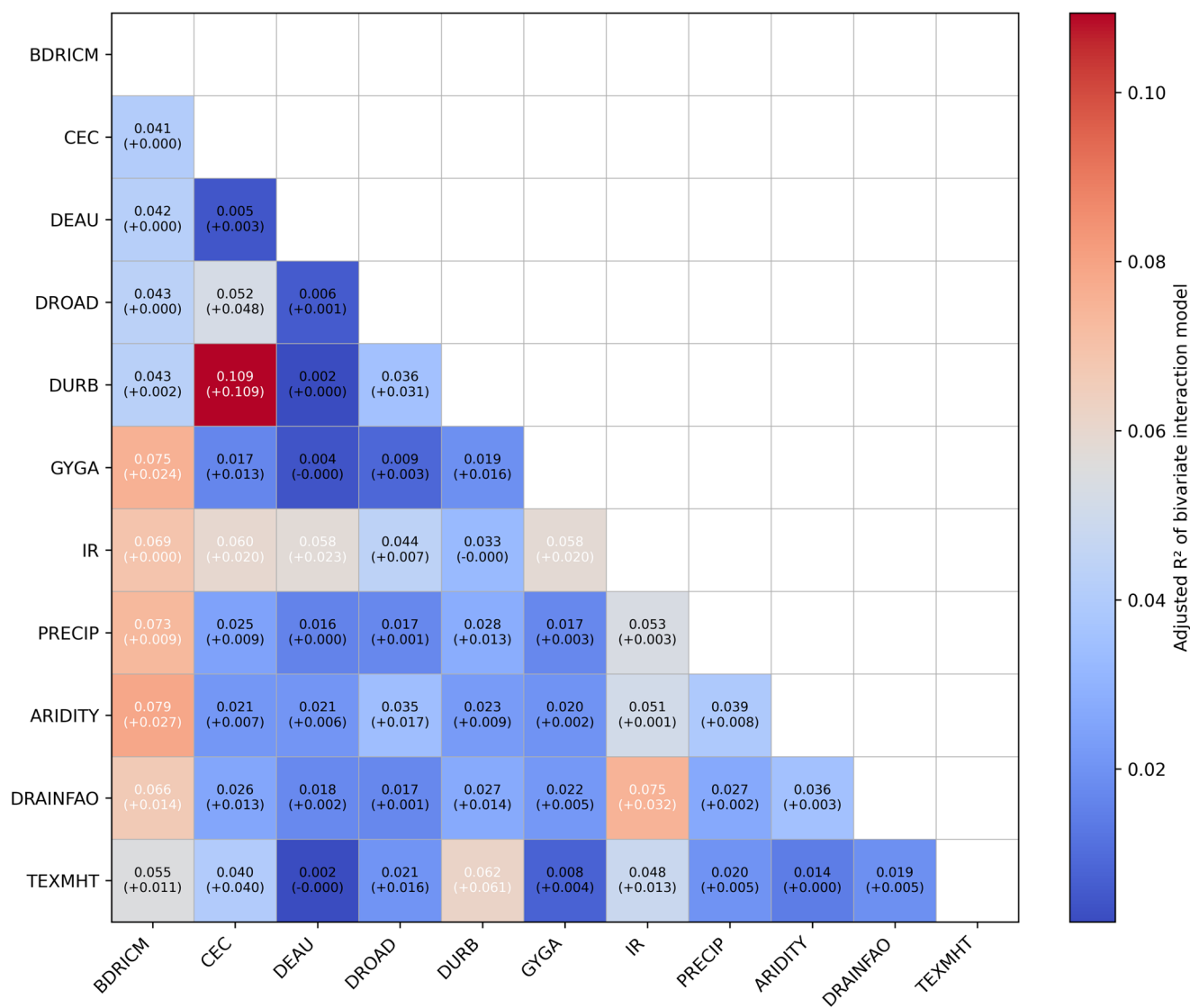


Figure 10. Explanatory performance of the 55 pairwise interaction models relating Δ LESI to biophysical and geographical variables. Cell colours and first-line values represent the adjusted R^2 of the full model including both main effects and their interaction. Values in parentheses represent the change in adjusted R^2 (Δ adjusted R^2) relative to the corresponding additive model. Positive Δ adjusted R^2 values indicate improved descriptive performance after inclusion of the interaction term, whereas values close to zero or negative values indicate little or no additional contribution of the interaction.

