Article

Multi-Criteria Assessment of the Environmental Sustainability of Agroecosystems in the North Benin Agricultural Basin Using Satellite Data

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Abstract

The intensification of anthropogenic pressures, particularly those related to agriculture driven by increasing demands for food and cash crops, generates negative environmental externalities. Assessing these externalities is essential to better identify and implement measures that promote the environmental sustainability of rural landscapes. This study aims to develop a multi-criteria assessment method of the negative environmental externalities of rural landscapes in the northern Benin agricultural basin, based on satellite-derived data. Starting from a 12-class land cover map produced through satellite image classification, the evaluation was conducted in three steps. First, the 12 land cover classes were reclassified into Human Disturbance Coefficients (HDCs) via a weighted sum model multi-criteria analysis based on nine criteria related to the negative environmental externalities of anthropogenic activities. Second, the HDC classes were spatially aggregated using a regular grid of 1 km² landscape cells to produce the Landscape Environmental Sustainability Index (LESI). Finally, various discretization methods were applied to the LESI for cartographic representation, enhancing spatial interpretation. Results indicate that most areas exhibit moderate environmental externalities (HDC and LESI values between 2.5 and 3.5), covering 63–75% (HDC) and 83–94% (LESI) of the respective sites. Areas of low environmental externalities (values between 1.5 and 2.5) account for 20–24% (HDC) and 5–13% (LESI). The LESI, derived from accessible and cost-effective satellite data, offers a scalable, reproducible, and spatially explicit tool for monitoring landscape sustainability. It holds potential for guiding territorial governance and supporting transitions towards more sustainable land management practices. Future improvements may include, among others, refining the evaluation criteria and introducing variable criteria weighting schemes depending on land cover or region.

Keywords: ecological sustainability; agroecosystems; satellite remote sensing; anthropogenic pressures; landscape resilience; Northern Benin

1. Introduction

Driven by population growth and rising per capita incomes, global demand for agricultural products has increased significantly and is projected to continue growing in the coming decades [1]. Sub-Saharan Africa, one of the regions of the world with the highest population growth, will need to increase its agricultural production to meet both the current and future food demand of its population [2]. Traditional strategies to boost production—such as intensifying yields per hectare, adopting intensive tillage practices, applying chemical fertilisers, and expanding farmland through deforestation—have led to substantial negative environmental externalities, including biodiversity loss [3], ecosystem service degradation, increased greenhouse gas emissions [4], and terrestrial and marine pollution [5].

The growing anthropogenic pressure on rural landscapes and, in particular, the increase in negative environmental externalities induced by the intensification of agriculture in response to the rise in demand for agricultural products, underscores the need to monitor environmental dynamics and provide land managers with accurate tools to assess and mitigate degradation [6]. This monitoring process involves the identification of appropriate indicators [7]. Several initiatives have led to the development of a variety of indicators [8]. The calculation of these indicators often requires field data collection surveys, which need to be updated regularly [7,9]. However, the implementation costs of these surveys, the challenges related to the representativeness of the results, and the biases in data collection required for informing the indicators represent significant limitations in their calculation [10]. Advances in remote sensing—particularly the increasing availability of free imagery with high spectral, spatial, and temporal resolution—offer cost-effective, scalable alternatives to overcome these challenges [11]. Satellite and airborne remote sensing provide up-to-date spatiotemporal data that can be used to quantify certain anthropogenic impacts on land, and, in particular, to assess certain negative environmental externalities associated with agriculture and its intensification, at various scales (landscape, region, etc.), by calculating indicators [12,13].

Several spatial indicators derived from remote sensing have been proposed to assess anthropogenic pressure, including the hemeroby index [14], agroecosystem quality index [15], landscape ecological security index [16], ecosystem health index [17], and farmland quality index [18]. Specifically, the hemeroby index measures the hemerobiotic state of an area, i.e., the degree of deviation caused by human activities in land use compared to the area's potential natural vegetation [19]. Thus, according to Sukopp [14], quoted by Walz and Stein [19], the hemeroby index is an integrated measure of the impact of human activities on ecosystems.

Over the past ten years, numerous studies have assessed the hemeroby index at the scales of landscape [19–26], forest system, and agroecosystem [21].

The hemeroby index is generally obtained by classifying remotely sensed images into land cover classes, which are then reclassified into categories reflecting the level of hemeroby. There are two approaches to this reclassification. The first approach consists of directly associating each land cover class with a predefined hemeroby class typically varying from 1 (no negative environmental externalities) to 7 (maximum intensity negative environmental externalities) [19,20,22–24]. The direct association of a land cover class with a hemeroby class is based on the intensity, duration and extent of the negative environmental externalities [27] that are observed in the said land cover class. The second reclassification approach initially involves calculating a hemeroby value for each land cover class, which may (i) be the result of a multi-criteria analysis based on the aggregation, by arithmetic mean, of scores assessed for a series of criteria and metrics (or sub-criteria) [21], or (ii) correspond to an 'anthropisation coefficient' obtained from existing reports and a simple

expert rating [25,26]. The hemeroby value calculated in this way is then associated with a hemeroby class. It should be noted, however, that the hemeroby index does not take into account all negative environmental externalities that may be associated with the different land cover classes (greenhouse gas emissions, biodiversity erosion, etc.) [21].

Concerning the presentation and communication of the hemeroby index derived from land cover classes, some are subject to spatial aggregation on a larger scale than the initial calculation scale (pixel scale), which may typically correspond to a regular grid (e.g., 1 km or 5 km square), administrative boundaries, landscape entities, etc. Aggregation is typically performed, for each target spatial feature, as a sum of the indicator (level of hemeroby or anthropisation coefficient) values related to each land cover class, weighted by the areal percentage of each class within the target feature [19,23].

Building on the hemeroby concept, this study proposes a novel approach for multi-criteria assessment of environmental sustainability in rural landscape based on satellite data. In particular, a new indicator, the Landscape Environmental Sustainability Index (LESI) is introduced, integrating key negative environmental externalities across various land cover types. The method is applied to three rural landscapes selected for their representativeness of the landscape diversity within the agricultural basin of northern Benin.

2. Materials and Methods

2.1. Description of Study Site

The study area is located in the agricultural basin of the Sudanian zone of Benin, which accounts for approximately 81% of the country's cultivated agricultural land [28] and serves as the main cotton production zone. This region is characterised by intensive agricultural activity, with high levels of both food and cash crop production, leading to the overuse of chemical fertilisers and pesticides [29]. A key feature of this area is that it contains the headwaters of several major rivers in Benin, including the Oueme River. Unsustainable farming practices in this basin contribute to downstream organic and inorganic pollution, particularly in the lower delta of the Oueme River, located in the southern part of the country, which is the zone with the highest fish biodiversity and productivity [30].

Within this agricultural basin, three research and development sites were selected based on their representativeness of the main types of agricultural landscapes. The selection was informed by a typology previously developed by the National Institute of Agricultural Research of Benin (INRAB), as detailed in their research report [31].

The three study sites—Bagou, Ouenou, and Parakou, named after their main urban centres—are situated within distinct agro-ecological zones (AEZs) of the North Benin agricultural basin: the North Cotton Zone (Zone II), the South Borgou Crop Zone (Zone III), and the Central Benin Cotton Zone (Zone V), respectively (Figure 1). This agricultural basin, located between 8.47° and 11.68° N latitude and 1.33° and 3.85° E longitude, spans a total area of 57,512 km^2 [32]. Each study site covers a 50 km × 50 km area.

Across the three AEZs, natural vegetation is primarily composed of tree savannas dominated by species such as Adansonia digitata, Bombax costatum, Lannea microcarpa, Parkia biglobosa, Ceiba pentandra, Blighia sapida, and Vitellaria paradoxa [33].

In AEZ II, the climate is predominantly Sudanian, with Sudano–Sahelian influence in its northern part, and annual rainfall ranges between 800 and 1200 mm. The dominant soils are ferruginous (Lixisols) [34]. This zone is particularly known for its cotton production, which is a major driver of regional development [35]. Within AEZ II, 60% of farmers use chemical fertilisers, 70% use herbicides, and 51% apply insecticides in their farming practices [31].

