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# Abstract

Agricultural systems are rapidly transforming, making regular mapping critical for policy guidance. Field-based surveys remain costly and spatially limited, while satellite data represent a promising avenue for characterising agricultural systems.

This study explores the use of freely available satellite and geospatial data to produce an exhaustive village-scale mapping of agricultural systems and their intensification levels in North and Centre Benin.

An agricultural system typology, including intensification levels, was developed from a sample of 178 surveyed villages using hierarchical clustering of production system variables derived from field surveys. A Random Forest model was then applied to predict agricultural system types using 20 explanatory variables, including vegetation indices, landscape configuration metrics, environmental variables, and socioeconomic indicators. This approach enabled the spatially complete mapping of agricultural system types across the entire study area.

Four agricultural system types were identified, reflecting a clear intensification gradient from low-input diversified agroforestry to mechanized and irrigated agropastoral systems. The Random Forest model achieved high accuracy (83.1%). MODIS-derived radiometric variables and environmental variables jointly dominated the prediction of agricultural system types, highlighting the key role of biophysical factors and farming practices in structuring landscapes. Except for distance to the nearest border, socioeconomic variables had a limited influence.

This study provides a scalable and transferable framework for spatializing agricultural system diversity and intensification levels in heterogeneous landscapes. It reduces dependence on repeated field surveys and offers a robust foundation for policy-relevant, spatially explicit agricultural monitoring.

**Keywords:** agricultural systems modelling, MODIS time series, landscape metrics, random forest, intensification, Benin.

# 1. Introduction

Agricultural systems in developing countries are experiencing rapid and complex transformations driven by population growth, climate variability, and market integration [1,2]. These dynamics are particularly pronounced in Sub-Saharan Africa, where smallholder farming dominates the landscape and land-use changes occur at an accelerating pace [3,4]. In Benin, the majority of agricultural households practice predominantly subsistence farming; however, several cash crops were introduced in the early twentieth century, including cotton, groundnut, and pineapple, and more recently cashew and soybean. Since the 1960s, production systems have undergone continuous transformation under the combined effects of rapid population growth, changing dietary patterns, public and private strategies and policies, and emerging market opportunities. Over the past decades, policies promoting agro-industrial processing and agricultural intensification (particularly for cotton, cashew, and soybean) have driven significant changes in traditional production systems, including increased tractor use, greater reliance on inputs, the expansion of orchard plantations, fallow abandonment and shifts in crop rotations.

Understanding these highly dynamic agricultural systems is essential for effectively guiding research and development policies [5–8]. Typology and characterization of agricultural systems constitute a key approach to achieving this understanding, as they provide a structured framework for identifying common patterns across a wide range of systems, describing their heterogeneity, and targeting policies and recommendations more effectively across diverse contexts [9,10]. Such typologies rely on detailed questionnaires, representative sampling, multivariate analyses, and, in some cases, participatory validation. In situ data collection is both logistically demanding and financially costly, and existing typologies are rarely spatially exhaustive as a result [11–13]. More critically, these survey-based approaches are poorly suited to tracking the rapid transformations currently affecting agricultural systems, as the pace of change increasingly outstrips the frequency at which such surveys can realistically be conducted.

A complementary approach to the household survey-based methods consists in characterizing agricultural systems through indirect observation. Indeed, changes in land use, including agricultural practices, are strongly reflected in landscape patterns and structures [14,15]. Thus, geography provides the spatial framework for understanding farming systems [16]. Historically, agro-geographic approaches were widely applied from the 1960s onward, and known as agrarian system [15,17,18]. Numerous geographers, particularly in West Africa, have described and mapped land-use patterns, landscapes, and agrarian structures at multiple scales [19,20]. One of the pioneering efforts to spatialize agricultural systems was conducted by Staal et al. [21] who showed in East African dairy systems that crop-livestock diversity could be explained by spatial variation in market access and agroclimatic conditions within a household-level framework. van de Steeg et al. [22] extended this approach in the Kenyan Highlands, using data from 3,000 households and logit models to derive a regional farming systems map shaped by agroclimatic, demographic, and socioeconomic factors. Yet these pioneering studies did not incorporate remote sensing, limiting their transferability to contexts with sufficiently rich survey data.

Since then, major advances in Earth observation have considerably expanded the potential of the geographic approach, by enabling systematic, repeated, and spatially explicit monitoring of land use dynamics. Earth observation data have become an essential tool for analysing agricultural systems due to their capacity to provide spatially explicit indicators of crop dynamics, land use, and vegetation status at local and regional scale [23,24]. The open access to Sentinel and Landsat archives has democratized data availability, while advances in machine learning approaches have enabled the mapping of complex agricultural mosaics [25,26].

Numerous studies draw on satellite imagery, GIS, and land-use or land-cover maps to identify systems from spatio-temporal signatures, often through phenological stratification, object-based segmentation, and hierarchical classification [27–30]. Yet, two main limitations emerge from these studies: (1) the spatial scale of analysis, which is often regional or continental [31,32], thereby obscuring locally specific patterns  global products primarily represent spatialised agricultural variables rather than agricultural systems captured in their full social and technical complexity [33]; (2) the growing reliance on annual agricultural land use maps, which are ill-suited to characterising complex agricultural systems that unfold across multiple seasons, and whose spatial resolution remains insufficient at the local scale, particularly in systems marked by smallholder fragmentation and high landscape heterogeneity, as is the case in sub-Saharan Africa [34–36].

Recent work on the mapping of agricultural systems has progressively shifted from crop-centered mapping toward more integrated approaches that combine production systems with socioecological frameworks [37–39]. These studies combine remote sensing, censuses, farm surveys, environmental data, and expert knowledge, underscoring that agricultural systems cannot be captured through any single data source [36,40]. Combined with geoinformation and machine learning techniques, satellite data now offer new opportunities to derive agricultural system typologies, while overcoming some of the limitations associated with conventional survey-based methods.

This study aims to address these opportunities by adopting an integrated approach to agricultural systems. Based on a geographical approach, the objective is to demonstrate that freely accessible Earth observation and geospatial data can be used to map agricultural system types at the village scale, enabling more frequent updates than traditional agricultural and socioeconomic surveys, which are constrained by cost and logistical challenges. It focuses on rural areas of West Africa, using North and Centre Benin as a case study.

The methodology unfolds in three sequential steps. First, a typology of agricultural systems is constructed from village-level data on production systems collected through conventional field surveys on a representative sample of the study area. Second, a predictive model of agricultural system types is developed using Earth observation and geospatial variables and assessed against the survey-derived typology. Third, the validated model is applied across all villages in North and Centre Benin to produce a comprehensive, spatially explicit map of agricultural systems.

# 2. Methods

## 2.1. General approach

The study aims to produce a village-scale map of agricultural systems in North and Centre Benin using multi-source EO and geospatial data combined with machine learning. The village scale is used as it best captures the spatial expression of agricultural systems in traditional contexts [17].

The workflow includes four steps (Fig 1.): (1) development of an agricultural system typology from 2017 field survey data; (2) construction of a geospatial database of radiometric, landscape, environmental, and socioeconomic predictors; (3) training and validation of a Random Forest model to identify key drivers and predict agricultural system types; and (4) production of a village-scale agricultural system map for the study area.

Predictor selection is guided by the assumption that rural landscapes reflect dominant agricultural practices shaped by environmental and human factors [14,41,42].

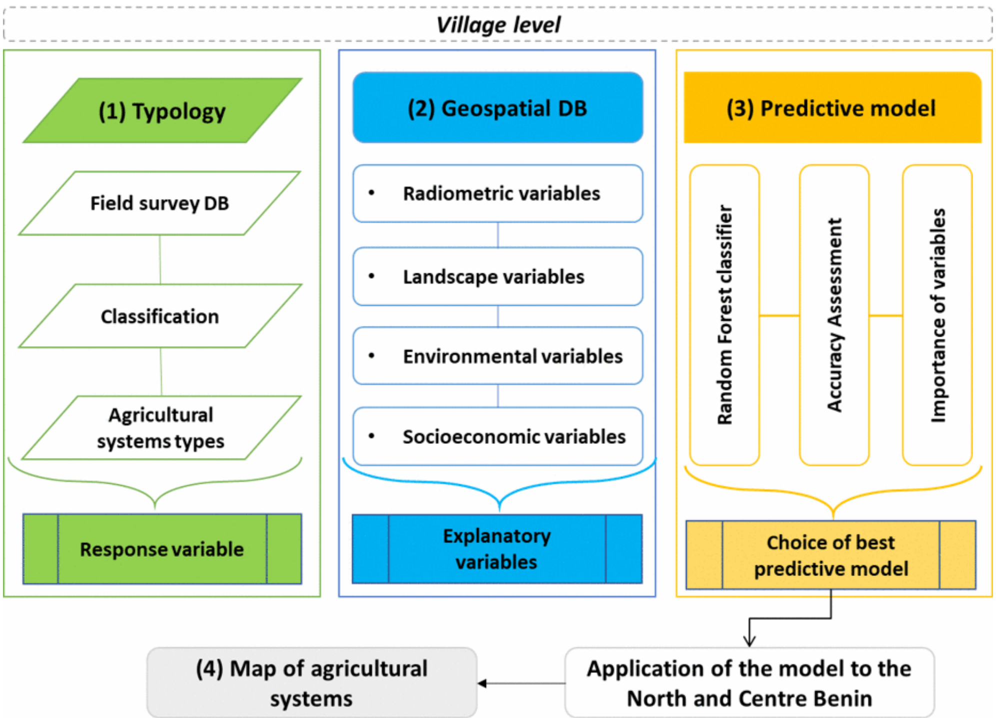



**Fig 1. Flowchart of the approach.**

## 2.2. Study area

The study area covers about 98 000 km² and five departments of the North and Centre Benin: Alibori, Borgou, Atacora, Donga and Collines (Fig 2A and B). These departments intersect five of the eight agro-ecological zones (AEZ) of the country [43] (Fig 2C).

