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From Wooded Savannah to Farmland and Settlement: Population Growth, Drought, Energy Needs and Cotton Price Incentives Driving Changes in Wacoro, Mali

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Abstract: Land includes vegetation and water bodies and provides the basis for human livelihoods through primary production, food and freshwater supply, and multiple other ecosystem services. The last three decades have recorded frequent drought events as well as rapid population growth, which has often resulted in adverse land use and land cover change (LULCC) in the Sahel of Sub-Saharan Africa. In order to propose sustainable land management strategies, it is a prerequisite to investigate the rate of LULCC and its driving factors in specific locations. This study investigated the case of Wacoro municipality in Mali using a combined approach of remote sensing, Geographic Information Systems, and focus group discussions. Satellite images and local people's perceptions on LULCC and drivers were collected and analyzed for the years 1990, 2000, 2010, and 2020. We found that the study area faced a rapid decrease in wooded savannah that was degraded and converted to shrub savannah and later to farmland and settlement. Changes were directly or indirectly related to the rapid population growth, high cotton price (which encouraged cropland expansion), drought, firewood extraction, and charcoal production, which was exacerbated by poverty. We suggest promoting integrated land management strategies that consider current and future livelihood needs and preserve the environment for the benefits of future generations. New agricultural policies, such as cotton price incentives, should always be accompanied by an assessment of their potential environmental impacts and design of adequate mitigation measures.

Keywords: land use; land cover; drivers; change; Sahel

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1. Introduction

Globally, land uses have been facing multiple changes during the last three decades. Their causes and driving factors are mainly related to human-induced activities but also to natural factors [1]. In dry lands, increasing farming activities, bush fires, and climate change and variability contribute to land use and land cover change (LULCC). Physical factors influencing the environment in dry areas particularly refer to desertification and droughts, while human-induced effects are related to farming activities, overgrazing, agricultural intensification and deforestation [2]. Land use corresponds to the socio-economic description (functional dimension) of areas. This includes areas used for residential, industrial, or commercial purposes, for farming or forestry, recreational or conservation purposes. Links with land cover are possible: it is, under certain circumstances, viable to infer land use from land cover and conversely [3]. Land cover data document how much of a region is covered by forests, wetlands, impervious surfaces, agriculture, and other land and water types [4]. Water types include wetlands or open water. Land use, on the other hand, describes how people use the landscape, i.e., development, conservation, or mixed uses [5]. The different types of land cover can be managed or used quite differently.

It is well established that the last decade has witnessed a rise in consumer-driven demand for sustainable land use and land management as well as commitments to restoring degraded land that is unprecedented in human history due to the negative impacts of land degradation on the food system [6]. The degradation of agricultural lands is one of the major threats to the future of humankind because of decreased food production and provision of other services including regional and global climate regulation and habitats for biodiversity [7].

In Sub-Saharan Africa, changes have been observed in the distribution and dynamics of distinct types of terrestrial ecosystems [8]. Grasslands, shrublands, savannahs, woodlands and forests as sources of livelihoods are severely threatened terrestrial ecosystems whose productivity has been diminishing throughout recent years [9]. Furthermore, Africa's population size is projected to double by 2036 and to represent about 20% of the world's population by 2050 [10], a trend that can drive the continuous loss of vegetation cover in the Sahel, provided that no major change in land use policies and management practices is taking place. This regional trend in degradation is also supported by country level data. For instance, a study conducted in the Tougou watershed in Burkina Faso concluded that the conversion of natural vegetation into cultivated areas led to a significant increase in the runoff potential [11]. As a consequence, the productivity of livelihood related activities will decline if appropriate decisions and measures are not taken to contain and reverse these trends.