In AEZ III, the climate remains Sudanian, with slightly higher rainfall ranging between 1100 and 1200 mm. Like AEZ II, the soils are largely ferruginous (Lixisols) [34]. The main

crops cultivated in this zone include yam, cotton, maize, and cashew [35]. The adoption of chemical inputs is also high, with 71% of farmers using fertilisers, 81% herbicides, and 70% insecticides [31].
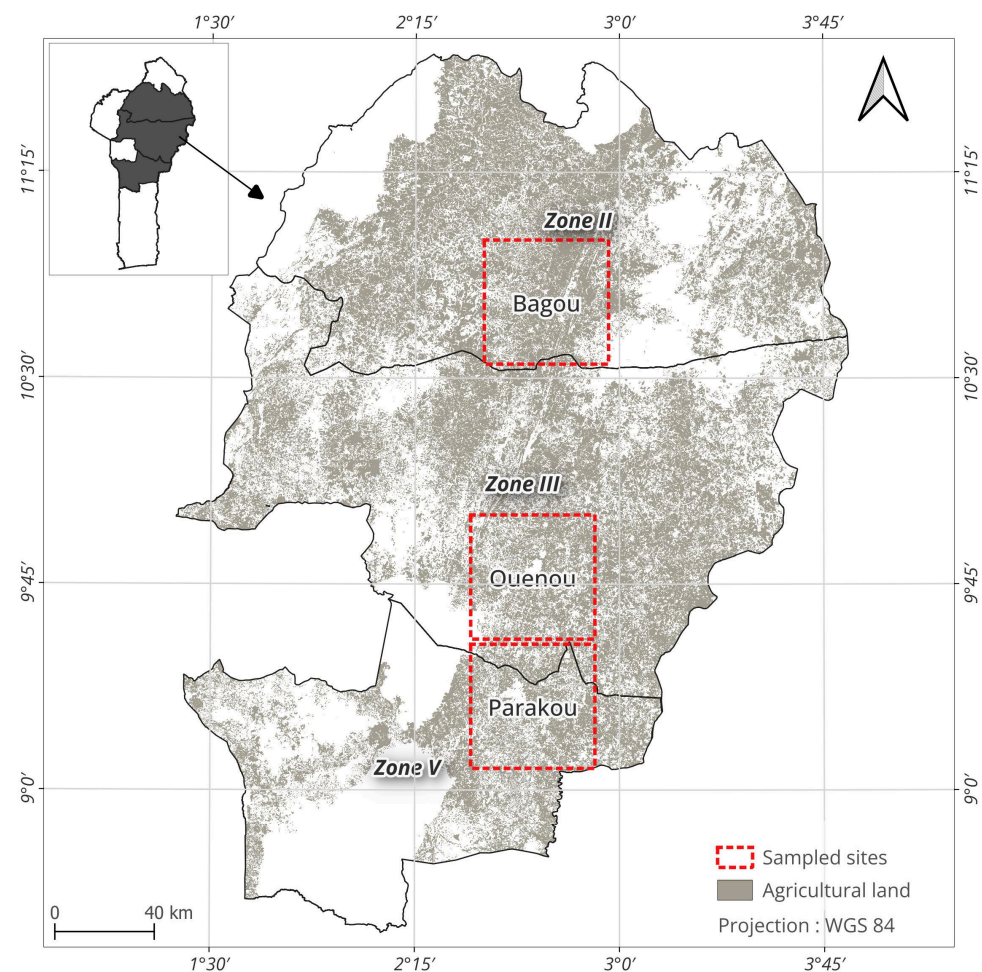

Figure 1. Study area (Zone II: North cotton zone; Zone III: South Borgou crop zone; Zone V: Central Benin cotton zone).

AEZ V, located in a Sudano–Guinean climatic region, receives variable annual rainfall ranging from 600 to 1400 mm. The dominant soil types include leached tropical ferruginous soils such as Leptosols and Luvisols [34]. This zone is characterised by a mix of tuber, legume, and cotton cultivation [35]. In terms of chemical input use, 50% of farmers use fertilisers, 70% herbicides, and 51% insecticides [31].

2.2. Description of the Land Cover Maps Used as Source Data

The present study is based on the use of 12-class land cover maps obtained for the three study sites (Bagou, Ouenou, and Parakou), which were produced as part of the OBSYDYA research project (https://www.obsydya.org) (Figure 2).

These land cover maps were generated using the Moringa processing chain [36]. Moringa integrates multiple sources of satellite data, including very high spatial resolution (VHSR) SPOT 6/7 imagery (1.6 m), high spatial resolution (HSR) Sentinel-2 optical image time series (10 to 20 m, Level-2A products), and a digital elevation model from the Shuttle Radar Topography Mission (SRTM) at 30 m resolution (Table 1).

The classification process employed by Moringa is based on functionalities from the Orfeo ToolBox (OTB), coordinated through Python 3.13.0 scripts and complemented by QGIS functions for intermediate processing steps. The approach involves two main stages.

First, VHSR satellite images are segmented into spectrally homogeneous objects. Second, these objects are classified using the Random Forest algorithm [37], calibrated and validated using a spatial reference database of land cover types established for the three sites. This reference database was developed through a combination of in situ field surveys and photo-interpretation [36]. The nomenclature of the 12 land cover classes used in the classification was established based on detailed knowledge of the land use and ecological characteristics of the study areas, acquired through prior field experience and local experts' consultations. These classes were designed to reflect ecologically and functionally distinct land cover types, including both natural and anthropogenic formations. To support the classification process, an extensive ground-truthing campaign was conducted across the three sites. Field observations were collected along transects selected from existing accessible tracks in order to ensure, representative coverage of landscape land cover classes diversity. Data collection was performed using the QField mobile application on GPS-enabled tablets, allowing for the georeferencing and in situ annotation of observed land cover types. These observations were subsequently converted into training and validation polygons through the digitisation of land cover boundaries using high-resolution SPOT 6/7 imagery as a visual reference for photo-interpretation.
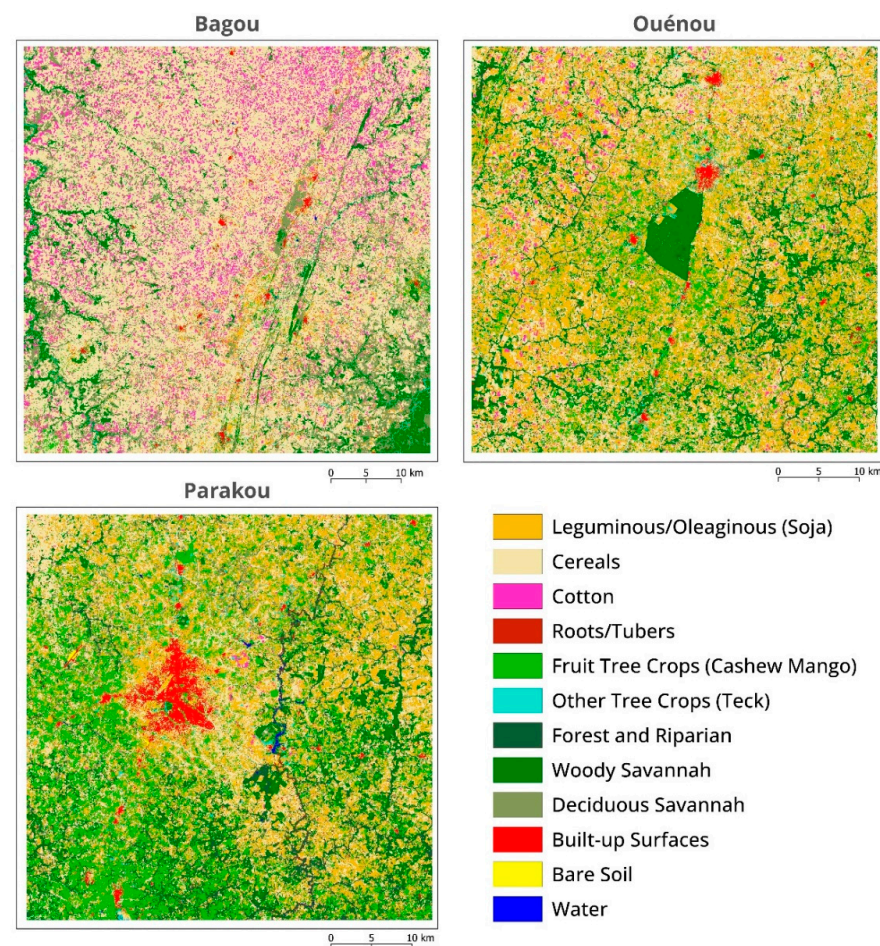
Figure 2. Types of land cover in the three study sites.

The smallest spectral objects in these land cover maps are 22 m^2 in size. The overall classification accuracies for the maps are 64% for Bagou, 76% for Ouenou, and 73% for Parakou (Figure 2). These accuracy values were obtained using a fivefold cross-validation procedure. The ground-truth dataset was divided into five equal subsets [38]. For each iteration, the Random Forest classifier was trained on four subsets and validated on the

remaining one, ensuring that each subset was used once for validation. The final classification accuracy for each site was calculated by averaging the overall accuracies—defined as the ratio between the surface area of correctly classified land cover objects in validation objects and the total surface area of validation objects—across the five folds.

Table 1. 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	21 and 27 October 2022
Sentinel-2	10 m	Time series from 1 January 2022 to 31 December 2022
SRTM	30 m	2000

The proportional surface areas of land cover types vary significantly across the three sites (Table 2). The Bagou site is predominantly covered by cereal crops (59%), followed by deciduous savannah (15%) and cotton fields (13%), with legumes representing only a minor portion (5%). In contrast, the Ouenou site is dominated by legume crops (38%), cereals (25%), and woody savannah (16%). At the Parakou site, land cover is mainly composed of legumes (29%), orchards (22%), and cereals (19%).

Table 2. Surface area (km^2) and proportional coverage (%) of each land cover type across the three study sites.

Land Cover Type	Bagou		Ouenou		Parakou	
	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)
Forest and Riparian	3.95	0.16	22.99	0.92	113.25	4.53
Woody Savannah	138.88	5.55	388.67	15.53	325.57	13.01
Deciduous Savannah	364.28	14.56	126.48	5.06	152.08	6.08
Water	0.78	0.03	0.13	0.01	3.93	0.16
Other Tree Crops (Teck)	13.33	0.53	26.91	1.08	27.12	1.08
Fruit Tree Crops (Cashew, Mango)	24.96	1.00	238.08	9.52	562.20	22.47
Leguminous/Oleaginous (Soja)	126.24	5.05	961.98	38.45	724.37	28.95
Cereals	1485.99	59.41	623.15	24.91	483.62	19.33
Roots/Tubers	0.03	0.001	30.47	1.20	29.97	1.20
Cotton	326.30	13.05	61.60	2.46	8.31	0.33
Bare Soil	1.06	0.04	2.97	0.12	6.62	0.26
Built-up Surfaces	15.56	0.62	18.50	0.74	64.93	2.60
Total	2501.36	100	2501.93	100	2501.97	100

Natural vegetation—comprising forest and riparian areas, woody savannah, and deciduous savannah—accounts for 20%, 22%, and 24% of the total surface area in Bagou, Ouenou, and Parakou, respectively. The "bare soil" class, representing an average of just 0.15% of the total surface area, is marginal. It is typically associated with exposed soil surfaces near built-up areas, dirt roads, or construction zones.