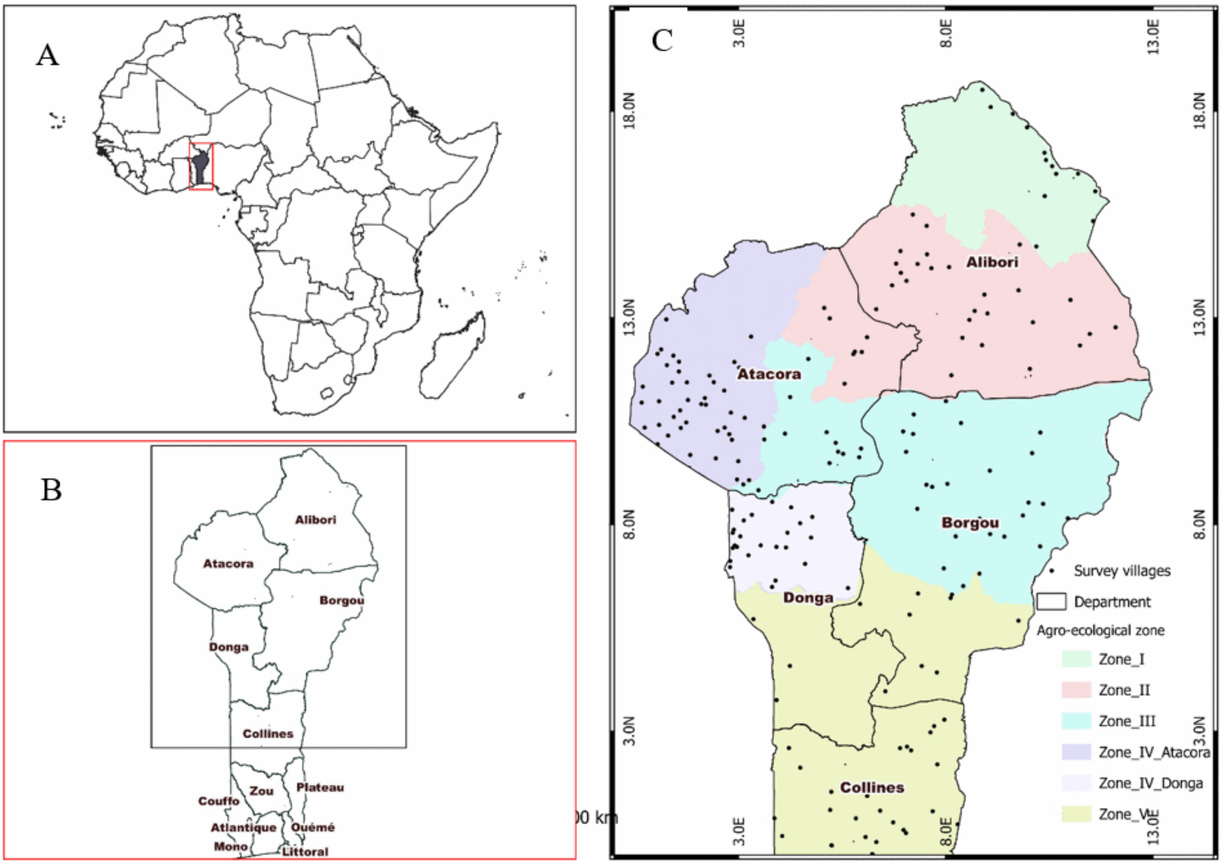



**Fig 2 A) Location map of the study area in Africa; B) Administrative boundaries of Benin departments; C) Agro-ecological zones (AEZ) of North and Centre Benin.**

## 2.3. Data

### 2.3.1. The village survey database

The village database used to construct the agricultural system typology was derived from a 2017 national survey conducted by the Agricultural Policy Analysis Program of the Benin

Agricultural Research Institute [44], covering 477 villages across all agro-ecological zones of Benin. Data were collected through focus group discussions with male and female farmers. For this study, a subset of 178 villages from North and Central Benin was used. The typology was based on 18 village-level variables (Table 1) grouped into production factors (7), cropping systems (9), and livestock systems (2). These variables, expressed as proportions of households per village, describe dominant agricultural practices and land-use patterns.

**Table 1. Names and descriptive statistics of the survey variables used to construct the agricultural system typology in North and Central Benin.** Values represent the percentage of households per village engaged in each activity.

| **Category** | **Variables** | **Variable codes** | Mean (%) | Sd (%) |
|---|---|---|---|---|
| **Production factors** | Animal traction | animal_traction | 40,7 | 40,2 |
| | Tractor use | tractor | 19,0 | 26,6 |
| | Chemical fertilizers | chem_fert | 73,7 | 32,5 |
| | Organic fertilizers | org_fert | 19,6 | 23,9 |
| | Pesticides | pesticide | 51,4 | 19,8 |
| | Hired labour intensity | labor | 48,9 | 19,1 |
| | Irrigated area | irrigation | 5,2 | 16,9 |
| **Cropping systems** | Cereals (excluding rice) | cereals | 89,0 | 15,2 |
| | Pulses & oilseeds | pulses_oilseeds | 65,6 | 21,0 |
| | Roots and tubers | roots_tubers | 63,8 | 38,7 |
| | Vegetables | vegetables | 10,1 | 26,0 |
| | Cotton | cotton | 51,6 | 40,6 |
| | Rice | rice | 32,8 | 38,9 |
| | Cashew | cashew | 59,9 | 36,7 |
| | Teak/Gmelina | teak_gmelina | 25,8 | 25,5 |
| | Mango | mango | 34,2 | 32,5 |
| **Livestock systems** | Cattle | cattle | 44,3 | 29,5 |
| | Small ruminants | small_ruminants | 76,9 | 22,9 |

### 2.3.2. The geospatial variables

Twenty explanatory variables, grouped into four categories (radiometric, landscape, environmental, and socioeconomic variables; Table 2) were computed at the village scale. Because Benin has no village administrative boundaries, we used village territory limits that were delineated using a population-weighted Voronoi model (see sedegnan et al. [45] for details).

All variables used are drawn from publicly available sources, and for each of them, we selected the data products that are closest in time to the survey data.

**Table 2. Geospatial explanatory variables.**

| Variables | Variable codes | Sources | Spatial resolution | Date |
|---|---|---|---|---|
| **Radiometric (5)** | | | | |
| Annual NDVI | ndvi | MODIS MOD13Q1 v6 | 250 m | 2016-2018 |
| PC2, PC3, PC4 | pc2, pc3, pc4 | | | |
| Haralick correlation | texture8 | | | |
| **Landscape (6)** | | | | |
| % cropland | pland | OBSYDYA land cover map (source: www.obsydya.org) | 10 m | 2023 |
| Cropland patch density | pd | | | |
| Cropland edge density | ed | | | |
| Cropland aggregation index | ai | | | |
| Cropland patch cohesion index | cohesion | | | |
| Cropland split index | split | | | |
| **Environmental (4)** | | | | |
| Annual rainfall (mm) | rainfall | CHIRPS | 5 km | 2015-2019 |
| Soil type | soil | HWSD v2.0 | 1 km | 2023 |
| Average temperature | temperature | WorldClim v2.1 | 1 km | 1970-2020 |
| Elevation (m) | elevation | SRTM GL1 | 30 m | 2000 |
| **Socioeconomic (5)** | | | | |
| Road density: total road length (km) | length_road | OSM | | 2025 |
| Travel time to the nearest city (min) | time_city | OSM, Global friction surface transport | 1 km | 2025, 2018 |
| Distance to the nearest paved road (km) | dist_road | OSM | | 2025 |
| Distance to the nearest border (km) | dist_border | OSM | | 2025 |
| Population density (inhabitants/km²) | density | INStaD Bénin | | 2018 |

### ***Radiometric Variables***

Radiometric variables were derived from MODIS NDVI (MOD13Q1 v6, 250 m, 16-day composites) over 2016–2018, selected to reduce interannual variability and match the 2017 survey period. A total of 69 images (23 per year) were obtained from NASA AppEEARS (https://appeears.earthdatacloud.nasa.gov). The product provides NDVI from atmospherically corrected reflectances with masking of clouds, shadows, and water. The time series was smoothed using a weighted Savitzky–Golay filter ([46]; polynomial order = 2), incorporating pixel reliability and a 13-observation window with exponential temporal decay. NDVI values were then averaged across the three years to produce a synthetic annual profile (23 dates), from which annual mean NDVI was computed. Annual NDVI is widely used in geospatial modelling applications [47,48].

The synthetic annual NDVI time series was analysed using principal component analysis (PCA) to summarize spatiotemporal variability [49]. PC1 corresponds to mean annual NDVI, while PC2 captures the dominant seasonal cycle linked to precipitation and vegetation phenology. PC3 reflects a secondary, phase-shifted seasonal pattern. PC4 shows two intra-annual cycles with peaks in both rainy and dry seasons. Components beyond PC3 mainly represent residual, episodic variability deviating from the main seasonal signal, likely associated with disturbances (e.g., fires, flooding, dry spells) and agricultural practices (e.g., cropping cycles) or their combinations.

The Haralick correlation index (texture), measuring grey-level dependency between neighbouring pixels, was computed from annual MODIS NDVI using a 6-pixel moving window.

The spatial distribution of radiometric variables is presented in Appendix A.1.

### ***Landscape variables***

Landscape variables were derived from the 2023 OBSYDYA land cover map for North and Centre Benin [50], produced at 10 m resolution using Sentinel-2 time series and the IOTA2 processing chain [51]. The map includes six classes, including annual and tree crops. Cropland proportion (pland) was computed as the share of these agricultural classes within each village. Landscape configuration metrics for cropland patch density, edge density, aggregation index, cohesion index, and split index were calculated using the R package landscapemetrics [52]. These indices respectively describe patch number, edge length, spatial clustering of similar pixels, landscape fragmentation, and overall patch connectivity.

The spatial distribution of landscape variables is presented in Appendix A.2.