For Mali, it has been reported that the major causes of LULCC stem from (a) climatic conditions, which include an arid environment and low and irregular rainfall patterns; (b) climatic processes such as wind and water erosion; and (c) human-induced land use changes [12]. Land-related issues are threatening the livelihoods of rural and peri urban communities to an extent that causes young people to migrate abroad or to gold mining sites in Western Mali in search of alternative income opportunities [13]. Moreover, as a consequence of complex challenges around livelihood insecurity and increasing food prices, community conflicts, jihadism and terrorism are spreading throughout Mali, especially in the Sahel agroecological zone [14]. For instance, as productive land is becoming increasingly scarce, relations between groups of farmers and pastoralists have shifted from one of complementarity towards one of increasing tension and conflict because of competition for land. At the same time, some regional studies have indicated signs of recovery or regreening in the area [15]. They found that even though the West African Sahel was once synonymous with land degradation and desertification, it is now often celebrated as a region of environmental rehabilitation and recovery [16]. This contradictory information in the literature makes it a prerequisite to have context-specific information across Sahelian countries for the purpose of proposing contextual sustainable land management options for resilient local livelihoods and a healthy environment. This study addresses the case of Wacoro municipality in Mali and aims to identify trends in land cover change in the past thirty years and the key drivers behind these changes.

2. Materials and Methods

2.1. Study Area

Wacoro is located in the Sahel agroecological zone of Mali in West Africa (Figure 1) at a latitude of 12°36′6″ north and a longitude of 6°41′34″ west. It is home to primarily Bambara and Malinke farmers and previously formed part of the pre-colonial Bambara Empire. Because of its rural character, Animism persisted in this area well into the 20th century. There are also populations of Muslim Maraka, Fula, and Bozo fishing communities. The municipality falls largely south of the dryer Sahel land, in the wetter Sudan, and is home to the headwaters of the Bani River. Major socio-economic activities are crop farming and livestock keeping. The main cultivated crop in the area is cotton, followed by maize and groundnut. In terms of livestock, small ruminants (goat and sheep) predominate, although there are also big ruminants such as cows and donkeys. The particularity of the study area is that it has common socio-economic and environmental characteristics compared to most municipalities within Mali's Sahel region which attract the large share of development interventions. Trees, shrubs, grass and animal species are representative for other areas within the Sahel region. In Wacoro, the dry season lasts from March to June, the rainy season from June to September, and the cold season from October to February with a drying Saharan wind called the harmattan. Over the course of the year 2021, the temperature varied from 17 °C to 39 °C and was rarely below 14 °C or above 41 °C with an annual average rainfall of 492.9 mm [17].