2.3. Global Methodological Framework

Figure 3 presents the overall methodological approach adopted in this study for each of the three sites. The methodology consists of three main steps. Firstly the 12 land cover classes are reclassified using a weighted sum model multi-criteria analysis based on

9 criteria related to negative environmental externalities. This multi-criteria analysis method was chosen because it is well-suited for evaluating multiple alternatives based on criteria expressed on cardinal scales, with assigned weights reflecting their relative significance [39]. Each criterion was assigned a weight derived from an equal distribution of a total weight of 1 across the four major environmental systems (hydrosphere, pedosphere (refers to the soil layer of the earth), atmosphere, and biosphere), with each system receiving 0.25. These system-level weights were then evenly distributed among the 2 to 3 criteria associated with each system, resulting in individual criterion weights ranging from 0.083 to 0.125. Each criterion was scored on a 1-to-7 scale to capture the relative contribution of each land cover type to human-induced negative environmental externalities. Secondly, the HDC values are spatially aggregated over 1 km^2 grid cells to produce the LESI. This index provides a spatial representation of environmental sustainability at the landscape scale, where lower values indicate less human disturbance and greater ecological sustainability. Thirdly, the LESI is visualised using various symbologies to highlight spatial differences in sustainability across the landscape.
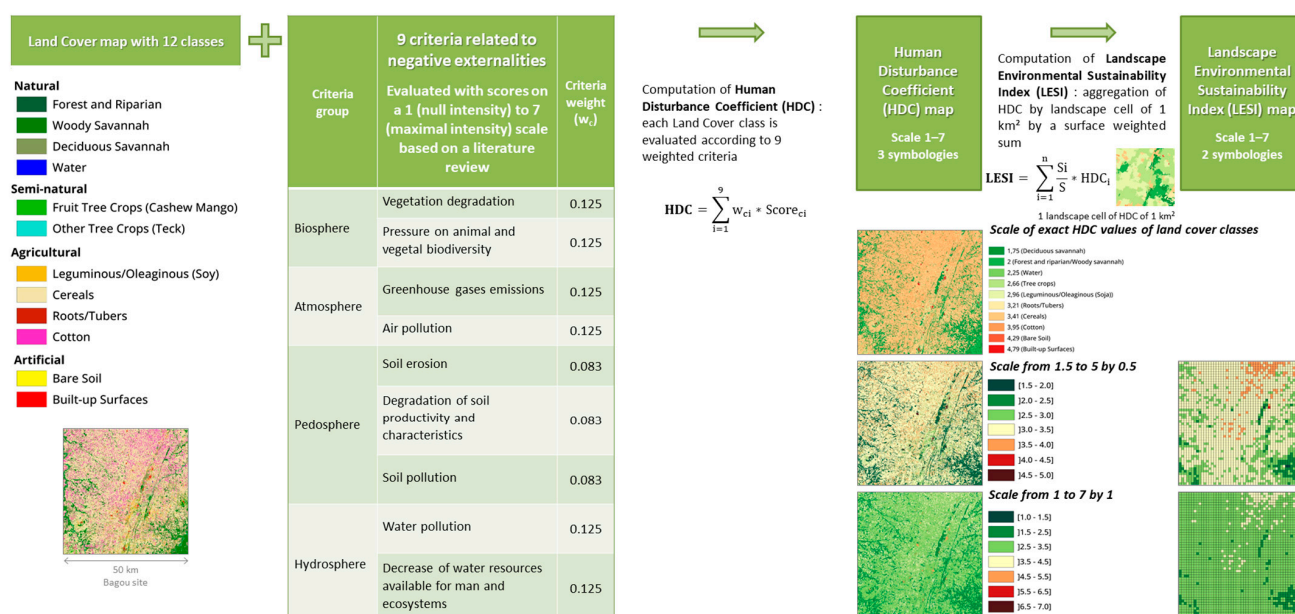

Figure 3. Methodological framework for computing the Landscape Environmental Sustainability Index (LESI) for each study site (illustrated with the Bagou site), derived from 12-class land cover maps and nine weighted criteria representing land cover-related negative externalities. The HDC and LESI are defined in Equations (1) and (2), respectively.

2.4. Definition of the Human Disturbance Coefficient (HDC)

The Human Disturbance Coefficient (HDC) of a given land cover class is calculated through a weighted multi-criteria analysis that evaluates its associated negative externalities, as described in Equation (1) where i corresponds to *i*th criteria, Score$_{ci}$ corresponds to the score (on a 1–7 scale, confer Table 3) of the negative externality evaluated by the *i*th criteria, and w$_{ci}$ corresponds to the weight of the ith criteria. The scores assigned to each land cover class are based on an analysis of the negative environmental externalities associated with these classes, conducted through a recent scientific literature review specific to the study area presented in the following sections.

$$\text{HDC} = \sum\nolimits_{i=1}^{9} w_{ci} * \text{Score}_{ci} \qquad (1)$$

Table 3. Analysis criteria and scores description.

Criteria	Score 1 (No Intensity)	Score 3 (Moderate)	Score 5 (High)	Score 7 (Maximum)
Degradation of vegetation	No degradation of the initial natural vegetation	Replacement of the original natural vegetation by tree plantations	Replacement of the original natural vegetation by intensive crops	Total disappearance of all forms of vegetation
Pressures on biodiversity	No pressure	Moderate intensity of the various pressures on biodiversity	High intensity of the various pressures on biodiversity	Total disappearance of all forms of animal and plant life
Greenhouse gas emissions	No emissions	Comparable to intensive agriculture	Comparable to that of an urban area with more than 10,000 inhabitants/km^2	Comparable to an industrial zone using energy from combustion
Air pollution	No pollution			
Soil erosion	No erosion	Sheet erosion	Sheet and rill erosion	Sheet, rill and gully erosion
Degradation of soil productivity and characteristics	No degradation	Soil with a reduction in organic matter, loose, and with diversified plant cover	Soil devoid of organic matter, moderately compact, with little plant cover	Soil devoid of organic matter, compact, with no plant cover
Soil pollution	No pollution	Moderate-intensity pollution linked to urban or low-intensity agricultural activity	High-intensity pollution linked to intensive urban or agricultural activity	Extremely intense pollution linked to industrial discharges
Water pollution	No pollution			
Reduction in water resources	No reduction in the water resources available to humans and ecosystems	Moderately problematic reduction in water resources available to humans and ecosystems	Highly problematic reduction in water resources available to humans and ecosystems	Extremely problematic reduction in water resources available to humans and ecosystems

In this study, Human Disturbance Coefficient (HDC) values range from 1 to 7, where higher values indicate greater negative environmental externalities. This scale is consistent with the conceptual framework of hemeroby levels, which represent degrees of anthropogenic disturbance in ecosystems, as proposed by Walz and Stein [19].

The reclassification of land cover classes into HDC values was performed using nine criteria, each reflecting a distinct dimension of negative externalities associated with land use. These criteria were adapted from the methodologies of Quintero, et al. [40], Vodouhe, et al. [41], and Tittonell [42].

2.5. Description of the Nine Evaluation Criteria for the Human Disturbance Coefficient (HDC)

- Degradation and Loss of Vegetation

Degradation of initial natural vegetation (i.e., vegetation that has not yet been significantly influenced by humans) is defined as an alteration in the structure of the initial natural vegetation without conversion to other types of land cover [43]. Timber exploitation, uncontrolled fires, overgrazing and the collection of wood for energy are the direct causes of this degradation. The loss of the original natural vegetation can be understood as the complete destruction of this vegetation and its conversion to other types of land cover [43]. Anthropogenic activities such as agriculture, mining, infrastructure development and urbanisation are direct causes of the loss of initial natural vegetation. The transition from initial natural vegetation to another form of land cover takes place in 3 stages: the extraction of woody species, which results in a moderate alteration to the structure and composition of the initial natural vegetation, which is thus degraded; the clearing of degraded natural vegetation, which results in a major alteration to the structure and composition of the remaining natural vegetation; and the total disappearance of the natural vegetation, which is replaced by another type of land cover [44].

- Pressure on Biodiversity

Human activities including intensive agriculture, fishing, logging, and urbanisation exert significant pressures on biodiversity [45,46]. Jaureguiberry, et al. [47] classify these pressures in descending order of impact as: land use change through habitat fragmentation and destruction, over-exploitation of species, proliferation of invasive species, pollution and climate change.

- Greenhouse Gas (GHG) Emissions

Anthropogenic greenhouse gas (GHG) emissions are closely linked to land use patterns [48] and to the human activity sectors (buildings, transport, agriculture, forestry and other land use, industry, energy) that are present [49]. Then, while greenhouse gas (GHG) emissions have global impacts, their land-based sources such as deforestation or biomass burning are assessed here.