### ***Environmental variables***

Annual rainfall (2015 - 2019) was derived from the CHIRPS dataset. Dominant soil types were extracted from the FAO Harmonized World Soil Database (HWSD v2.0). Mean elevation came from the Shuttle Radar Topography Mission (SRTM GL1, 30 m), and temperature data from WorldClim v2.1, based on 1970 - 2000 climate normals at ~1 km resolution.

The spatial distribution of environmental variables is presented in Appendix A.3.

### ***Socioeconomic variables***

Socioeconomic variables, widely used in predictive studies [48,53,54], include road density computed from OpenStreetMap (OSM) data within each village. Travel time to the nearest city was derived from the Global Friction Surface [55], while distances to the nearest paved road and national border were calculated from OSM networks and village centroids. Population density was defined as total population divided by village area.

The spatial distribution of socioeconomic variables is presented in Appendix A.4.

## 2.4. Methods

### 2.4.1. Typology of agricultural systems

Agricultural systems are typically classified according to study objectives and context [22], using methods such as factor analysis [56], cluster analysis[57], classification trees [58], and discriminant analysis [59–61]. Here, agricultural systems were identified by hierarchical clustering (Ward's method) with the number of classes determined from the dendrogram and validated through discriminant analysis.

### 2.4.2. Predicting and Mapping the Agricultural Systems

The agricultural systems were predicted in R (v4.5.1) using a Random Forest model [62] implemented via the *randomForest* package [63]. Random Forest is an ensemble learning method based on bootstrap aggregation of decision trees and random feature selection, enabling robust modelling of complex, non-linear relationships without distributional assumptions [64]. The model was trained on 178 villages and 20 predictor variables, with agricultural system type as the response variable. Key parameters were set to mtry = 4 and ntree = 1000, based on minimization of the out-of-bag (OOB) error.

Model performance was evaluated using OOB error and overall accuracy from the confusion matrix. Different predictor sets (radiometric, landscape, environmental, and socioeconomic variables, individually and in combination) were also tested to assess their relative contributions.

Variable importance was assessed using the mean decrease in accuracy (%IncMSE) and the increase in node purity (IncNodePurity). Finally, the calibrated model was applied to all villages in North and Central Benin to generate a spatially complete map of agricultural system types.

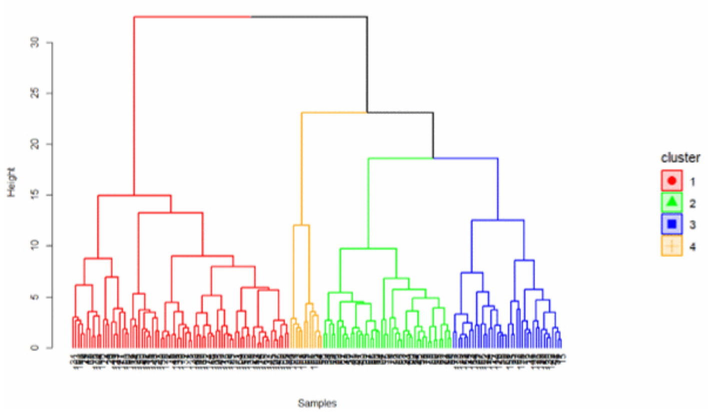
# 3. Results

## 3.1. Typology of agricultural systems

### 3.1.1. Types of agricultural systems

The classification identified four types of agricultural systems (Fig 3A). Discriminant analysis revealed that 95.51% of the observations are correctly classified (Fig 3B).

(A)




(B)

| | Predicted | | | |
|---|---|---|---|---|
| Observed | 1 | 2 | 3 | 4 |
| 1 | 78 | 0 | 1 | 0 |
| 2 | 0 | 46 | 1 | 0 |
| 3 | 2 | 1 | 36 | 1 |
| 4 | 0 | 2 | 0 | 10 |

**Fig 3. (A) Dendrogram with four clusters of survey variables; (B) Confusion matrix for the agricultural systems types.**

Fig 4. presents the distribution of villages across the four identified agricultural system types and their spatial location. Type 1 dominates with 44.4% of villages and is highly concentrated in the central part, followed by Type 2 (26.4%), present in the northern and north-western areas of the country, and type 3 (22.5%) with an intermediate distribution between the areas occupied by Types 1 and 2. Type 4 is marginal (6.7%) and is located in the extreme northern area of the country.

(A) (B)

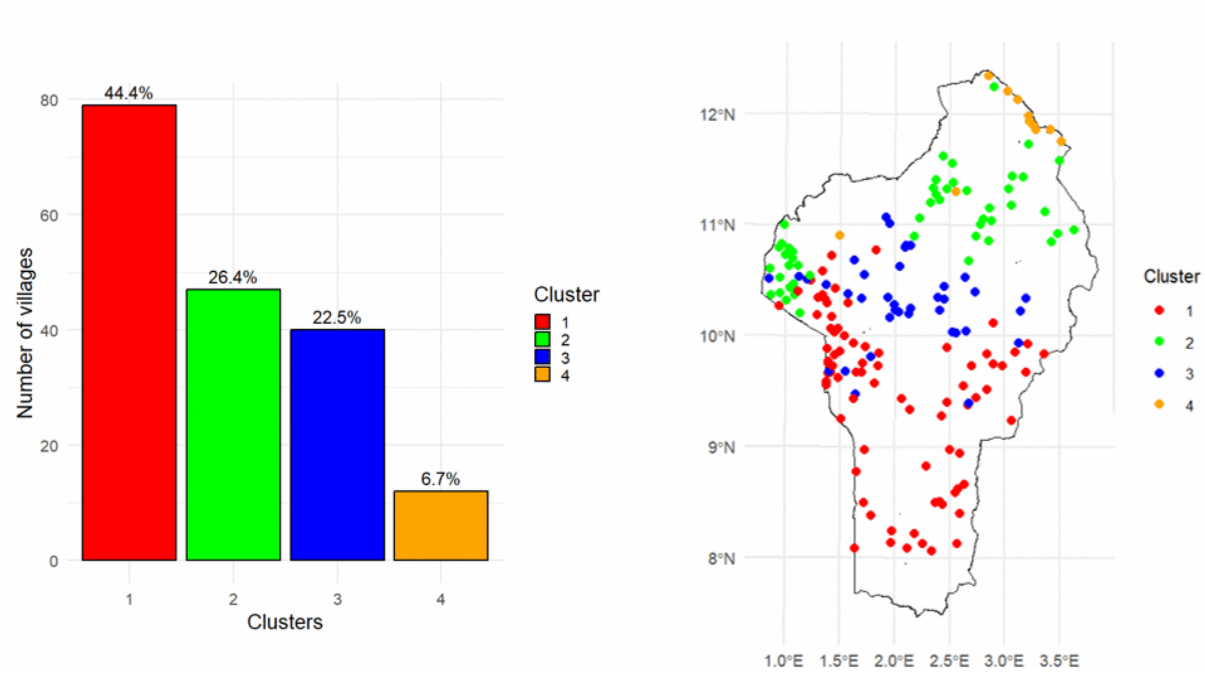



**Fig 4. (A) Proportion of villages by type of agricultural system; (B) Geographical distribution of types of agricultural systems in North and Centre Benin.**

### 3.1.2. Characterisation of types of agricultural systems

The main discriminating factors between the types of agricultural systems (Fig 5) include all categories of variables. In terms of factors of production, the proportions of households that use animal traction, hired labour and tractors have the highest contributions. Regarding cropping and livestock systems, the most influential variables are the proportions of households producing cashew, cotton, and roots and tubers, as well as those engaged in cattle farming.

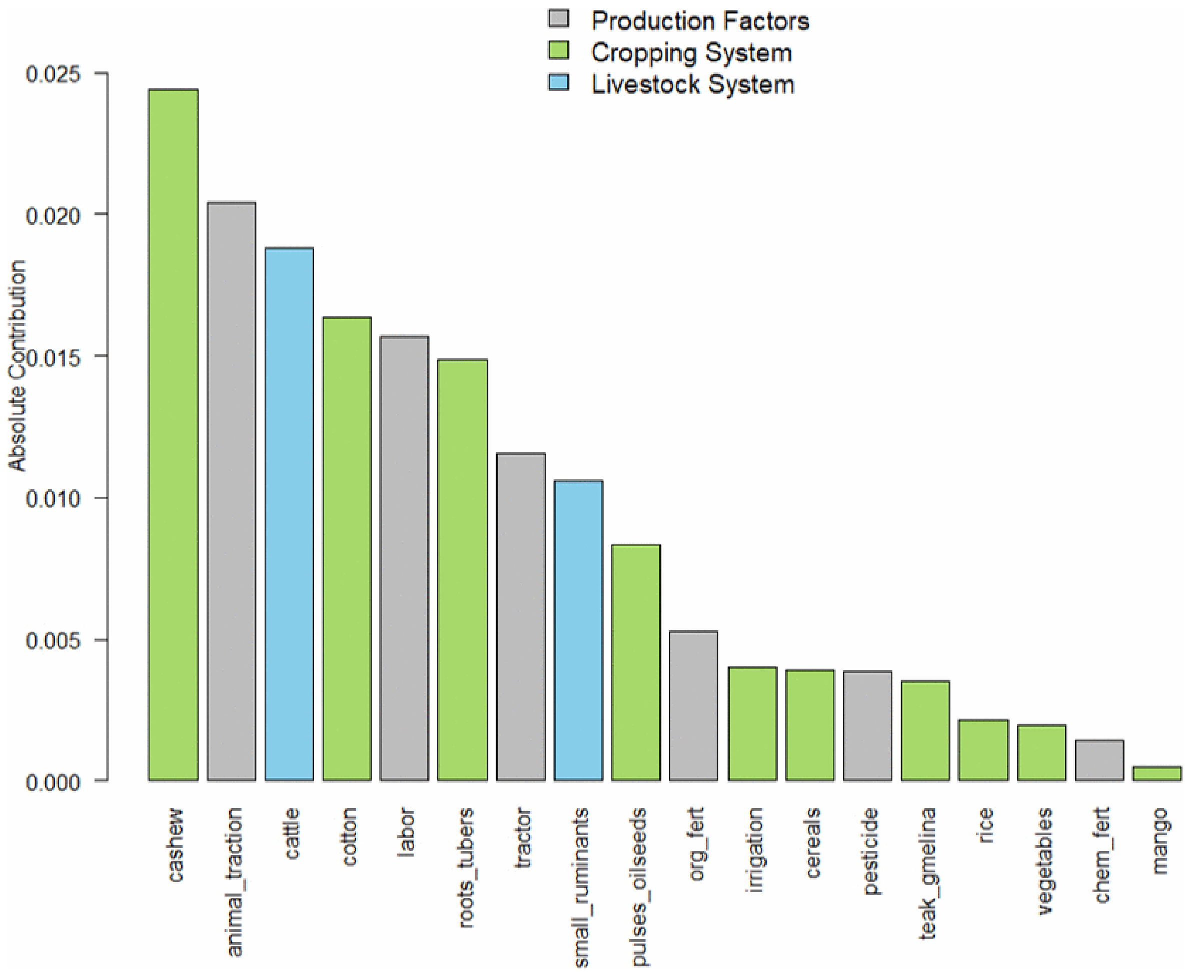



**Fig 5. Discriminating factors of agricultural systems types in North and Centre Benin; Different colours correspond to the categories of the variable.**