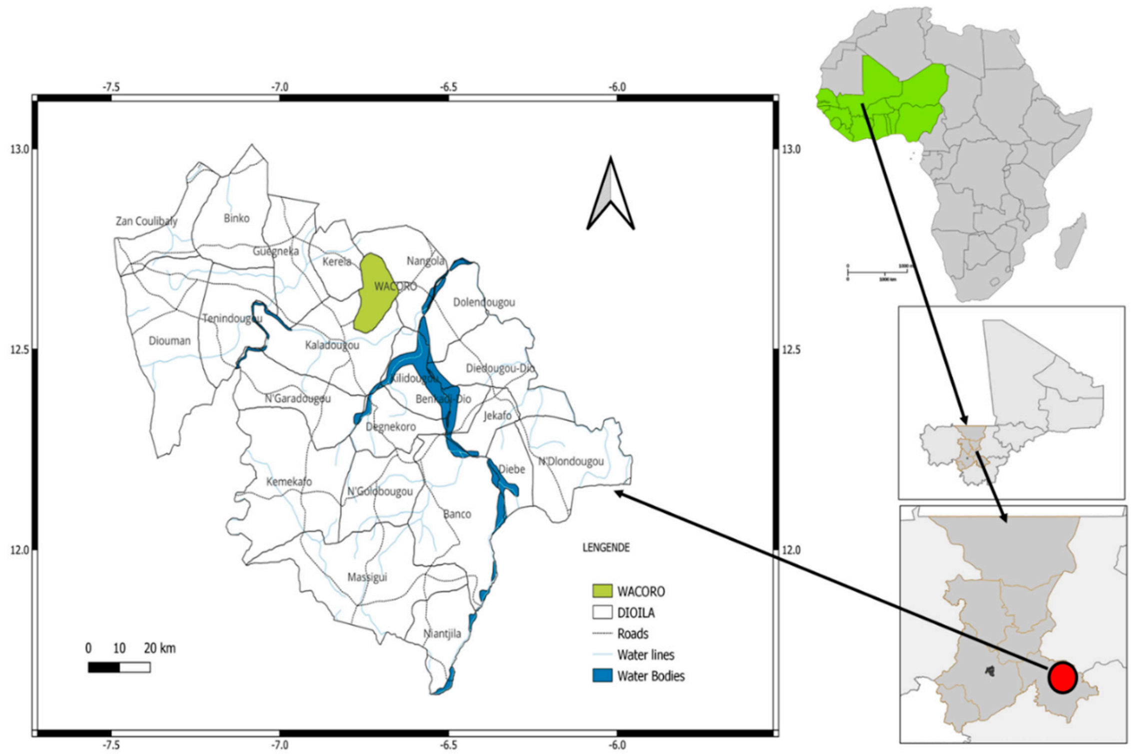

Figure 1. Map of the study area.

2.2. Work Flow and Land Cover Classes for Data Collection and Processing

A mixed-methods approach, suggested as a key approach in land change research [18,19], was chosen to assess LULCC quantitatively (through remote sensing) and the drivers behind these changes qualitatively (through social valuation in focus group discussions). The different steps followed in this study for data collection and analysis are presented in Figure 2.

Ground truthing was conducted in October 2021 to validate all land use and land cover classes. GPS coordinates were also taken at each selected plot per class [20,21]. The criteria considered during the class determination follow the definitions presented in Table 1.

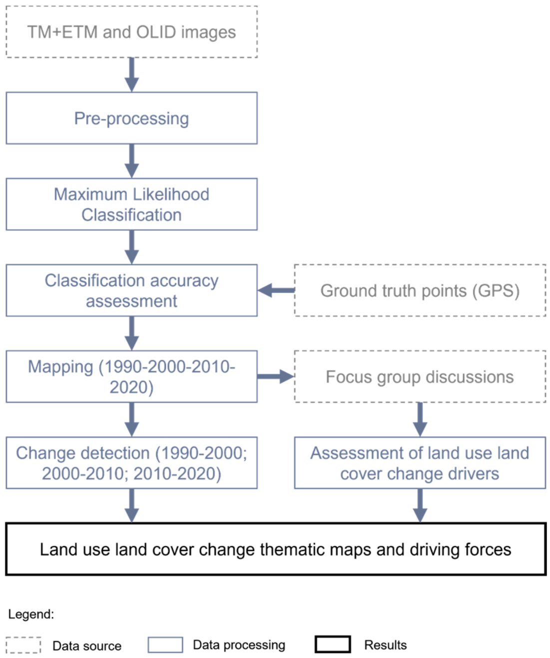

Figure 2. Schematic view of the working steps applied in this study (own illustration).

Table 1. Definitions of land use land cover classes (adapted from [22,23]).

Land Cover Class	Definition
Wooded savannah	Wooded savannah is a mix of woody and grass layers where the canopy of the woody component is not closed.
Shrub savannah	Shrub savannah is a mix of shrubs and grass layers.
Farmland	Farmland corresponds to cultivated land that can also show presence of woody components.
Water bodies	Water bodies represent standing water surfaces during most of the year.
Grassland	Grasslands are characterized as lands dominated by grasses and herbaceous annuals rather than trees or large shrubs.
Settlement	Settlements consist of residential areas, roads and other concrete infrastructure including areas for sheltering people, animals, or machinery.
Bare soil	Bare soil is barren land that has sand, rocks, and thin soil. It includes dry salt flats, sand dunes, deserts, beaches, gravel pits, quarries, exposed rock, strip mines, etc.
Rocky	Rocky areas are covered mainly by blocks of rock.