The most important GHGs in terms of emissions in the world, in a context marked by heavy dependence on fossil fuels for energy generation, are, in order of importance, CO_2 (76%) emitted mainly by the combustion of fossil fuels and deforestation fires, CH4 (13%) emitted by the combustion of biomass and agricultural waste, N2O (7%) due to the use of fertilisers in agriculture, and CFCs and HCFs (1%) emitted during refrigeration processes [50]. The main anthropogenic sources of CO_2 in the world are, in descending order of billions of tonnes of CO_2: electricity from fuel combustion (147), manufacturing (from cement, aluminium, steel, and other manufacturing processes) (107), fossil fuel operations (oil and gas production, refining, and coal mining) (96), transportation (on-road vehicles, aviation, shipping, railways and other modes of transportation) (84), agriculture (77), buildings (onsite fuel combustion in residential, commercial and institutional buildings) (40), waste (22), fluorinated gas (14), and mineral extraction (2) [51]. From the above, land use patterns can be classified in order of importance of the quantity of GHG emitted as follows: industrial areas dependent on the combustion of fossil fuels, intensive agricultural areas heavily dependent on the use of nitrogen-based fertilisers and intensive livestock farming and densely populated urban areas dependent on the combustion of fossil fuels for transport and electricity and generating large quantities of waste [49].

- Air Pollution

Air pollution is the fifth leading cause of morbidity and mortality worldwide [52]. Anthropogenic activities are the main cause of air pollution [53]. According to Kampa and Castanas [53], there are four categories of air pollutants: (i) gaseous pollutants mainly due to the combustion of fossil fuels; (ii) persistent organic pollutants generated by the use of pesticides, herbicides, the combustion of biomass and various wastes; (iii) heavy metals mainly due to combustion, wastewater discharges and factories; (iv) particulate matter, the main sources of which are factories, fossil fuel power stations, waste incinerators, motor vehicles, construction activities, fires and natural dust carried by the wind. The main sources of pollutant emissions into the air are, in descending order: the combustion of fossil fuels by industrial processes, transport, the combustion of biomass energy and agricultural systems [54]. The intensities of air pollution by type of land use are similar to those of GHG emissions described in the previous paragraph.

- Soil Erosion

Soils are non-renewable resources on a human timescale, and their degradation due to erosion as a result of poor management leads to their depletion and a significant reduction in the services they provide [55]. Soil erosion (transport and accumulation of uprooted soil particles) is caused by three factors: rainwater or river run-off (hydric erosion), strong winds (wind erosion) and the use of ploughing tools (dry mechanical erosion) [56]. Because of the aggressive nature of rainfall, hydric erosion is predominant in tropical environments [56]. Depending on the intensity of the soil particle removal mechanism, a distinction is made between: sheet erosion (transport of soil by raindrops and run-off water), rill erosion (removal of soil by concentrated water flowing through small streams, or notches), and gully erosion (uprooting of soil or soft rock by water, forming narrow and distinct channels, larger than rills) [56].

- Degradation of Soil Productivity and Properties

Soil productivity encompasses soil fertility and soil management factors that affect the growth and development of plants [57] that provide food, fibre and other goods. A soil's productivity depends on its organic matter content, its level of compactness and its capacity to retain water [58], which is essential for the development of a diversity of vegetation. Maintaining soil productivity is essential for the development and survival of populations [59]. Human activities such as repetitive deep ploughing degrade the physico-chemical and biological properties of soils [60], thereby reducing their productivity. On the other hand, certain approaches, such as those based on conservation agriculture, which recommend minimal soil disturbance by banning ploughing, promote soil regeneration by increasing soil organic matter [61].

- Soil Pollution

Soil pollution is caused by a variety of sources: agrochemical, urban, industrial, atmospheric and incidental [62]. The most important of these sources are agrochemical and urban.

Pollutants from agrochemical sources emanate mainly from the application of fertilisers and pesticides [62]. The application of fertilisers introduces the heavy metals they contain and their derivatives into the soil [62]. The concentration of some of these heavy metals in the soil can be toxic to soil fauna because their metabolism is disrupted [62]. The use of pesticides (insecticides, herbicides, fungicides) releases organic compounds into the soil, disrupting the functioning of the soil fauna on which soil ecology depends [62].

The main pollutants from urban sources come from emissions generated by: power stations (COx, NOx, SOx, UOx and polycyclic aromatic hydrocarbons); transport (COx, NOx, SOx, as well as certain heavy metals); waste and sewage sludge, which release heavy metals into the soil [62].

- Water Pollution

Pesticides (insecticides, herbicides and fungicides) used to manage insects, weeds and fungal pests release organic chemical compounds which are dispersed by wind and water to areas far from their point of application and which persist beyond the time of application [63]. These chemical compounds, which first pollute the soil, are then diffused into water, thereby affecting human health as well as that of other species [5]. The same applies to mineral fertilisers, which are responsible for high emissions of pollutants (methane, nitrates) into the soil, air and water [64].

According to Xie, et al. [65] who looked at non-point sources of pollution, the types of land use that contribute most to water and soil pollution are, in order of importance: agricultural land, the use of which involves practices that emit a variety of pollutants into the soil and water (application of chemical inputs, for example); urban areas, the wastewater from which is laden with heavy metals, polycyclic aromatic compounds and microplastics. In addition, natural run-off (in the event of heavy rainfall), which is laden with pollutants from other types of semi-natural (planting, grazing) and artificial land use, is a relatively minor source of non-point source pollution. Finally, waste and discharges from industrial estates are a source of large quantities of heavy metals in soil and water [66].

- Reduction in Water Resources

Water scarcity is determined by the availability of water resources and the level of demand for water [67]. According to Leijnse, et al. [68], the drivers of global water scarcity are, in order of importance: agricultural uses of water (unsustainable irrigation practices), hydro-climatic changes (reduced rainfall, increased temperatures), urban uses of water, population growth (increased demand for water and changes in land use), and industrial uses of water. In Africa, agriculture is the largest water-using sector, with large populations dependent on rain-fed agriculture [69].

2.6. Definition of Scores for the 9 HDC Evaluation Criteria

Table 3 presents the guideline narrative for assigning scores to the 9 criteria used to carry out the qualitative multi-criteria analysis of the negative externalities of each land cover class. The scores range from 1 to 7, as for the hemeroby index. Only the extreme and intermediate [3 and 5] score values are defined in Table 3

The scores for the 9 criteria of negative externalities from human activities were assessed on the basis of a review of recent scientific literature for each of the 12 land cover classes.

2.7. Weighting of HDC Evaluation Criteria

The HDC for each land cover class was calculated using the weighted sum model method, as proposed by Rao, et al. [70], by aggregating the scores for each criterion according to Equation (1) above.

The weights of the nine environmental criteria were determined in a two-step process. First, each criterion was assigned to one of the four major subsystems of the natural environment: hydrosphere, pedosphere, atmosphere, and biosphere. An equal weight of 0.25 was allocated to each subsystem, based on the assumption that all four play equally critical and interdependent roles in sustaining rural landscape functionality. Second, within each subsystem, this 0.25 weight was distributed equally among the associated criteria. For instance, if a subsystem contained two criteria, each was assigned a weight of 0.125 (Table 4). While ensuring methodological transparency and reproducibility, this weighting framework was designed to prevent subjective or arbitrary bias, particularly in the absence of consensus from a panel of experts that would clearly hierarchize the importance of these criteria in regards of human induced environmental negative externalities. Unlike other multi-criteria evaluation methods that rely on expert judgement (e.g., AHP, Delphi), our approach follows a logic of equal ecological representation of the 4 major subsystems of the natural environment, assuming no a priori dominance of one subsystem over another.

Table 4. Weight of the 9 criteria used to compute the human disturbance coefficient and associated environmental systems.

Environmental Systems	Criteria	Criteria Weights
Hydrosphere	Water pollution	0.125
	Reduction in water resources	0.125
Pedosphere	Soil pollution	0.083
	Soil erosion	0.083
	Degradation of soil productivity	0.083
Atmosphere	Air pollution	0.125
	Greenhouse gases emissions	0.125
Biosphere	Vegetation degradation	0.125
	Pressures on biodiversity	0.125

2.8. Justification of Criteria Scores for Each Land Cover Class Based on Scientific Literature Review

- Natural land cover types

The natural land cover types are Forest and Riparian, Woody Savannah, Deciduous Savannah. In the study area, the natural land cover classes face various pressures, such as overgrazing caused by extensive livestock farming, excessive logging and vegetation fires [71]. All these pressures lead to the degradation of natural vegetation, resulting in a loss of biodiversity, in general, and plant biodiversity more specifically [72]. Similarly, the loss of woody vegetation as a result of logging reduces carbon stocks and increases

greenhouse gas emissions. CO_2 emissions from the combustion of plant species, particularly during the fire season in savannah formations, are a major source of atmospheric CO_2 and contribute substantially to the global greenhouse effect [73]. According to Kim, et al. [74], the rewetting process of dry soils in forests, plantations and woodlands in sub-Saharan Africa during rainfall emits an average of 34.3 ± 5.7 $MgCO_2$ eq. ha-1yr-1, while savannah soils emit an average of 10.1 ± 2.4 $MgCO_2$ eq. ha-1yr-1. Vegetation fires, 95% of which are of human origin in Benin [75], also release pollutants into the air (aerosols and particulate matter [76].

In natural plant formations, the risk of soil erosion is generally low because the soil is covered by litter [77] and because the canopy absorbs the kinetic energy of raindrops [78]. Protecting soils against erosion in natural plant formations also helps to maintain their productivity [77].