The following four agricultural systems can be described and named based on the analysis of the variables by system type (Table 3):

***Type 1: Low-input diversified agroforestry systems***

Type 1 systems are characterised by very little use of animal traction (8.4%) and mechanisation (8.1%). The use of inputs remains moderate for chemical fertilizers (55.5%) and pesticides (43.3%), and low for organic fertilizers (10.4%). Cropping systems are dominated by cereals (88.0%) and roots and tubers (83.9%), associated with a high presence of tree crops, particularly cashew tree (81.9%). Irrigation is marginal (2.5%). Livestock farming is not very developed for cattle (26.0%) but relatively more important for small ruminants (65.4%).

***Type 2: Input-intensive specialized agropastoral systems***

Type 2 systems are characterised by a high use of animal traction (77.6%) and moderate use of tractors (22.4%). The use of chemical fertilizers (94.8%) and pesticides (61.2%) is high. Cropping systems are highly specialized around cereals (93.2%) and cotton (87.1%), with a notable presence of rice (61.0%). Tree crops are poorly represented (cashew tree: 21.4%). Livestock farming is particularly developed, with high proportions of cattle (68.6%) and small ruminants (87.8%).

***Type 3: Mechanized and input-intensive diversified agroforestry systems***

Type 3 systems are characterised by high tractor use (40.5%) and intermediate animal traction (47.1%), as well as a high use of chemical fertilizers (84.5%) and pesticides (58.1%). Cropping systems are the most diversified, combining cereals (88.5%), pulses and oilseeds (63.1%), roots and tubers (83.9%), cotton (75.8%) and tree crops such as cashew tree (75.0%) and mango tree (55.3%). Irrigation remains low (1.1%). Livestock farming has intermediate levels for cattle (46.8%) and high levels for small ruminants (86.3%).

***Type 4: Irrigated input-intensive agropastoral systems with organic emphasis***

Type 4 systems are distinguished by a very high use of animal traction (89.1%) and high irrigation (58.2%), combined with a high use of fertilizers, especially organic fertilizers (59.5%), and a moderate use of pesticides (42.2%). Cropping systems are dominated by rice (74.5%) and vegetable crops (49.7%). Cattle (60.5%) and small ruminants (79.1%) are also well represented.

**Table 3. Production factors and crop/livestock systems of the four agricultural systems; The five most discriminating variables are shown in bold.** Values represent the percentage of households per village engaged in each activity.

| Category | Variables | Agricultural system type | | | |
|---|---|---|---|---|---|
| | | Type 1 | Type 2 | Type 3 | Type 4 |
| Production factors | **Animal traction** | **8,4** | **77,6** | **47,1** | **89,1** |
| | Tractor use | 8,1 | 22,4 | 40,5 | 8,2 |
| | Chemical fertilizers | 55,5 | 94,8 | 84,5 | 75,5 |
| | Organic fertilizers | 10,4 | 20,2 | 26,4 | 59,5 |
| | Pesticides | 43,3 | 61,2 | 58,1 | 42,2 |
| | **Hired labour intensity** | **46,3** | **51,7** | **50,0** | **51,5** |
| | Irrigated area | 2,5 | 1,0 | 1,1 | 58,2 |
| Cropping system | Pulses & oilseeds | 68,1 | 71,3 | 63,1 | 30,9 |
| | Cereals (excluding rice) | 88,0 | 93,2 | 88,5 | 78,5 |
| | Roots and tubers | 83,9 | 28,7 | 83,9 | 4,5 |
| | Vegetables | 12,5 | 3,5 | 2,2 | 49,7 |
| | **Cotton** | **21,0** | **87,1** | **75,8** | **31,8** |
| | Rice | 14,5 | 61,0 | 22,9 | 74,5 |
| | **Cashew** | **81,9** | **21,4** | **75,0** | **20,0** |
| | Teak/Gmelina | 30,4 | 17,2 | 34,6 | - |
| | Mango | 30,5 | 22,4 | 55,3 | 40,0 |
| Livestock system | **Cattle** | **26,0** | **68,6** | **46,8** | **60,5** |
| | Small ruminants | 65,4 | 87,8 | 86,3 | 79,1 |

## 3.2. Predicting and mapping agricultural systems

### 3.2.1. Spatial characterisation of agricultural system

Differences are observed across the four types of agricultural systems types for several variables, reflecting distinct spatial patterns (Fig 6.).

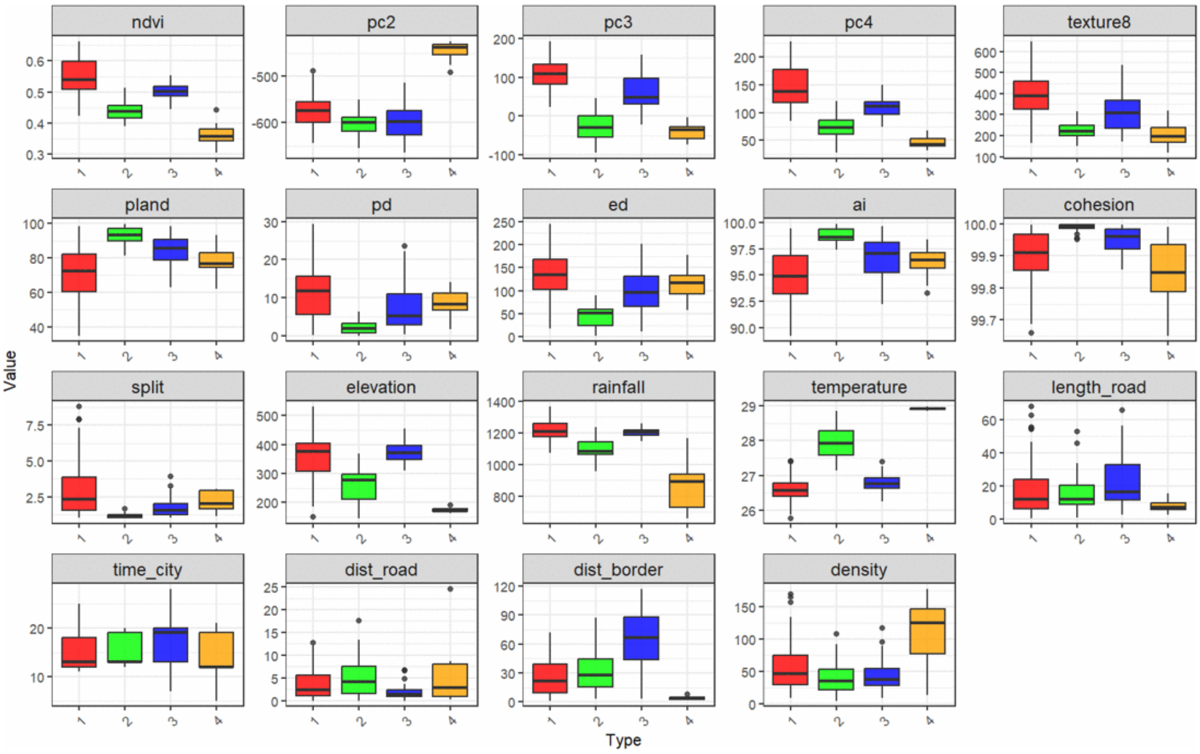



**Fig 6. Explanatory geospatial variables (excluding soil type) by agricultural system.**

The four agricultural systems can be described and named based on the analysis of the geospatial variables:

***Type 1: Fragmented high-biomass highlands***

Type 1 occurs at the highest elevations (~380 m) and rainfall (~1220 mm), with relatively low temperatures (~26.5°C). It shows high NDVI (~0.55) and Haralick correlation, indicating dense and structurally complex vegetation. The landscape is highly fragmented cropland (~72%), with elevated split, edge density, and patch density. Soils are mainly Ferric Lixisols (~65%), with Lixic Plinthosols and Lithic Leptosols (~15–18%), and minor Rhodic Nitisols and Gleyic Luvisols.

***Type 2: Aggregated intensive agricultural plains***

Type 2 corresponds to the most contiguous intensive agricultural areas, with >95% cultivated land and the highest aggregation (AI) and cohesion indices. Fragmentation is minimal, as shown by the lowest edge density and patch density. It occurs at moderate elevations (~280 m) with relatively low population density and the highest temperatures (~28°C), reflecting large-scale structured cropping systems. Soils are highly homogeneous, dominated by Ferric Lixisols (>90%), with minor Fluvisols and Lithic Leptosols.