4. Discussion

4.1. Spatial Heterogeneity of Interannual Ecological Sustainability in Agricultural Landscapes

Among the six study sites, four experienced a decline in interannual ecological sustainability between 2023 and 2024, primarily driven by the expansion of agricultural land-cover classes at the expense of natural vegetation, particularly shrub savannas, and, to a lesser extent, semi-natural formations such as teak plantations. This pattern reinforces the findings of Ahononga et al. [56] and Biaou et al. [57], who reported a marked expansion of cultivated land, agricultural fallows, and human settlements in northern Benin between 2005 and 2015. It is also consistent with the broader trend observed across West Africa, where the progressive conversion of natural vegetation into cropland has resulted in declining woody cover and biodiversity [58]. Several studies attribute these changes to evolving agricultural practices, particularly the shortening of fallow periods, population growth, climate variability, and increasing demand for food and energy resources [59]. Declining soil fertility,

access to services, and local biophysical conditions have likewise been identified as factors promoting agricultural expansion [60–62].

By contrast, Gbanlin was the only study site to exhibit an overall improvement in interannual ecological sustainability, confirming that the trajectories of agricultural landscapes in northern Benin remain spatially heterogeneous [56,57]. This pattern may be partly explained by the presence of Wari-Maró–Mont Kouffé National Park in the western part of the site, which is likely to have constrained agricultural expansion. Indeed, Sassen, et al. [63] showed that protected areas can effectively limit the conversion of natural habitats when conservation measures are properly enforced, although their effectiveness ultimately depends on the institutional capacity to implement and enforce these regulations [64]. Moreover, forest formations within the site were converted to agricultural land to a much lesser extent than shrub savannas. This contrast is consistent with previous studies showing that agricultural expansion generally targets vegetation types that are easier and less costly to clear, particularly savannas, whereas topographic constraints, clearing costs, and certain physical characteristics of the land may limit the conversion of forested areas [65]. In other contexts, however, prior forest degradation, for example through charcoal production, may facilitate their subsequent conversion to agricultural land [66].

Finally, the Global Moran's I and LISA analyses indicate that degrading landscape cells are predominantly organised into spatial clusters, revealing a clear spatial dependence in land transformation processes. This finding is consistent with the work of Mitsuda and Ito [67], who demonstrated that land-cover changes tend to spread to neighbouring parcels. Several authors attribute this pattern to spillover effects, whereby existing agricultural land promotes the expansion of land conversion into adjacent areas, and to the agricultural frontier mechanism, in which land clearing progresses contiguously under the influence of factors such as accessibility, infrastructure, land tenure, and proximity to already cultivated areas [68]. These mechanisms provide a plausible explanation for the spatial organisation of the degradation hotspots identified in the present study.

4.2. Land-Cover Transitions Associated with Changes in Interannual Ecological Sustainability

The results indicate that the conversion of shrub savannas to cereal crops was the most widespread land-cover transition across the majority of the study sites, making it the principal factor associated with changes in interannual ecological sustainability. This finding is consistent with the recent evolution of agricultural systems in northern Benin, where landscapes formerly dominated by cotton cultivation have undergone a gradual shift towards food and cash crops, particularly cereals and tubers, in response to market opportunities in southern Benin and neighbouring border regions [69]. This transition has been accompanied by an expansion of cultivated land at the expense of savannas and forest formations [69].