In these natural plant formations, because there are no agricultural cultivation practices, the intensity of tillage is very low, or even non-existent. Similarly, no plant protection products or fertilisers are used.

Natural formations in general, and forests in particular, intercept rainfall and evaporate water through their leaves, thereby regulating groundwater flows and river flows [79]. The degradation of these natural formations disrupts their regulatory role in the water cycle by reducing evapotranspiration and especially infiltration, as vegetation loss leads to soil compaction, reduced porosity, and surface crusting, thereby limiting water infiltration and increasing runoff, ultimately affecting water availability for both human use and ecosystem functioning. However, in the study area, these factors do not lead to a problematic reduction in the water resources available to humans and ecosystems.

- Surface water

Surface waters correspond to natural land cover type that is directly affected by anthropogenic disturbances to other land cover type (natural, semi-natural, agricultural and artificial). Disturbances to the catchment areas in which these bodies of water are located, including the conversion of natural formations to farmland and the artificialisation of surfaces through urbanisation, have a negative impact on surface waters [80] through the transport of sediments and various pollutants that alter their physicochemical and biological parameters. Then, it is important to clarify that the inclusion of surface waters in the Human Disturbance Coefficient (HDC) scoring does not imply that all criteria are directly applicable within these areas. Furthermore, the score assigned to surface water bodies under each evaluation criterion does not result from a spatially explicit analysis of upstream or adjacent land use configurations. Instead, it reflects indirect but ecologically significant pressures presumed to arise from landscape-level land use dynamics. This assumption is based on widely recognised ecological principles, particularly the sensitivity of aquatic systems to diffuse pressures such as sedimentation, nutrient inflows, and riparian degradation, even when such influences are not directly quantified through hydrological or spatial connectivity modelling. Therefore, scores attributed to surface water classes integrate their vulnerability to cumulative anthropogenic disturbances occurring across the catchment, while acknowledging that the current approach does not model direct adjacency or flow paths.

As a result of phosphorus leaching, a high algal biomass has been noted in certain bodies of water in the study area, indicating eutrophication of these waters [81].

Surveys of macroinvertebrates in the main rivers in the study area revealed a high specific richness of diptera of the Chironomidae family (insects indicative of high concentrations of pollutants of anthropogenic origin) and a low specific richness of Ephemeroptera, Plecoptera and the total absence of Trichoptera (insects indicative of low disturbance of aquatic ecosystems) [82]. As a result of the pollution of water bodies by leaching of

agricultural inputs (fertilisers, herbicides and pesticides), the biodiversity of the macro-invertebrates they host has been simplified. In addition, soil erosion leads to the deposition of sediment in surface waters, and in some cases to their filling in, thus impacting on their biodiversity.

Fertilisers, plant protection products and other pollutants used on farmland and in built-up areas are transported to and pollute surface waters [80]. According to Adechian, et al. [83], common phytosanitary practices in the study area involve the use of herbicides, the dominant active ingredients of which are glyphosate and atrazine, and insecticides, the most commonly used active ingredients of which are flubendiamide, spirotetramat and pyrethroids. The use of these products, and more specifically insecticides, is more intense in fields located close to bodies of water, implying a high level of pollution of the latter [83]. Indeed, the humidity of the soil in the vicinity of bodies of water encourages the rapid proliferation of insects harmful to crops [84]. The intense pollution of water bodies in the study area by chemicals used systematically in agriculture is demonstrated by the disruption of the endocrine function of fish species analysed by Agbohessi, et al. [85].

According to Kim, et al. [74], wetlands and water bodies in sub-Saharan Africa emit an average of $121.3 \pm 39.7 \, \mathrm{MgCO_2}$ eq. $\mathrm{ha^{-1}yr^{-1}}$. In the study area, paddy rice cultivation in the lowlands and close to bodies of water contributes to GHG emissions, particularly CH_4. Submerging rice increases methane emissions [86]. Also, although it is accepted that sediments contained in surface waters store large quantities of carbon [87], discharges of polluted water into these waters lead to an increase in GHG emissions (carbon and nitrogen in particular) [88].

Finally, in the 'water' land cover class of the study area, it is considered that there is no degradation of soil productivity or characteristics. Similarly, there are very few surfaces water use practices in the study area, practices that do not lead to a problematic reduction in the water resources available to humans and ecosystems.

- Semi-natural land cover

In the study area, the semi-natural land cover types include fruit tree plantations (such as mango and cashew) as well as timber (such as teak). These plantations are generally monospecific, although in some cases, a few understorey species may be present [89]. The silvicultural practices associated with these plantations (pruning, thinning, weeding, and firebreak maintenance) are intended to increase fruit or timber yields [90], but they tend to further reduce plant biodiversity. Nevertheless, these plantations can help conserve a certain degree of insect and small fauna biodiversity. On the other hand, within the study area, tree plantations contribute to the reduction in natural land cover types [72].

Tree plantations in the study area serve as carbon sinks, storing significant amounts of carbon throughout their production cycle [91]. At the end of their productive life, the wood is either used for energy—thereby releasing CO_2 (mango, cashew, and teak residues)—or for construction timber (teak trunks), which allows carbon to be stored over a longer period.

As with natural land cover types, soil erosion in tree plantations is generally low due to the anti-erosive effect of the canopy. However, the anti-erosive role of leaf litter is often undermined, as in order to protect plantations—particularly fruit plantations—from fire, this litter is burned annually at the start of the dry season. These protective fires lead, on the one hand, to a substantial decline in soil productivity due to the loss of organic matter and, on the other, to an increase in greenhouse gas emissions. Soil disturbance is also minimal, which means that the biological and physicochemical properties of soils within the plantations are preserved, and no chemical fertilisers or pesticides are used on these types of land cover [90].

The removal of litter in tree plantations tends to promote rainwater runoff, which can, through reduced infiltration, affect the availability of water resources for both humans

and ecosystems. However, in the study area, these impacts do not result in a problematic reduction in available water resources for human populations or ecosystems.

- Agricultural land cover

In the study area, agricultural land covers include soybean, cotton, cereals, and root/tuber crops. For soybean cultivation, soil tillage is light, but herbicide use is common in weed management. Farmers do not apply chemical fertilisers to this crop, as they do not deem it necessary [92]. Similarly, the use of pesticides in soybean farming is very low. Furthermore, this crop has a positive effect on soil nitrogen storage, thereby contributing to the maintenance of soil fertility. However, the limited ground cover during the growing season increases the risk of soil erosion. The minimal use of fertilisers and pesticides, as well as the absence of slash-and-burn practices, limits greenhouse gas (GHG) emissions from soybean cultivation. These emissions are not negligible, however, as the expansion of soybean farming is one of the drivers behind the conversion of natural formations. In the agroecological zones studied, soybean cultivation increased from 152 hectares in 1995 to 134,809 hectares in 2022 [93].

Regarding cotton and cereals, in the study area, the use of herbicides, pesticides, and chemical fertilisers is widespread. For cotton, the quantities of fertilisers and phytosanitary products applied are generally above recommended levels [94]. It is worth noting that organic cotton is also promoted in the study area. However, in 2014, it accounted for only 1% of the total cotton area [41,93], and is therefore considered negligible in the context of the present study. In addition, cotton farming typically involves deep tillage using ploughs [95], whereas soil disturbance is lighter for cereal crops. For both crops, the limited soil cover during the growing season increases the risk of erosion and leads to declining soil productivity. The intensive use of fertilisers and pesticides significantly contributes to GHG emissions associated with cotton and cereal cultivation, which are further exacerbated by emissions linked to the conversion of natural formations, with maize and sorghum being the main drivers. In the agroecological zones studied, cotton cultivation expanded from 177,809 hectares in 2002 to 415,003 hectares in 2022 [93].

Root and tuber cultivation requires the creation of mounds, which causes substantial soil disturbance. However, these mounds significantly reduce soil erosion during the cropping period by increasing surface roughness and thus limiting the speed of rainfall runoff. On the other hand, the sparse ground cover during the cropping season contributes to declining soil productivity. The use of fertilisers and pesticides in these systems is virtually non-existent. As such, GHG emissions from these crops are limited to those generated by the conversion of natural vegetation, with yam being one of the main drivers.

According to Kim, et al. [74], agricultural areas in sub-Saharan Africa emit on average $26.1 \pm 6 \ \mathrm{MgCO_2}$ eq. ha^{-1} yr^{-1}.

Generally, the limited soil cover in agricultural zones tends to promote rainwater runoff, which, by reducing infiltration, may affect the availability of water resources for humans and ecosystems. However, in the study area, these effects do not lead to a problematic reduction in available water resources for people or ecosystems.

- Artificial land cover

Artificial land cover types in the study area include built-up surfaces and bare soils, both of which are associated with the near-total loss of natural vegetation and biodiversity. These areas are significant sources of greenhouse gas emissions due to economic activities such as transportation, industry, air conditioning, and energy production.

The lack of vegetation and anti-erosion structures leads to a high risk of soil erosion, while soil productivity is generally very low or non-existent. Territorial planning in the study area does not integrate measures to maintain or restore soil fertility in these zones.

While tillage is largely absent in built-up areas, soils are often disturbed through compaction and construction-related activities.

Although plant protection products are rarely used, artificial land covers contribute to soil and water pollution through toxic residues (e.g., sludge, waste oils, solid and household waste). Water consumption in urban zones is relatively high, and soil sealing, which refers to the permanent covering of soil by impervious materials such as asphalt or concrete, exacerbates runoff while limiting infiltration. This can potentially affect water availability. However, in the study area, these hydrological changes have not yet resulted in a critical reduction in water resources for human and ecological needs.