***Type 3: Continuous remote-yet-accessible highlands***

Type 3 occurs at high elevations (~380 m) with high rainfall (~1200 mm), similar to Type 1, but is mainly defined by strong geographical isolation (high distance to borders and long travel time to cities). Despite this remoteness, it has well-developed local accessibility, with the highest road density and close proximity to paved roads. The landscape is a continuous agricultural matrix (~85% cultivated land) with high cohesion and aggregation and low fragmentation. Soils are mainly Ferric Lixisols (~70%), with Lithic Leptosols (~15%) and Lixic Plinthosols (~10%).

***Type 4: Border lowlands under high human pressure***

Type 4 occurs at the lowest elevations (~180 m) with low rainfall (~900 mm) and is the most human-impacted type, with the highest population density (~125 inh./km$^2$) and proximity to borders. It has relatively low cultivated land (~78%) and the lowest NDVI. The landscape is highly fragmented, with the lowest cohesion (~99.85%) and higher split values. It also shows the greatest soil diversity, dominated by Protoargic Arenosols and Ferric Lixisols (~40%), with Lithic Leptosols (~10%) and Eutric Gleysols (~10%).

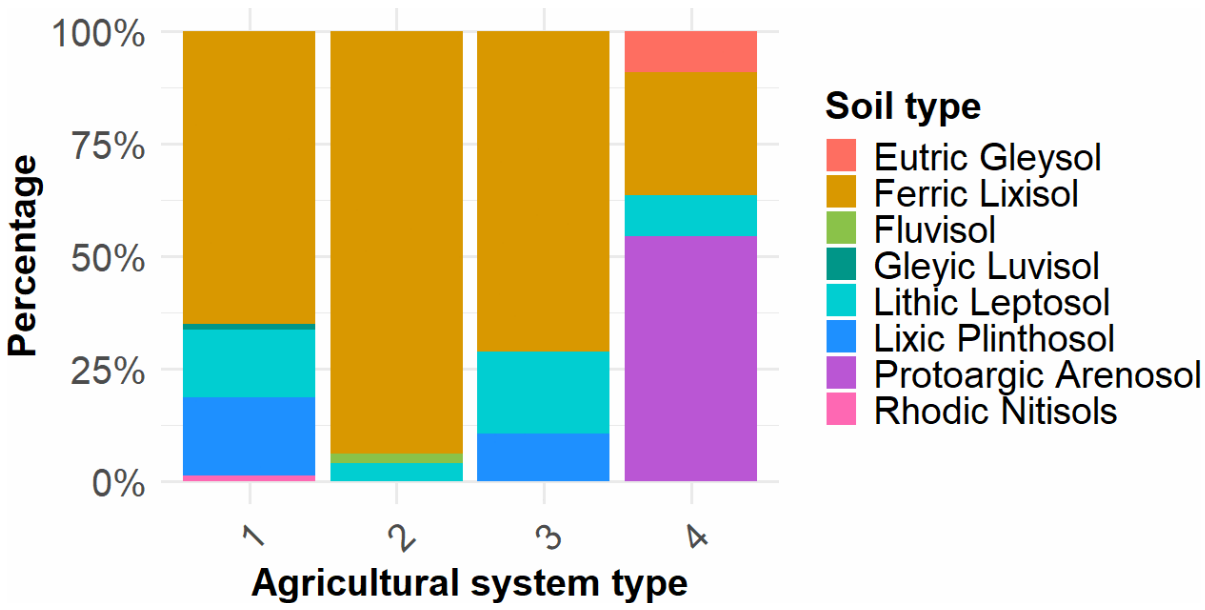



**Fig 7. Dominant soil types by agricultural system.**

### 3.2.2. Agricultural systems prediction model

The Random Forest algorithm was applied to assess the ability of variables derived from satellite imagery and geospatial data to identify agricultural system types at the village level. Model performance shows marked differences depending on the groups of explanatory variables considered (Table 4). When used individually, environmental variables (M3) and radiometric variables (M1) exhibit the highest overall predictive capacity, with 1−OOB accuracy rates of 82.6% and 78.1%, respectively. In contrast, models based solely on landscape variables (M2) and socioeconomic variables (M4) show lower performance, with accuracies of 51.7%.

Combining variable sets leads to an overall improvement in performance compared to single-variable models. The combination of environmental variables with radiometric (M1+M3), socioeconomic (M3+M4) and all variables (M1+M2+M3+M4) yield the highest accuracy (83.1%).

Analysis by agricultural system reveals heterogeneous performance across types. The highest accuracies for Types 1 are obtained with the “All variables”, M1+M3 and M3+M4 combinations, reaching 93.8%. All variables model yields the highest accuracy for Type 2 (91.8%). Type 3 is more difficult to predict, with accuracies of 63.2% (M3) or lower. The accuracy for Type 4 is relatively stable across several variable sets, reaching up to 81.8%, except for models based on landscape variables alone and socioeconomic variables (0% and 9.1%) and their combination (18.2%).

**Table 4. Model accuracy; the best-performing models for each type and modelling sets are indicated in bold.**

| Models | 1-OOB (%) | Accuracy by type (%) | | | |
|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** |
| Count | 178 | 80 | 49 | 38 | 11 |
| M1 : radiometric variables | 78.1 | 86.3 | 87.8 | 44.4 | **81.8** |
| M2 : landscape variables | 51.7 | 67.5 | 71.4 | 7.9 | 0.0 |
| M3 : environmental variables | **82.6** | 88.8 | 89.8 | **63.2** | 72.7 |
| M4 : socioeconomic variables | 51.7 | 67.5 | 32.7 | 55.3 | 9.1 |
| M1+M2 | 77.5 | 88.8 | 89.8 | 36.8 | **81.8** |
| M1+M3 | **83.1** | **93.8** | 89.8 | 52.6 | **81.8** |
| M1+M4 | 82.6 | 92.5 | 87.8 | 55.3 | **81.8** |
| M2+M3 | 80.3 | 90.0 | 87.8 | 52.6 | 72.7 |
| M2+M4 | 70.2 | 83.8 | 75.5 | 50.0 | 18.2 |
| M3+M4 | **83.1** | **93.8** | 87.8 | 57.9 | 72.7 |
| All variables | **83.1** | **93.8** | **91.8** | 50.0 | **81.8** |

Fig 8A shows the spatial distribution of the observed agricultural system types, whereas Fig 8B presents the types predicted from remote sensing and geospatial data using the “All variables” model. Residuals, calculated as the difference between predicted and observed values, are displayed in Fig 8C. Spatial analysis of the observed and predicted types reveals a slightly more homogeneous distribution for the predictions. Moreover, the system types are accurately identified, as evidenced by the residuals.

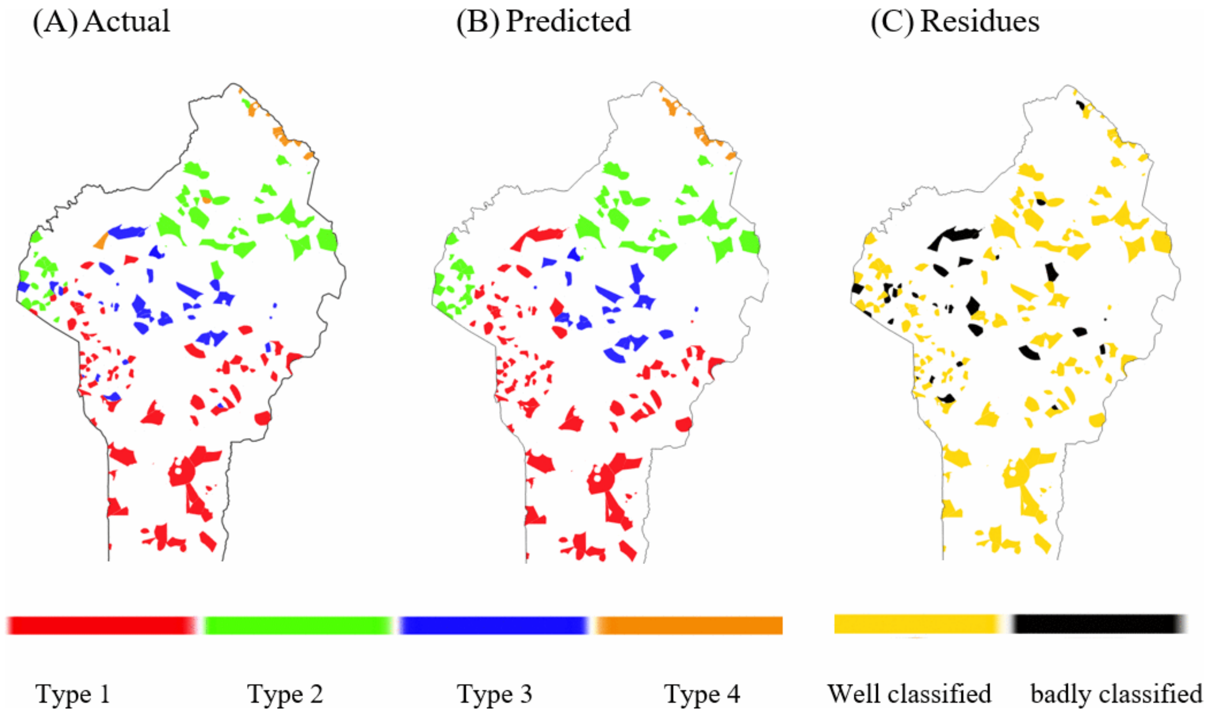



**Fig 8. Spatial distribution of agricultural system types: (A) observed, (B) predicted using the "All variables" model, and (C) residuals (difference between predicted and observed types).**

### 3.2.3. Importance of variables from the overall model

The joint analysis of %IncMSE and node purity from the "All variables" model reveals a clear hierarchy among the explanatory variable groups with radiometric and environmental variables collectively dominating the prediction of agricultural system types (Fig 9.). PC4, distance to the national border, temperature, and NDVI were the dominant predictors (%IncMSE = 27-31%), followed by PC3. Soil type, elevation, rainfall, and edge density showed moderate contributions (17-19%), whereas most landscape and socioeconomic variables had limited influence.