Furthermore, this pattern reflects the functioning of the post-forest agrarian systems described by Mazoyer and Roudart [70]. In these systems, shrub savannas often correspond to medium-term fallows (4–7 years) that are periodically brought back into cultivation to produce short-cycle food crops, particularly cereals. The observed transitions between shrub savannas and cultivated land therefore reflect a farming system based on the alternation of fallow and cultivation phases. However, increasing food demand, coupled with the progressive shortening of fallow periods, may intensify these cultivation cycles, thereby reducing the regenerative capacity of semi-natural vegetation and contributing to the gradual decline in the interannual ecological sustainability of agricultural landscapes.

Finally, the results demonstrate that the ecological significance of a land-cover transition depends not only on its spatial extent but also on the nature of the land-cover classes involved. Consequently, transitions affecting relatively small areas may make a substan-

tial contribution to changes in a site's ΔHDC when they involve marked differences in anthropogenic disturbance between the initial and final land-cover classes. Conversely, more extensive transitions may have a comparatively limited ecological effect because they involve smaller contrasts in disturbance levels. This observation is consistent with the findings of Padonou et al. [49], who showed that land-cover classes are subject to different levels of anthropogenic pressure and therefore differ in their ecological intensity. These findings highlight the value of complementing conventional land-cover change analyses, which are generally based solely on the extent of converted areas, with approaches that also account for the ecological intensity of land-cover transitions. Such an approach provides a more robust basis for prioritising landscape transformation processes and identifying the transitions with the greatest implications for interannual ecological sustainability.

The sensitivity analysis provides additional support for the interpretation of the interannual changes derived from the post-classification comparison. Classification errors can propagate when independently classified maps are compared and may generate uncertainty in both estimated transitions and their resulting ecological implications. However, the persistence of positive ΔHDC values across all simulations in Awanla, Bagou, Ouenou, Parakou, and Soadoudou indicates that the overall direction of increasing human disturbance in these landscapes is unlikely to be solely attributable to plausible variations associated with global classification uncertainty. This result is particularly noteworthy for Soadoudou, where the largest uncertainty envelope was applied (30.48%), yet the direction of ΔHDC remained unchanged in all simulations.

Conversely, Gbanlin illustrates the importance of explicitly considering classification uncertainty when interpreting small interannual changes. Its near-zero observed ΔHDC and sensitivity interval spanning both negative and positive values indicate that the magnitude and direction of such a small change cannot be reliably distinguished from the uncertainty considered in the analysis. Rather than suggesting a clear improvement or degradation, these results support the interpretation of Gbanlin as relatively stable between the two observation dates. More generally, the analysis suggests that large interannual changes in ΔHDC are comparatively robust, whereas changes close to zero should be interpreted more cautiously. Nevertheless, because the sensitivity analysis relies on Overall Map Accuracy rather than class-specific transition error probabilities, it does not account for differences in classification uncertainty among individual land-cover classes. The results should therefore be interpreted as evidence of robustness to plausible global classification uncertainty rather than as accuracy-adjusted estimates of land-cover change.

4.3. Biophysical and Geographical Determinants of Interannual Ecological Sustainability Change

The univariate analyses showed that no individual biophysical or geographical variable explained a substantial proportion of the observed variation in ΔLESI . Moreover, the predominance of cubic models among the best-fitting regressions indicates that the relationships between these variables and changes in interannual ecological sustainability are generally non-linear. These findings suggest that interannual ecological sustainability does not result from the influence of a single driving factor.

This interpretation is consistent with the work of Marshall [71] and Vasseur et al. [72], who demonstrated that landscape biophysical characteristics, including geomorphology, topography, soil fertility, climate, and drainage, generate environmental gradients that shape the spatial organisation of agroecosystems. These gradients promote the persistence of a landscape mosaic composed of natural, semi-natural, and agricultural land-cover types, whose structural diversity is a key component of the ecological sustainability of agricultural landscapes. However, this spatial organisation is not determined solely by biophysical constraints. Farmers' decisions regarding crop selection, production systems, and land

management practices continuously modify this landscape mosaic and, consequently, influence the level of anthropogenic disturbance associated with different land-cover classes. These decisions are themselves shaped by economic, social, cultural, and institutional factors [73–75]. In this context, changes in interannual ecological sustainability most likely arise from the interaction between the biophysical characteristics of the landscape and management decisions that govern changes in the composition and spatial configuration of agricultural landscapes.