2.9. Spatial Aggregation for LESI Determination

The use of a regular grid of cells offers five key advantages for cartographic representation. First, it ensures a uniform level of spatial detail, facilitating spatiotemporal comparisons between successive grids [96]. Second, it enhances the visualisation of information at smaller scales (e.g., when zooming out), by allowing the simplification of highly detailed spatial information through aggregation. Third, it improves the representativeness of landscape patterns by displaying average values per landscape cell, which can integrate highly heterogeneous and contrasting land cover types. Fourth, it helps avoid biases and interpretation difficulties related to irregular or unevenly sized spatial units (e.g., municipal boundaries) [19]. Lastly, grid-based approaches are well-suited for advanced spatial analysis and modelling.

However, the choice of landscape cell size significantly influences the resulting LESI values. Larger cells tend to homogenise spatial variability, reducing the index's ability to reflect fine-scale ecological differentiation [19]. To balance spatial detail and cartographic readability, this study adopts a 1 km^2 grid cell size, which offers sufficient differentiation in LESI values while maintaining clarity at the scale of the study areas.

The LESI for each 1 km^2 landscape cell is computed using Equation (2) (below). In this equation, i refers to the ith land cover class within the cell (with n = 12 total classes), S_i represents the area occupied by land cover class i within the cell, HDC_i is its associated Human Disturbance Coefficient, and S denotes the total surface area of the cell (1 km^2).

$$\text{LESI} = \sum_{i=1}^{n} \frac{S_i}{S} * \text{HDC}_i \qquad (2)$$

2.10. HDC and LESI Mapping

The HDC and LESI indicators are visualised using two complementary symbology approaches, each offering distinct advantages.

The first approach applies a reference symbology based on the full theoretical range of the indicators, from 1 to 7, with increments of one unit. This standardised classification facilitates comparative analysis, enabling direct comparison between the present maps and those produced in other studies, even when the actual values observed differ across contexts. Moreover, it provides a neutral and objective framework for interpreting results, remaining faithful to the theoretical definitions of the HDC and LESI indices.

The second approach uses a context-specific symbology, adapted to the actual range of values observed in the study area, with increments of 0.5 units. This classification enhances visual contrast and spatial differentiation, allowing for a more nuanced and detailed interpretation of local variations in ecological stress and human disturbance.

Together, these two symbology methods offer both comparability across studies and context-sensitive insights, reinforcing the interpretive value of the mapped indicators.

3. Results

3.1. Human Disturbance Coefficient

Table 5 presents the weights assigned to the criteria, the scores attributed to each land cover type based on the literature review (see the Methods section) for each criterion, and the resulting Human Disturbance Coefficients (HDCs) calculated from their weighted sum. These HDC values range from 1.75 to 4.79. The lowest HDCs are associated with natural land cover classes, while artificial surfaces exhibit the highest disturbance coefficients.

Table 5. Criteria scores (as defined in Table 3) by land cover class and Human Disturbance Coefficients (HDC) resulting from the weighed sums of the scores. A score of 1 corresponds to no impact related to this criteria and a score of 7 corresponds to an impact of maximal intensity related to these criteria.

Criteria	Weight	FR	WS	DS	WA	TC	FTC	LO	CER	RT	COT	BS	BUS
Degradation of vegetation	0.125	2	2	2	1	3	3	4	4	4	5	6	6
Pressures on biodiversity	0.125	3	3	3	4	5	5	5	5	5	5	6	6
Greenhouse gas emissions	0.125	3	3	2	2	2	2	2	3	3	3	2	4
Air pollution	0.125	3	3	2	2	2	2	2	3	3	3	2	4
Soil erosion	0.083	1	1	1	1	3	3	4	4	4	4	6	6
Degradation of soil productivity and characteristics	0.083	1	1	1	1	3	3	4	4	4	4	6	6
Soil pollution	0.083	1	1	1	4	2	2	2	3	2	5	5	5
Water pollution	0.125	1	1	1	4	2	2	2	3	2	5	5	5
Reduction in water resources	0.125	2	2	2	1	2	2	2	2	2	2	2	2
Human Disturbance Coefficient (HDC)		2.00	2.00	1.75	2.25	2.66	2.66	2.96	3.41	3.21	3.95	4.29	4.79

FR: Forest and Riparian; WS: Woody Savannah; DS: Deciduous Savannah; WA: Water; TC: Other Tree Crops (Teck); FTC: Fruit Tree Crops (Cashew Mango); LO: Leguminous/Oleaginous (Soja); CER: Cereals; RT: Roots/Tubers; COT: Cotton; BS: Bare Soil; BUS: Built-up Surfaces. The colors reflect the level of anthropogenic disturbance, ranging from green (low disturbance) to red (high disturbance).

3.2. Spatial Variation in Human Disturbance Coefficient

Figures 4 and 5a,b illustrate the spatial distribution and surface proportion of Human Disturbance Coefficient (HDC) categories across the Bagou, Ouenou, and Parakou sites.

Across all three sites, HDC values range from 1.75 to 4.79 (Figures 4 and 5a). Land cover classes associated with either very low anthropogenic disturbance (HDC in the interval]1; 1.5]) or very high disturbance (HDC in the interval [5.5; 7]) are entirely absent from these landscapes (Table 5; Figure 4).

Land cover classes reflecting low to moderate levels of disturbance (HDC in the range]1.5; 2.5]), corresponding to natural classes (riparian forest, woody savannah, deciduous savannah) and water bodies, account for approximately 20% of the Bagou site, 22% of Ouenou, and 24% of Parakou (Figure 5b). These lightly disturbed natural areas are mostly located within protected zones (e.g., the classified forest in the central-western part of Ouenou) or in areas that are less accessible for agriculture, such as rocky outcrops and riparian corridors. Notably, the Bagou site records the highest surface proportion (15%) for the land cover class associated with the lowest HDC in the study (1.75 for deciduous savannah) (Figures 4 and 5b).

Land cover classes with moderate anthropogenic disturbance (HDC within the range]2.5; 3.5]), which include most agricultural classes except cotton (i.e., legumes, roots/tubers, and cereals), as well as semi-natural plantations (tree crops and fruit trees), are predominant across all sites. These classes represent 63% of the Bagou site, 75% of Ouenou, and 73% of Parakou (Figures 4 and 5b).

Land cover classes exhibiting intermediate disturbance between moderate and high (HDC in the interval]3.5; 4.5]), specifically cotton fields and bare soil, cover 13% of the Bagou site, but only 3% of Ouenou and 1% of Parakou. This is largely due to the importance

of cotton cultivation in Bagou, where it alone accounts for 13% of land cover, compared to just 2% in Ouenou and 0.3% in Parakou.
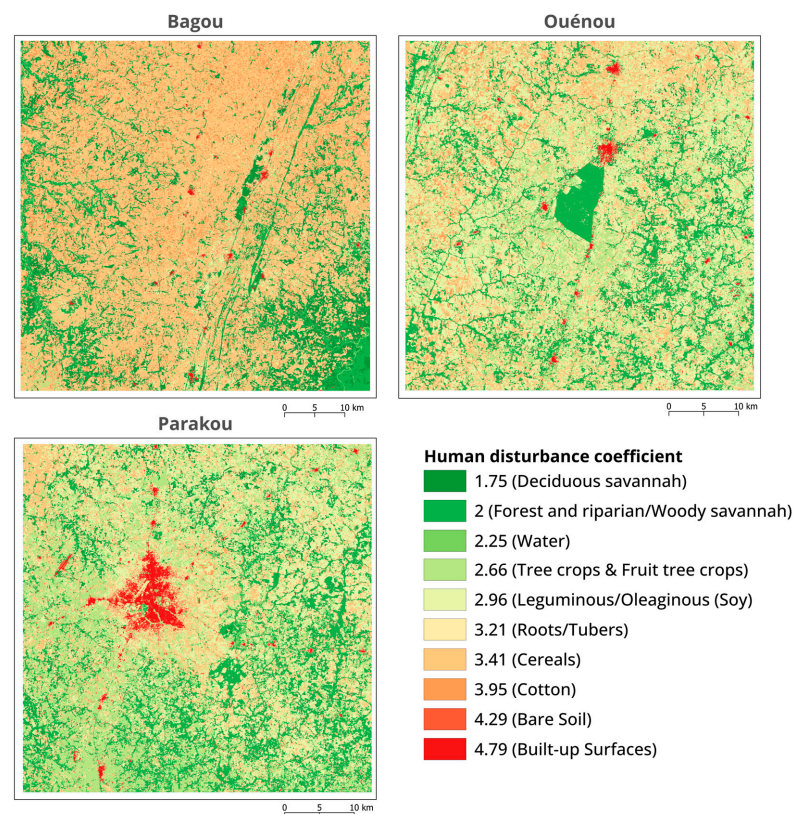