2.3. Sources of Land Use/Land Cover Data and Supervised Classification

Landsat images for the study site for the years 1990, 2000, 2010, and 2020 were downloaded from the USGS website (https://earthexplorer.usgs.gov/, accessed 10 March 2021). Landsat 4 and 7, which we used in this research, are the most accurately calibrated Earth-observing satellites and the latest in a long history of land remote sensing spacecraft, spanning 40 years of multispectral imaging of the Earth's surface. The annual time series of land cover maps (collection 3) were obtained at 30 m resolution through the classification of Landsat images [22,23]. The remote sensing literature presents a number of supervised methods to tackle the multispectral data classification problem [23]. The statistical method employed for the earlier studies of land cover classification is the maximum likelihood classifier [24]. More recently, various studies have applied artificial intelligence techniques as substitutes to remote sensing image classification applications [25]. In addition, the diverse ensemble classification method has been proposed to significantly improve classification accuracy [26,27]. Scientists and practitioners have made great efforts in developing efficient classification approaches and techniques for improving classification accuracy [28]. Among them is supervised classification. The quality of a supervised classification depends on the quality of the training sites [29]. All supervised classifications usually have a sequence of operations that must be followed: (1) definition of training sites, (2) extraction of signatures, (3) image classification. The training sites are carried out with digitized features. Usually, two or three training sites are selected but more can be selected to gain better results [30]. We have decided to apply supervised classification, which has been used in previous studies and shown to yield valid results [31]. It is a process of pattern recognition in remote sensing which consists of carrying out the correspondence between the elements of an image scene, generally materialized by their radiometric values, and classes known a priori or not by a user [32]. The correspondence is carried out by discriminant functions in the form of a decision rule such as the maximum likelihood of probabilities, or geometric distances. The chosen classification algorithm is the "Maximum likelihood" [33]. Indeed, this algorithm has the advantage of being a probabilistic method. It allows the classification of unknown pixels by calculating for each class the probability that the pixel falls in the class with the highest probability [34]. If probability does not reach the expected threshold, the pixel is classified as unknown.

2.4. Estimation of the Precision of Image Interpretation

To validate the results obtained from classification, the error matrix or confusion matrix was generated in ENVI 5.5.2 to identify the proportion of well-classified pixels. Thus, errors of omission and commission errors were calculated. For a land use study, the results can be considered valid if the Kappa coefficient is equal to or higher than 50% [35]. We tried a method based on the evaluation of control points. This method consisted of field verification, from the minute of interpretation, of the points previously identified before the field mission for each land use class and determination of the percentage of these verified points corresponding to those defined beforehand [36]. The ground truthing in this study was carried out as follows:

- Stratified sampling was adopted so that the control points to be verified in the field were defined in proportion to the size of the stratum; 30 control points were determined for each of the classes;
- A total of 210 points were defined for the entire study area (seven land cover classes);
- At the level of each stratum, the control points were as dispersed as possible over the entire study area;
- A confusion matrix was constructed to report the results; the matrix revealed not only the general errors made at the level of each class during the interpretation but also the errors due to confusion between land cover classes;
- Errors of omission and confusion were calculated for each land cover class; the values obtained reflect the details of the interpretation of each class. Considering a class such as woodland savannah, it was referred to as an error of omission whenever this woodland class had been omitted from the map. It was a confusion error when the wooded savannah area had been classified as another class. Coordinates of each land cover class were collected from the field and incorporated into the maps for validating classified areas.

The Kappa coefficient was used to assess the precision of the classification adopted as described above [37]. Its formula is $P0 - Pc/Pp - Pc$ where P0 is equal to the actual percentage obtained from the classification of land use elements; it is equal to the quotient of the sum of the figures on the diagonal of the matrix with the total number of observations.

Pc is the estimate of the probability of obtaining a correct classification; to calculate Pc, we proceeded as follows: we calculated the marginal products of the column and row values at the level of each cell of the matrix; then, the sum of the values of the diagonal was divided by the total of the products of each cell of the matrix. For correct classification, the value of Pc is generally less than P0, whereas Pp is the percentage obtained when the classification is perfect, i.e., 100%.

From the above, the previous formula can be written K = P0 − Pc/1 – Pc.

All maps were drawn with ArcGIS software version 10.8.

The primary application of the classification was to establish maps and statistics of land use. It also allowed, possibly associated with other characteristics, following the evolution of vegetation formations to support forecasting production and preventive action against degradation and deforestation. An accuracy assessment was conducted using the confusion matrix to compare the classification results of 2020 with ground truth data collected on the field. As shown in Table 2, the Kappa coefficient on each image analyzed is above 50% [37].

Table 2. Analyzed image accuracy.