The bivariate interaction analysis nuances the weak relationships observed in the univariate models by showing that the associations between biophysical and geographical factors and Δ LESI are partly context-dependent. Rather than acting independently, environmental conditions may modulate one another, so that their association with interannual ecological sustainability varies according to the combination of conditions prevailing within a landscape. In particular, the interaction between soil properties and geographical factors suggests that the ecological implications of biophysical conditions cannot be considered independently of the accessibility and human-pressure context in which they occur. This interpretation is consistent with recent studies showing that agricultural landscape change emerges from the interplay between biophysical constraints and opportunities and farmers' land-use decisions, which are themselves shaped by economic, social, and geographical conditions [76,77].

Nevertheless, the limited explanatory power of the bivariate models indicates that pairwise interactions capture only part of this complexity. Interannual changes in ecological sustainability are likely associated with multiple interacting processes, including socio-economic, institutional, and land management factors [77] not represented in the present analysis. Moreover, because several biophysical variables are relatively static over the study period, they should primarily be regarded as underlying environmental conditions that may modulate the spatial expression of land-cover change rather than as direct causes of Δ LESI. The identified interactions should therefore be interpreted as context-dependent statistical associations rather than causal ecological mechanisms.

4.4. Innovations of the Approach

The main methodological contribution of this study lies in the integration of several complementary dimensions of agricultural landscape ecological sustainability within a single spatially explicit and reproducible framework. Rather than considering ecological condition, land-cover change, spatial organisation, and associated environmental factors separately, the proposed approach links them through a common landscape-level analytical unit. Specifically, the framework combines fine-resolution land-cover information with land-cover-specific Human Disturbance Coefficients (HDCs) to quantify ecological sustainability at the landscape-cell scale, measures interannual changes through Δ LESI, and relates these changes to the land-cover transitions occurring within the same spatial units. The explicit quantification of the contribution of individual land-cover transitions to changes in HDCs provides an additional means of identifying which landscape transformations are most strongly associated with improvement or degradation in ecological sustainability. Spatial autocorrelation analysis further characterises the geographical organisation of these changes, while complementary univariate and multivariate analyses assess their associations with biophysical and geographical conditions. This integration constitutes an important advantage of the framework because it moves beyond simply mapping ecological sustainability by providing information on where changes occur, which land-cover transformations contribute to them, and which environmental and geographical conditions are most informative for understanding their spatial variability.

A second methodological contribution is the capacity of the framework to reconcile fine-resolution land-cover information with landscape-level assessment without reducing each landscape unit to a single dominant land-cover class. The 1 km² grid is used as an analytical unit rather than a resampling resolution: the proportional area of each land-cover class is retained within each cell and combined with its corresponding HDC to calculate LESI. This preserves information on internal landscape composition and makes it possible to apply a common analytical unit across study sites with contrasting land-cover configurations. The framework is also modular and reproducible: provided that comparable land-cover maps and appropriate HDC values are available, the same analytical sequence can be repeated across observation dates and geographical contexts. This provides a basis for longer-term ecological sustainability monitoring and supporting spatially explicit agricultural landscape planning.

4.5. Limitations of the Approach

Despite these methodological advantages, several limitations must be considered when interpreting the results. First, the framework depends strongly on the quality of the input land-cover maps, with, in this case, overall classification accuracies ranging from 0.79 to 0.90. Classification errors may come from, among other things, mixed land-cover signals in satellite imagery pixels and undetermined transition zones between land cover classes. Because LESI weights the HDC of each class according to its proportional area within a 1 km² cell, classification errors can propagate into LESI and Δ LESI, particularly when confusion occurs between classes with contrasting HDC values.