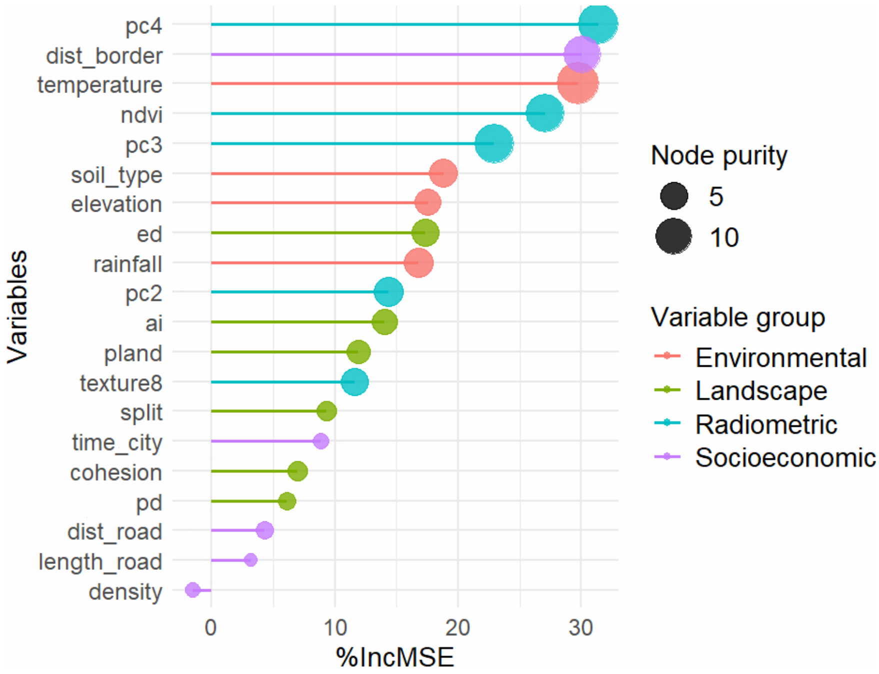



**Fig 9. Importance of variables in the model for predicting types of agricultural systems.**

A map of agricultural systems was produced for the other village of the study area using the "All variables" model (Fig 10.).

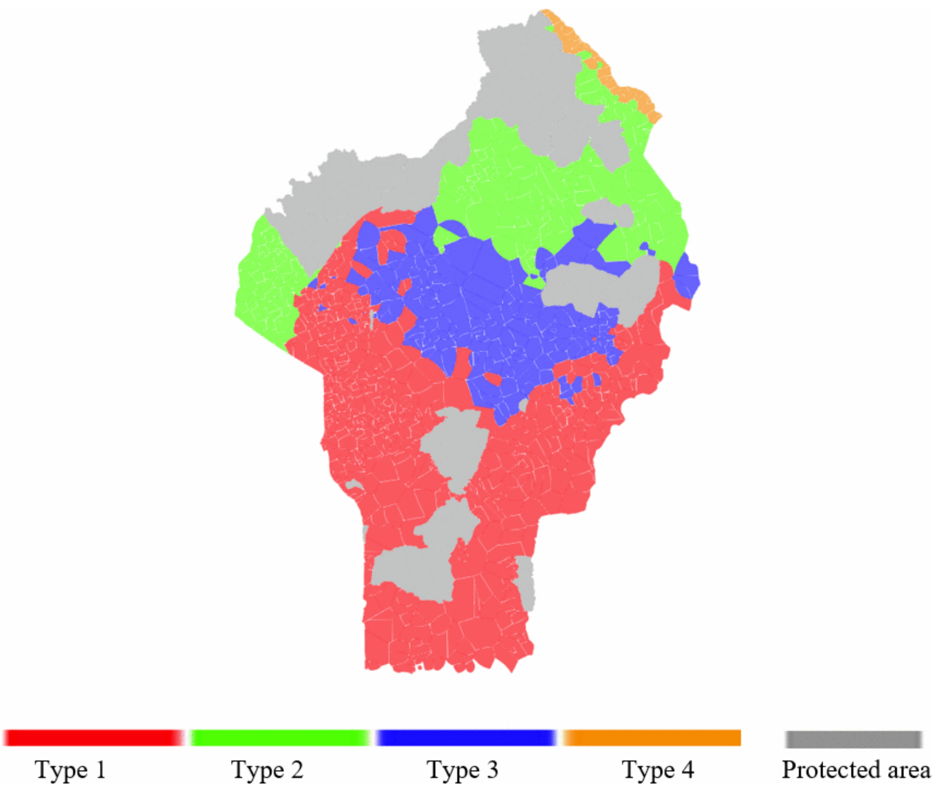



**Fig 10. Map of the agricultural systems types in North and Centre Benin villages. Grey areas indicate natural protected areas.**

# 4. Discussion

## 4.1. Performance and drivers of agricultural system spatial modelling

### 4.1.1. Strong model performance

The Random Forest model demonstrates a strong capacity to predict agricultural system types at the village scale using geospatial data. The achieved accuracy (83.1%) exceeds those reported in comparable studies. For instance, van de Steeg et al. [22] reported 55% accuracy for a five-class farming system typology in Kenya, based on household and environmental variables. Similarly, Ribeiro et al. [65] obtained an overall accuracy of approximately 36% for 22 farming system classes, a result considered acceptable given the classification complexity. In contrast, Silva et al. [66] achieved 70.3% accuracy for six farming system types in northern Portugal.

### 4.1.2. Biophysical versus socioeconomic drivers

The high predictive performance of environmental variables and their strong importance indicate that agricultural systems are mainly constrained by local biophysical conditions, consistent with previous studies. Ribeiro et al. [65] identified temperature and precipitation as key drivers in southern Portugal, while Silva et al. [66] showed topography as the main factor in mountainous northern regions. Similarly, van de Steeg et al. [22] highlighted the strong role of physical location, particularly growing period length.

Among socioeconomic variables, only distance to national borders emerged as highly influential, likely reflecting the role of border areas as hubs of agricultural exchange and cross-border markets in West Africa [67]. Other socioeconomic factors showed low importance, although their influence may increase where environmental constraints are weaker, as shown by Silva et al. [66] and Chen et al. [68] in more favourable or developed contexts.

In North and Centre Benin, strong environmental gradients (rainfall, elevation, soils) appear to dominate agricultural system differentiation, with agroforestry systems (Types 1 and 3) in wetter, higher areas and agropastoral systems (Types 2 and 4) in drier or hydromorphic zones. Socioeconomic accessibility variables (distance to borders, travel time to cities) contribute only marginally to model performance.

#### 4.1.3. Landscapes as fingerprints of agricultural systems

The four agricultural system types identified through conventional survey-based approaches exhibit consistent radiometric and landscape signatures. This confirms that landscape organization can serve as a reliable proxy for farming practices, as previously suggested by several studies [41,42,69].

Unexpectedly, variables derived solely from MODIS time series enable accurate mapping of agricultural systems (78.1% accuracy compared to 82.6% using environmental variables). This result is notable given the relatively coarse spatial resolution of MODIS data and the use of raw NDVI values without prior land cover classification. However, the potential of low-resolution satellite image time series to discriminate landscape configurations has been highlighted in earlier studies [70] and, as well as their capacity to map cropping systems in large-scale agricultural landscapes [29,71].

These results can be explained by the multidimensional information contained in remote sensing data [49]. Spectral information reflects biophysical properties such as vegetation status and soil characteristics. Spatial (textural) information captures landscape structure, including landform, infrastructure, and hydrographic networks. Temporal information, derived from dense time series, reflects vegetation phenology, climatic variability, and cropping practices.

## 4.2. Applicability of the approach and limitations

### 4.2.1. Contrasting pathways of intensification and diversification

Agricultural system types correspond to distinct landscape patterns shaped by trajectories of intensification, diversification, and environmental constraints.

Low-input agroforestry systems (Type 1) occur in humid highlands with high biomass and strong heterogeneity. Their fragmented mosaic reflects subsistence crops, plantations, forests, and uncultivated areas under extensive, low-mechanization practices, highlighting agroforestry as a driver of landscape complexity [72].

Input-intensive agropastoral systems (Type 2) show highly homogenized landscapes, with high cropland proportion and strong aggregation driven by intensification and crop specialisation (e.g., cotton, cereals), illustrating the trade-off between productivity and ecological heterogeneity [73].

Mechanized diversified agroforestry systems (Type 3) combine intensification and diversification. Despite similar biophysical settings to Type 1, they exhibit greater landscape continuity and lower fragmentation, reflecting mechanization and improved accessibility, with crop diversity maintained within a more coherent matrix.

Irrigated agropastoral systems (Type 4) are highly fragmented and strongly human-impacted, driven by low rainfall, high population density, and irrigation, particularly along the Niger River. Fragmentation here reflects land pressure rather than ecological diversity, further influenced by protected areas and cross-border dynamics.

Overall, fragmentation can reflect either ecological diversification or human pressure, while aggregation is linked to intensification and specialization. Landscape structure thus acts as a proxy of agricultural trajectories, integrating production choices, environmental constraints, and territorial dynamics, consistent with previous studies [14,29,70,71].

### 4.2.2. Rethinking agricultural zoning through system mapping

The proposed approach is consistent with existing agricultural zoning frameworks and the strong role of biophysical controls aligns with classical FAO agro-ecological zoning principles [74]. Agro-ecological zones (AEZs) and development hubs (PDAs) are widely used in Benin, combining climate, topography, soils, and administrative boundaries.

However, our results reveal substantial internal heterogeneity within most AEZs and PDAs (Fig 11.A and B), with multiple agricultural system types coexisting in the same zones. Only Zone 5 and PDA4 appear relatively homogeneous. This highlights the limitations of zoning based mainly on biophysical and administrative criteria, and the need to better integrate socio-productive systems, here captured through agricultural practices linked to specific social groups.