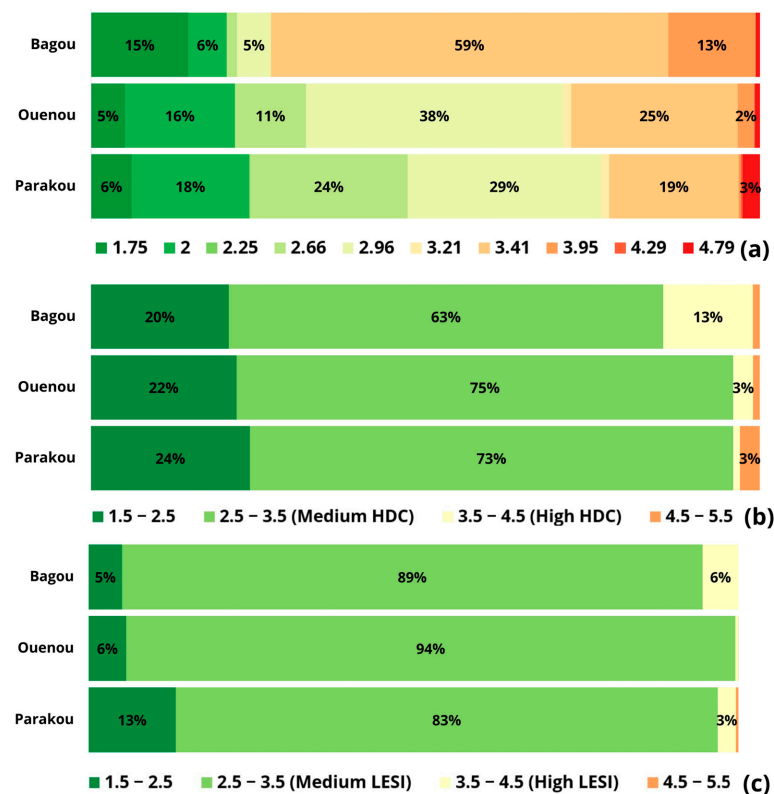**Figure 4.** Spatial variation in Human Disturbance Coefficient (HDC) by site.

Figure 5. Surface proportion by sites of (**a**) each unique Human Disturbance Coefficient (HDC) values encountered in this study, (**b**) regular classes of HDC values (with increment of 1), and (**c**) regular classes of LESI values (with increment of 1).

The land cover class with high anthropogenic disturbance (HDC in the range]4.5; 5.5]), corresponding to built-up areas, represents 1% of the Bagou and Ouenou sites, and 3% of the Parakou site (Figures 4 and 5).

The next section of the analysis focuses on the Landscape Environmental Sustainability Index (LESI), which aggregates HDC values at the landscape cell scale (1 km × 1 km).

3.3. LESI Maps

The Human Disturbance Coefficient (HDC) and the Landscape Environmental Sustainability Index (LESI), derived from HDC through spatial aggregation, are represented using two distinct symbologies in Figure 6a,b (see Methods section). Figure 6a displays the full theoretical range of values (1 to 7) with increments of one unit, whereas Figure 6b illustrates the actual range observed in the study area (1.75 to 4.79), using half-unit intervals. Additionally, Figure 5c presents the surface proportion of the Landscape Environmental Sustainability Index (LESI) categories across the Bagou, Ouenou, and Parakou sites.
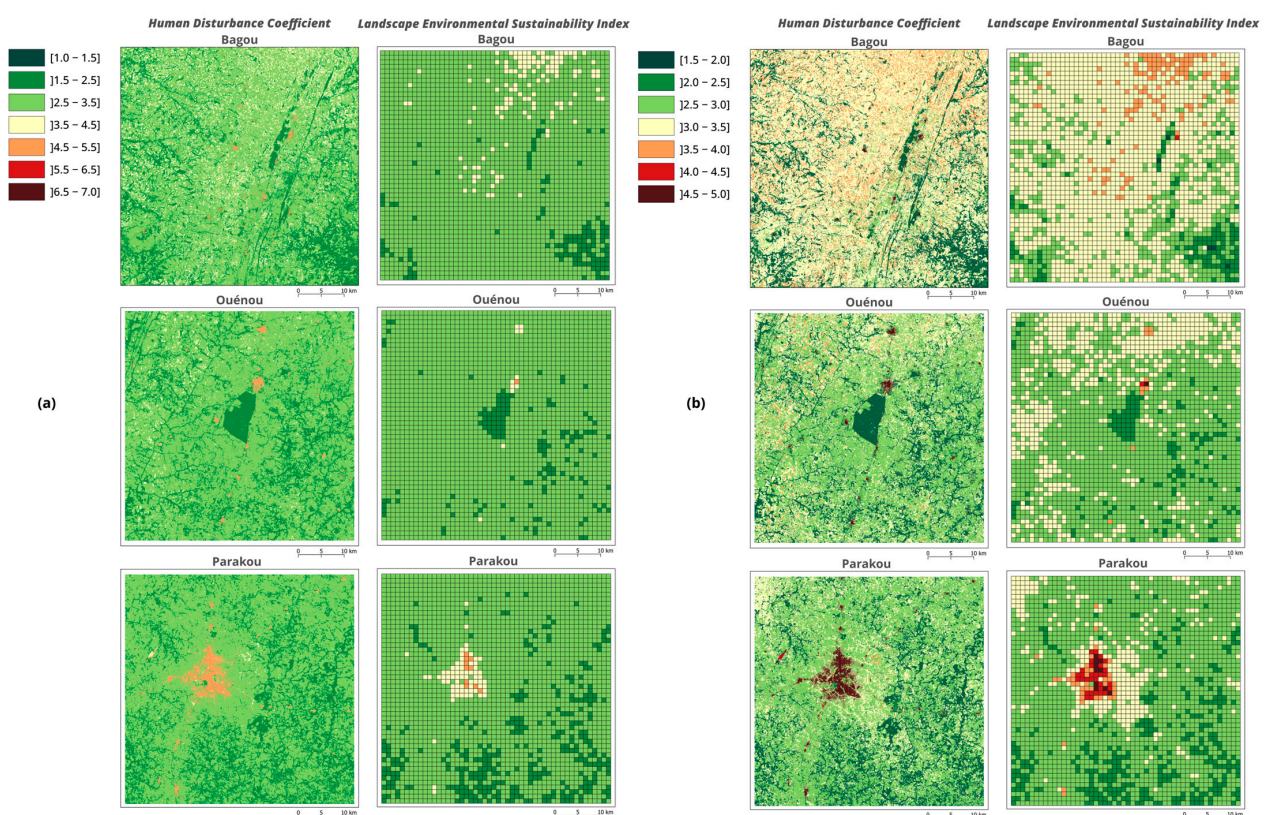

Figure 6. Variation in the Human Disturbance Coefficient (HDC) based on pixel-wise reclassification of land cover maps into HDC scores, and Landscape Environmental Sustainability Index (LESI) based on surface-weighted aggregation of these HDC scores within 1 km × 1 km landscape cells by site. Colour legends correspond to (**a**) the theoretical value range of the indicators (1 to 7, increments of 1), and (**b**) the observed value range in the study sites (1.75 to 4.79, increments of 0.5).

For the Bagou site, Figure 5c shows that landscape cells are distributed across three LESI classes within the interval]1.5; 4.5], with 89% falling in the]2.5; 3.5] range, 5% in]1.5; 2.5]—mainly in the southeast—and 6% in]3.5; 4.5], mostly in the northeast and central parts of the site. Figure 6b clearly highlights a stronger human impact in Bagou's rural landscape compared to the other two sites.

In the case of Ouenou, landscape cells span four LESI classes within the interval]1.5; 5.5], with 94% in]2.5; 3.5], 6% in]1.5; 2.5]—concentrated in the centre of the site,

corresponding to the N'Dali classified forest—and less than 0.5% in the two higher classes (11 cells in]3.5; 4.5] and 1 in]4.5; 5.5]).

At the Parakou site, landscape cells are similarly distributed across four LESI classes in the interval]1.5; 5.5], with 83% in [2.5; 3.5], 13% in]1.5; 2.5]—mainly in the south—and the remaining 4% corresponding to the two upper classes, located in the central-western area which includes the urban core and periphery of Parakou. Figure 6b reveals the extent of urban influence in Parakou, with anthropogenic impacts reaching up to 10 km from the city centre in some directions, especially towards the east and southeast.

4. Discussion

4.1. LESI Results and Implications for Rural Landscape Sustainability in the Study Area

The LESI results reveal a moderate level of anthropogenic impact across all study sites. While this suggests a relatively balanced state of landscape disturbance, ongoing agricultural intensification—particularly the expansion of cropland at the expense of natural ecosystems—poses a long-term threat to agricultural landscape resilience in the study area. In fact, strengthening agricultural landscape resilience requires enhancing the ecological and functional diversity of agricultural landscape [97–100]. In this context, regular LESI assessments could help to track agricultural landscape degradation and inform timely, targeted interventions to support the sustainability.

The spatial distribution of the LESI across the three study sites shows that Parakou exhibits the highest proportion of landscape cells characterised by intense anthropogenic disturbances (LESI ranging from 3.5 to 5.5). These cells are located primarily within the urban centre of Parakou, where artificial land covers dominate. This observation aligns with findings from numerous authors concerning current dynamics in most African cities. Indeed, these cities experience high demographic growth rates [101], rapid urban expansion [102], and a strong dependency of urban populations on natural resources, which results in profound environmental changes [103], and significant pressure on environmental systems.

Moreover, the Bagou site is characterised by an agroecosystem dominated by cereal and cotton fields, leading to a large number of landscape cells with LESI values within the range of]3; 3.5]. In contrast, the Ouenou site features an agroecosystem mainly composed of leguminous crops, which require fewer chemical inputs and consequently exhibit lower levels of disturbance. These observations are consistent with the analysis of Tilman, et al. [5], who indicate that increasing the productivity of cereal and cotton crops often entails agricultural practices that exert greater pressure on agroecosystems. These include deep soil tillage and the use of chemical inputs (especially herbicides and pesticides in cotton farming), resulting in the degradation of natural formations, water and soil pollution, and soil erosion.