Second, the choice of a fixed 1 km² landscape unit introduces scale dependence. Although this resolution provides a consistent operational unit across the six study sites while retaining the proportional composition of the original fine-resolution land-cover information, different grid sizes could produce different LESI values and spatial patterns. A formal multi-scale sensitivity analysis was beyond the scope of the present application. Future applications should therefore evaluate alternative landscape-unit sizes to determine the robustness of LESI patterns to spatial scale and identify appropriate analytical scales according to landscape heterogeneity and specific management objectives.

Third, the present application is constrained by its short temporal coverage. Because only two consecutive observation dates (2023 and 2024) were available, the results represent interannual changes rather than long-term ecological dynamics or trajectories. The two-date comparison also prevents temporary land-cover fluctuations, such as cultivation–fallow cycles, from being reliably distinguished from persistent land conversion. Consequently, in this study the observed transitions and associated Δ LESI values should not be interpreted as evidence of persistent, long-term ecological improvement or degradation. It is important to note that this limitation concerns only the short-term temporal implementation made in this study (2023–2024) and does not apply to the developed conceptual methodological framework itself that, if applied to longer time series, would allow for transient fluctuations to be separated from persistent transformations and provide a stronger basis for assessing spatio-temporal dynamics and ecological sustainability trajectories.

The regression analyses have several limitations that should be considered when interpreting the identified associations. Although the bivariate models extend the univariate analyses by accounting for pairwise interactions, they cannot capture the broader multivariate complexity underlying changes in Δ LESI. More importantly, they do not explicitly account for the significant spatial autocorrelation observed in Δ LESI, meaning that the assumption of independence among landscape cells may not be fully satisfied and that statistical significance should therefore be interpreted cautiously. Future applications could address these limitations using spatial multivariate regression approaches and by incor-

porating socio-economic, institutional, and land management variables. Finally, because several biophysical predictors are relatively static over the short observation period, the relationships identified here should be regarded as context-dependent associations rather than direct drivers of interannual ecological sustainability change.

5. Conclusions

This study developed and applied an integrated framework for assessing interannual changes in the ecological sustainability of agricultural landscapes in northern Benin using Earth observation data. Between 2023 and 2024, ecological sustainability decreased in four of the six study sites, increased slightly in one, and remained relatively stable in another, with marked spatial heterogeneity within and among landscapes. Land-cover transition analysis identified the conversions contributing most to these changes and showed that their contribution to anthropogenic disturbance depends on both the magnitude of the difference in HDCs between the initial and final land-cover classes and the spatial extent of the transition. The sensitivity analysis further showed that the direction of the observed interannual changes was robust to plausible classification uncertainty in five of the six landscapes. The complementary statistical analyses further showed that individual biophysical and geographical variables had limited explanatory power when considered separately, while the bivariate interaction analyses revealed that some associations with Δ LESI were conditional on combinations of factors. However, the generally limited explanatory power of these models indicates that the observed interannual variability cannot be adequately accounted for by individual factors or simple pairwise interactions alone.

Beyond these empirical findings, the main contribution of this study is methodological. The proposed framework integrates, within a common spatial analytical structure, the assessment of ecological sustainability and its interannual change, the identification of underlying land-cover transitions, the quantification of their contributions to changes in anthropogenic disturbance, the characterisation of spatial patterns, and the analysis of associated biophysical and geographical factors. It therefore provides a reproducible approach for moving from the simple detection of land-cover change towards an assessment of its ecological significance at the landscape scale. However, because the present application covers only two consecutive years, the results should be considered as interannual changes rather than long-term trends or ecological trajectories. Extending the framework to longer time series, additional dynamic socioeconomic and land management variables, and contrasting agroecological contexts would strengthen its potential as an operational tool for monitoring and supporting the sustainable management of agricultural landscapes.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18189542/s1>: S1: Detailed classification assessment reports; S2: Detailed results of the sensitivity analysis.

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