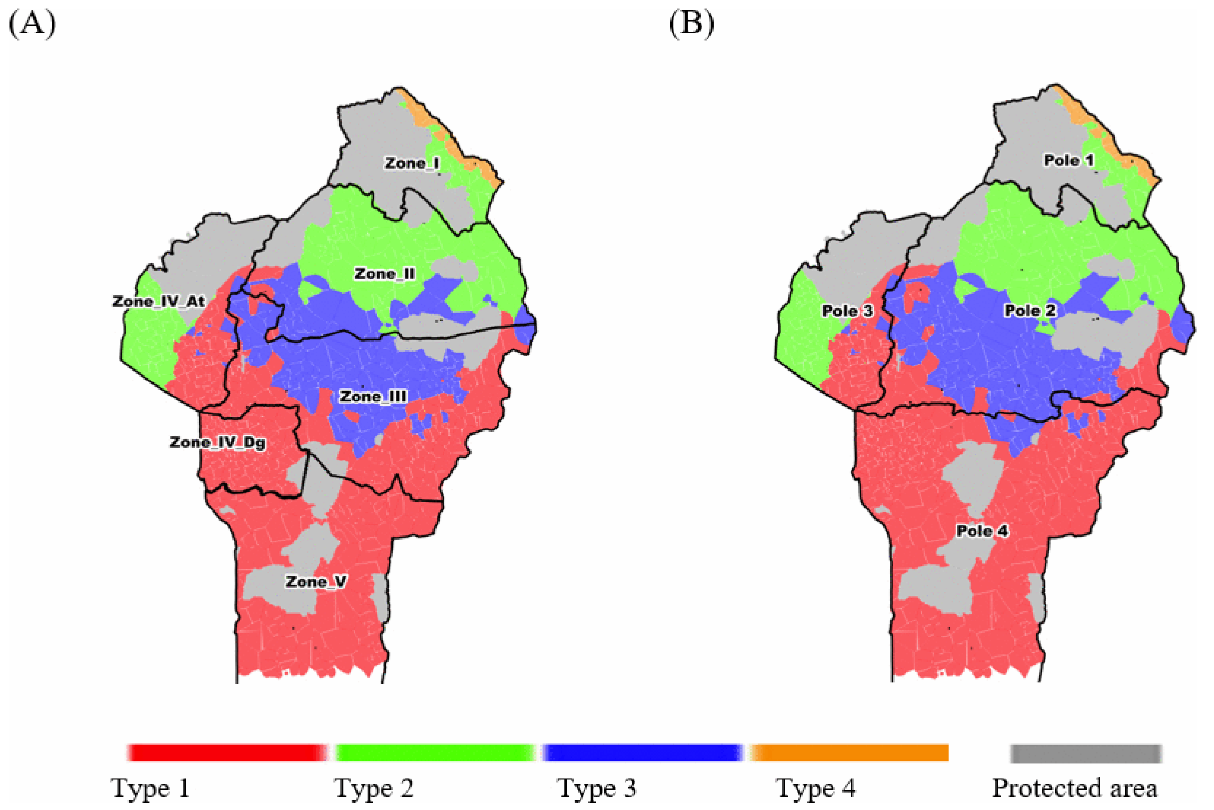



**Fig 11. Map of agricultural system types in North and Centre Benin overlaid with (A) agro-ecological zones and (B) agricultural development hubs.**

Moreover, the fact that the identified system types are not constrained by administrative boundaries is a key advantage, as it provides a more functional and potentially more objective representation of agricultural dynamics. In the perspective of designing agricultural zoning frameworks that explicitly incorporate agricultural systems, this approach therefore appears to be a relevant and promising method.

### 4.2.3. Methodological limitations and sources of uncertainty

As with any modelling exercise, several methodological choices and uncertainties must be acknowledged.

First, the number of agricultural system types derived from survey data is a key assumption. Hierarchical clustering resulted in four distinct systems, representing a compromise between minimizing within-class variance and ensuring interpretability for national experts and stakeholders [22].

Second, the aggregation of household survey data at the village scale introduces uncertainty. Although this approach follows established practices, it inevitably masks intra-village variability. In addition, uncertainties in village boundary delineation may affect aggregated variable values, although previous studies in the same area suggest that local landscape homogeneity limits this effect [45].

Moreover, as in most geospatial studies, combining heterogeneous datasets (remote sensing, geospatial layers, and census data) may propagate inconsistencies and biases. In the absence of fully harmonized datasets, such limitations are unavoidable [75].

Finally, a potential limitation of this study lies in the temporal mismatch between data sources; however, agricultural systems are generally characterized by relatively slow structural change, which mitigates  but does not eliminate  the risk of temporal inconsistency.

# 5. Conclusion

This study demonstrates that Earth Observation and geospatial data provide a credible alternative to conventional survey-based approaches for mapping agricultural systems.

The Random Forest model developed using a combination of radiometric, landscape, environmental, and socioeconomic variables showed high performance in predicting agricultural system types in North and Centre Benin. The models integrating all variables, as well as those combining environmental with either radiometric or socioeconomic variables, achieved the highest predictive performance, underscoring the importance of an integrated approach. The high contribution of radiometric and environmental variables to model accuracy, underscores the importance of biophysical factors in discriminating agricultural systems. Notably, the strong performance obtained using remote sensing data alone opens new perspectives for bridging natural and social sciences. Such approaches can improve understanding of human-environment interactions and support evidence-based policymaking-key challenges in land system science.

Beyond methodological contributions, this study demonstrates that agricultural system types and their intensification levels are associated with distinct and detectable landscape patterns. The approach supports regular updates, making it particularly suitable for operational applications in resource-constrained contexts.

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# 7. Ethics declarations

**Conflict of interest**

The authors declare that they have no conflicts of interest.

# 8. Appendices

**Appendix A.** Spatial distribution of predictor variables

# 9. Acknowledgements

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# 10. Data availability

Data and code supporting the findings of this study are available in the Open Science Framework repository at https://doi.org/10.17605/OSF.IO/95FN6 . The version corresponding to the results presented in this manuscript is permanently archived and accessible via this DOI.

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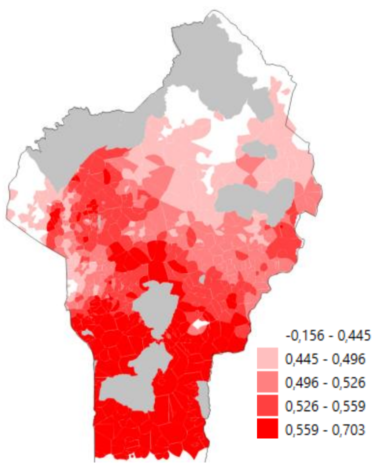
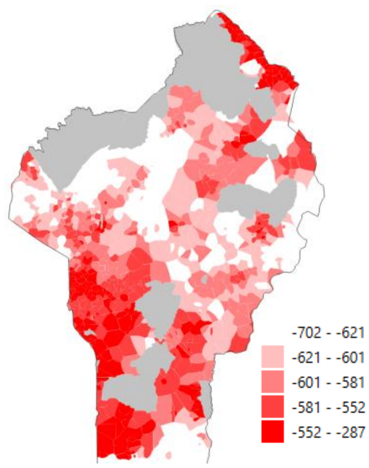
## **Appendix B.** Supplementary data: Spatial distribution of predictor variables

**Appendix A.1**. Maps of the radiometric variables derived from MODIS NDVI time series (2016–2018) and aggregated at the village scale. Quantile classification method. Grey areas indicate natural protected areas.

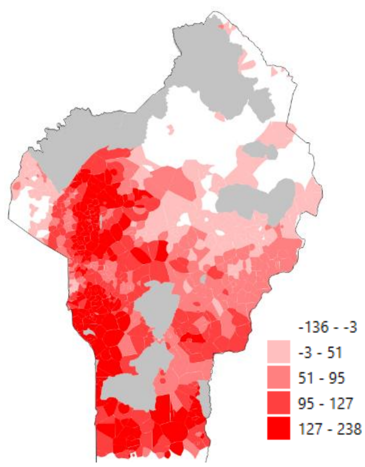
**Annual NDVI MODIS (2016-2018)**



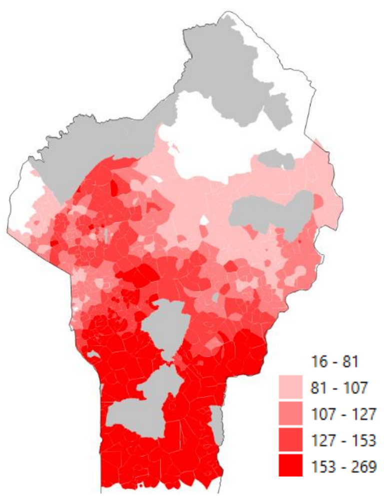

**PC2 MODIS (2016-2018)**



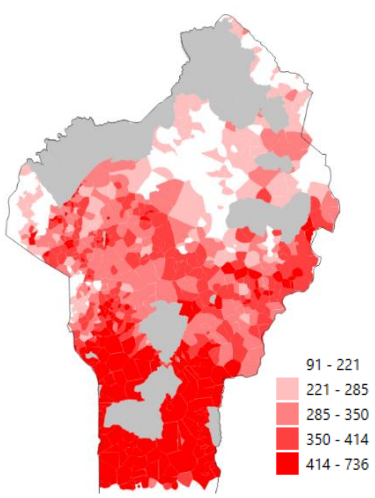

**PC3 MODIS (2016-2018)**




**PC4 MODIS (2016-2018)**

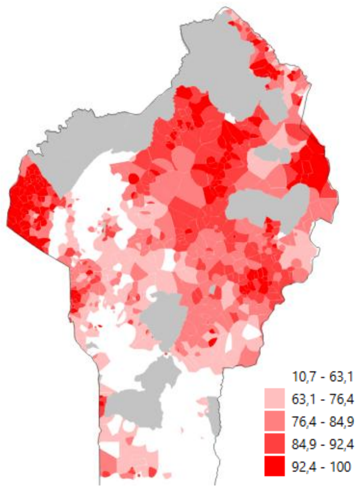



**Haralick correlation, MODIS (2016-2018)**

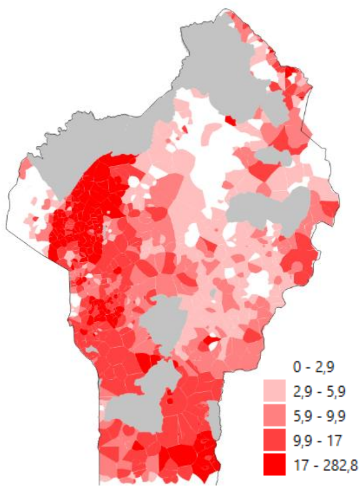


**Appendix A.2.** Maps of the landscape variables derived from the OBSYDYA land cover map and aggregated at the village scale. Quantile classification method. Grey areas indicate natural protected areas.