Furthermore, across all three sites, landscape cells predominantly containing riparian forest ecosystems are located in hydromorphic depressions unsuitable for the establishment of agroecosystems. These areas show very low levels of anthropogenic disturbance. This finding corroborates the conclusions of dos Santos, et al. [104] in Brazil and Niño, et al. [105] in Colombia, who observed that topographic heterogeneity within agroecosystems results in a mosaic of land cover and, more broadly, of landscapes. It also supports the conclusions of Marshall [106], who noted that the natural configuration of biophysical landscape features (geomorphology, topography, soil fertility, temperature, and drainage) often gives rise to gradients favourable to the establishment of diverse agroecosystem mosaics.

4.2. Advantages of the LESI

Compared with the hemeroby index, one advantage of the LESI method proposed in this study is its multi-criteria analysis of anthropogenic disturbances based on land cover types, taking into account the four core environmental systems: hydrosphere, pedosphere, atmosphere, and biosphere. Moreover, the multi-criteria analysis required by some hemeroby index assessment methods often relies on inventory data (e.g., number of ruderal species, presence of rare species), which are not always available and can be costly to obtain. In comparison, the LESI method developed in this study allows for the assessment of anthropogenic disturbance levels generated by different types of land cover, based on a multi-criteria analytical framework that can be easily implemented across a wide range of agroecosystems worldwide, using land cover maps and detailed documentation of anthropogenic activities related to those land covers.

The LESI adds substantial value beyond conventional land cover classification by providing an integrated and quantifiable measure of the environmental sustainability of agricultural landscapes. Unlike land cover maps, which primarily describe spatial distribution of land use categories, LESI synthesises multiple dimensions of anthropogenic disturbance—such as soil erosion, water and soil pollution, and biodiversity pressures—into a single composite index. This approach offers an understanding of landscape health, reflecting both the intensity and spatial variability of environmental negative externalities linked to human activities.

Furthermore, the use of small, uniform landscape units (1 km^2 cells) enables detailed spatial aggregation and mapping of sustainability levels, allowing stakeholders to precisely identify areas experiencing higher degradation. This spatial granularity is critical for efficient design of site-specific agroecological interventions.

Importantly, LESI leverages widely accessible land cover data derived from increasingly precise and affordable satellite imagery, making it a practical and scalable tool for monitoring landscape sustainability. By translating remote sensing data into actionable insights, LESI supports evidence-based decision-making, early detection of emerging threats, and the promotion of sustainable land management practices adapted to local conditions and socio-environmental challenges.

4.3. Methodological Limitations and Development Perspectives

Nevertheless, the multi-criteria analysis approach developed in this study to determine the Human Disturbance Coefficient (HDC) presents several limitations that may affect its accuracy and relevance.

First, the proposed method is based on the use of nine generic criteria to assess anthropogenic disturbances across different land cover types. While this allows for a simplified and accessible evaluation of negative externalities linked to human activities, it may limit the capacity to fully represent the complexity of anthropogenic impacts on ecosystems [21]. For instance, biodiversity loss or water pollution involves each a diversity of negative environmental externalities that would benefit from being assessed using more specific sub-criteria (e.g., by species under threat, by type of pollutants identified).

Second, the approach does not account for uncertainties in the assignment of scores to the criteria, which are treated deterministically, with no consideration for potential imprecisions. Since these scores were determined through literature review, there is a potential risk of bias. One avenue for improvement would be the collection and use of empirical data from field measurements of the negative externalities associated with various land cover classes. However, such measurements represent a challenge in terms of time and financial resources. Another potential enhancement would involve conducting a sensitivity analysis of the score assignment method and/or adopting a probabilistic approach in score

attribution [107], which would better address these uncertainties and improve the reliability of the results.

Third, it should be recalled that in this study, a uniform weighting (equal to 0.25) was assigned to each of the four groups of evaluation criteria corresponding to the four environmental systems considered (hydrosphere, pedosphere, atmosphere, and biosphere), regardless of the land cover types analysed. As a perspective, it is worth noting that this type of method could easily evolve, depending on specific objectives being pursued, into an approach that differentiates and accounts for the relative importance of these systemic criteria according to geographic contexts and/or land cover classes analysed, through simple modulation of the criteria weights between these land cover classes. For example, in an agroecosystem where the pedosphere plays a crucial role (soil fertility and conservation), a greater weight could be attributed to the group of criteria related to the pedosphere, whereas in an urban area where air quality may be considered paramount, a greater weight could be assigned to the criteria group concerning the atmosphere. For this type of analysis, the multicriteria environmental assessment with multiple weight assignments proposed by Agarski, et al. [108] would serve as a relevant example.

Fourth, another limitation of our methodology concerns the treatment of surface water bodies. While these ecosystems are highly sensitive to anthropogenic pressures, our approach does not incorporate spatially explicit modelling of hydrological connectivity or land–water interactions. Consequently, the scores assigned to surface water classes are based on expert reasoning and literature-derived assumptions only, and empirical spatial data on upstream land use or adjacency are not integrated into the methodology. This limitation restricts the ability of the LESI to capture fine-scale interactions between land disturbances and aquatic vulnerability. Future methodological developments could address this by example, by integrating flow accumulation models, riparian buffer analyses, or hydrological network data to better represent pressure propagation within landscapes.

Finally, the LESI is derived from land cover maps produced using the Moringa processing chain, which combines multi-source satellite data, including very high spatial resolution SPOT 6/7 imagery, Sentinel-2 optical time series, and SRTM-derived topography. While this methodological multi-source integration enhances thematic discrimination and spatial detail, it also presents accuracy limitations which in turn affect the accuracy of the final LESI outputs. Despite the robustness of the Random Forest classifier and the quality of the reference database—built from in situ surveys and systematic photo-interpretation—the accuracy levels achieved remain heterogeneous across the study sites. Specifically, the overall classification accuracies are 64% for Bagou, 76% for Ouenou, and 73% for Parakou. These values were obtained through fivefold cross-validation and reflect, among other factors, the spectral complexity of the landscapes, class confusion (e.g., between Forest and Riparian and Other Tree Crops (Teck)), and the challenges of delineating small or fragmented land cover features. The spatial resolution gap between the SPOT 6/7 objects used for segmentation and the Sentinel-2 series used for classification also introduces potential inconsistencies in object attribution. Furthermore, although the field reference data used for training and validation were extensive, they may not fully capture the heterogeneity of all ecological configurations, particularly in peripheral or rapidly changing zones. This may result in misclassification of land cover types especially in areas of ecological transition. Given that LESI scores are directly derived from land cover classes, any classification error propagates into the final LESI values, potentially underestimating or overestimating environmental negatives externalities levels in certain areas. The relatively lower accuracy observed for Bagou, for instance, implies a greater degree of uncertainty in LESI interpretation for this site. Improving the precision of land cover classification—whether through finer spatial resolution, enhanced spectrotemporal analysis, or more diversified ground-truth data—would

therefore strengthen the analytical robustness of LESI and its utility for landscape-level decision-making. In future applications, integrating complementary data sources such as agro-ecological inventories, or participatory mapping, could enhance accuracy of land cover classification maps and provide a more nuanced representation of land systems. As a consequence, these enhancements would also directly contribute to reducing uncertainty and increasing the accuracy of the LESI. However, it is important to emphasise that the primary contribution of this article lies in the methodological conceptualization of a novel, innovative, and integrative indicator for assessing landscape environmental sustainability. And the accuracy of the specific input data used in this study to demonstrate the operationalization of the indicator in a particular context should not be seen as undermining the validity of this methodological framework, in particular given the current technological context of rapid and continuous improvement in the accuracy of land cover classifications derived from satellite imagery.

5. Conclusions

In sub-Saharan Africa, the increase in agricultural production driven by population growth and the resulting increase in demand for food is causing various negative externalities that affect environmental systems. Evaluating the intensity of these impacts is essential to monitor the ecological sustainability of rural landscapes and to provide timely information to land managers—such as policymakers, researchers, and agricultural stakeholders—who can then take action through mitigation, protection, or restoration measures.

The LESI, which can be calculated from land cover maps generated via satellite remote sensing—an approach that is cost-effective, repeatable on an annual basis, and applicable over large areas—offers a way to assess the degree of anthropogenic pressure in diverse landscapes, particularly rural ones.

The main contribution of this study lies in the conceptualization and operationalization of a Landscape Environmental Sustainability Index (LESI), designed to capture, from satellite-based land cover classification maps, the associated human-induced environmental negative externalities on the four major environmental systems: hydrosphere, pedosphere, atmosphere, and biosphere. Applied to case studies in northern Benin (West Africa), this approach reveals a gradient of increasing anthropogenic disturbance from south to north, with higher impacts in areas characterised by greater artificialisation of land cover, while regions dominated by riparian vegetation or rocky outcrops—less favourable to agroecosystem expansion—show minimal disturbance.

The LESI, developed through this methodological framework, offers land use planners and decision-makers a spatially explicit, multi-criteria tool to assess and monitor anthropogenic disturbances across rural landscapes at a fine resolution (1 km^2 cells). Unlike traditional land cover classifications that merely describe land use types, the LESI provides a spatially explicit and integrative measure of environmental disturbance by aggregating weighted systemic criteria related to the environment sub-systems. This allows for more precise targeting of areas most in need of intervention, thereby supporting prioritised resource allocation and more effective strategies for promoting ecological sustainability and agroecological transition in less-developed rural landscapes.

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