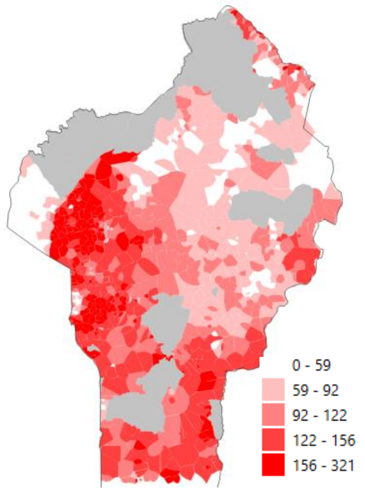
**% Cropland (2023)**



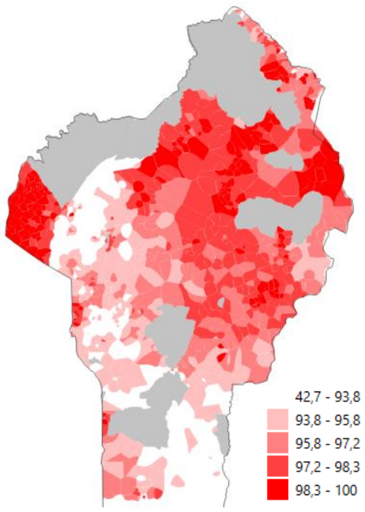

**Cropland patch density (2023)**



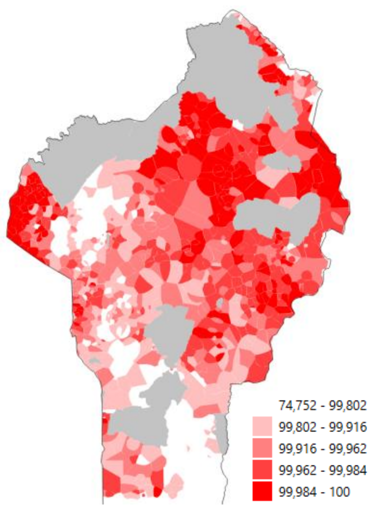

**Cropland edge density (2023)**



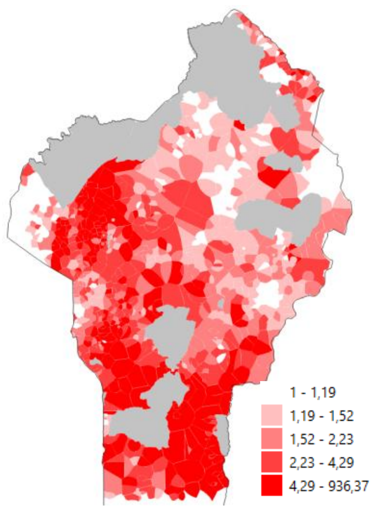

**Cropland aggregation index (2023)**



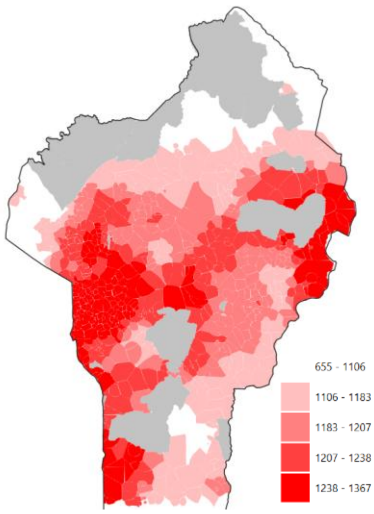
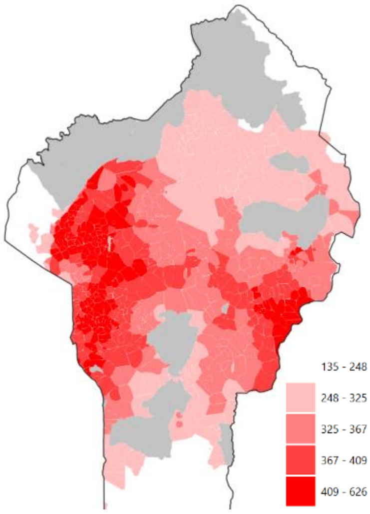
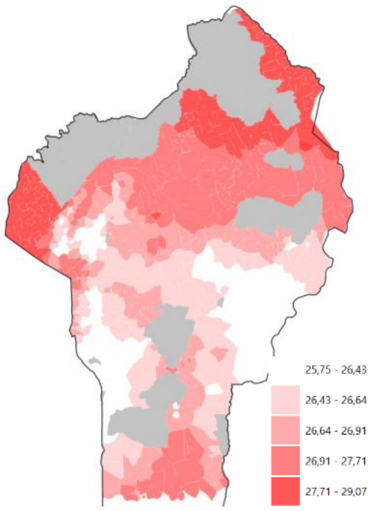
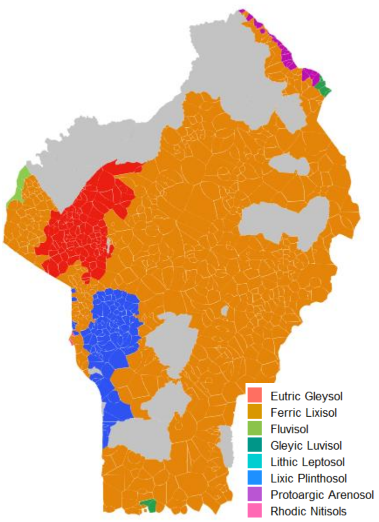

**Cropland patch cohesion index (2023)**



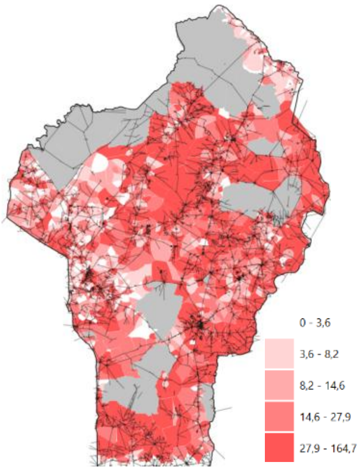
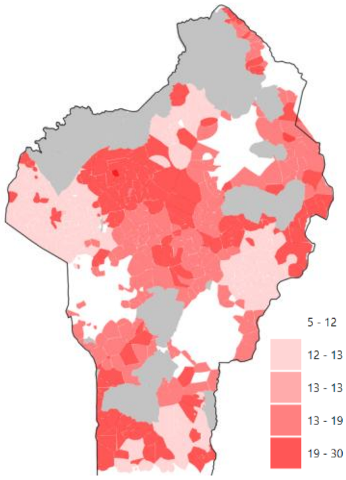
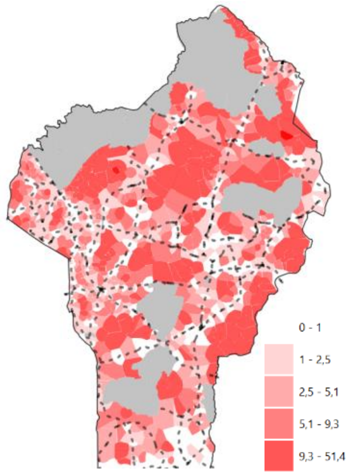
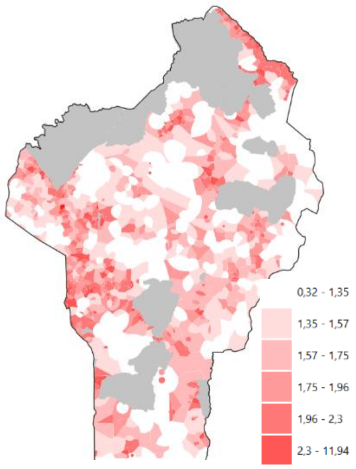
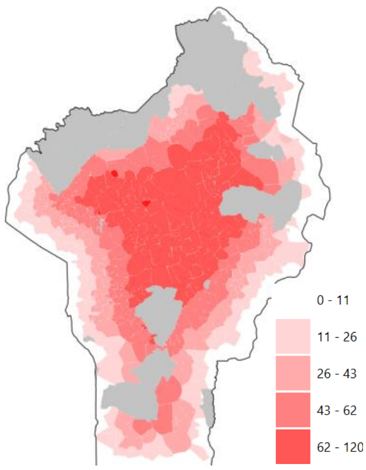

**Cropland split index (2023)**



**Appendix A.3.** Maps of the environmental variables aggregated at the village scale. Quantile classification method. Grey areas indicate natural protected areas

<table>
<tr><th>Annual rainfall (mm), CHIRPS (2015 – 2019)</th><th>Elevation (m), SRTM GL1 (2000)</th><th>Temperature (°C), WorldClim v2.1 (1970-2020)</th></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
<tr><th>Soil type, HWSD v2.0 (2023)</th><th></th><th></th></tr>
<tr><td>
</td><td></td><td></td></tr>
</table>

**Appendix A.4.** Maps of the socioeconomic variables aggregated at the village scale. Quantile classification method. Grey areas indicate natural protected areas

| **Road density: cumulative road lengths (km), OSM (2025)** | **Travel time to the nearest city (min), Global Friction (2018)** | **Distance to asphalt road (km), OSM (2025)** |
|---|---|---|
|  |  |  |
| **Population density ($log10\_hab/km^2$), INStaD (2018)** | **Distance to the nearest border (km), OSM (2025)** | |
|  |  | |