Images	Global Precision	Coefficient Kappa
TM 1990	88.70%	0.87
ETM+ (2000 and 2010)	87.41%	0.85
OLI 2020	93.51%	0.93

2.5. LULCC Driving Factors Assessment

After having produced the maps, several focus group discussions (FGD) with communities were organized in the study site to assess the potential driving factors for the changes observed on the land use maps over time (1990–2000–2010 to 2020). LULCC data (maps and graphs) were presented in the form of posters to the participants during the FGDs. The land cover changes observed on the posters over time were clearly explained to the groups to set the basis for discussing the potential drivers of change (Figure 2).

FGDs were carried out in six villages in the study site. Overall, a total of 37 villagers were purposively selected for FGDs considering gender (male and female), socio-economic groups and the requirement to be old enough to have experienced LULCC over the time period considered (1990 to 2020). All participants were selected by local leaders based on the following criteria:

- Age (50 and above);
- Knowledge of the long-term biophysical and socio-institutional context of the study sites;
- Experience in local decision-making approaches;
- Experience in working with extension workers.

Each FGD consisted of 5–7 people and had a duration of two to three hours [38,39]. Driving factors for LULCC were discussed by participants, who then agreed on a score in order of importance. The interval score was from 0 to 5 for each direct or indirect driving factor. The following scores were used: 0 = no effect, 1 = low effect, 2 = medium effect, 3 = relevant effect, 4 = very relevant effect, and 5 = highly relevant effect. Each focus group was expected to provide a common score. In case of disagreement among the participants in the scoring of a given driving factor, all members in the focus groups were asked to provide a score [40]. Then, the modal value (score that was most frequent) was retained. The scores for different criteria for each driving factor were then summed up and the results announced to the participants. Ethical guidelines for research with people were followed and all participants were kept anonymous.

The mean value for each factor was calculated using SPSS 24 and the comparative frequency of each factor was drawn using bare 2D. The score of each indicator was presented as the mean score given by all six groups, which determined the level of the effect on LULCC. The higher the score, the more likely it was classified as a main driving factor.

Population data for our study years 1990, 2000, 2010 and 2020 were derived from the 2009 national census (INSTAT, 2009) obtained from the Malian National Institute of

Statistics. These data do not take into account people who passed away or migrated out of the village during these periods. The following equation was used:

$$Pn = Po * (1 + r)\hat{}n$$

where Pn is the population projection for year x, Po is the population at the beginning, r is the growth rate, and n is the number of years [41]. Due to limited data availability related to internal population mobility, we could not include the out-migration in the final estimation of the population.

Pearson correlation analysis was computed between population data and land use/cover classes in the last 30 years (1990 to 2020). One assumption of the Pearson statistic is that the relationship to be tested is a linear one. In this case, the outcome is easy to derive.

$$r = \frac{C(xy) - C(x)C(y)}{\sqrt{CxxCyy}} = \frac{A}{\mid A \mid} = \pm 1$$

In other words, if y and x are exactly linearly related, $r = \pm 1$, depending on whether the slope is positive or negative (correlation or anti-correlation). More likely, with real data of any kind, there will be a spread in the values of x and y, in which case the correlation will be less than maximal, i.e., $[r] < 1$ [42]. Additionally, correlation was computed among LULCC classes in order to detect possible specific conversions.

3. Results

3.1. Land Use Land Cover Change between 1990 and 2020 in Wacoro, Mali

We observed remarkable changes in land use and land cover in Wacoro municipality over the past thirty years. Figure 3 shows the spatiotemporal dynamics between the years 1990, 2000, 2010 and 2020.

From these results, all land cover classes have recorded spatial and temporal changes. However, the degree of change varies from class to class. Wooded savannah recorded the most significant decrease while settlement, shrub savannah, grassy steppe, and farmland coverage increased consistently (Figure 4). The most important LULCC, in particular the decrease in wooded savannah and increase in shrub savannah, took place between 1990 and 2010. This change can be interpreted as a pattern of degradation. Our findings indicate that between 2010 and 2020 mostly shrub savannah was converted to farmland. Over the entire study period (1990–2020), there seems to be a two-stage change where part of the wooded savannah is first converted to shrub savannah and then converted to farmland.

Bivariate correlation (Table 3) shows that within the time frame of 30 years (1990 to 2020), the increase in farmland significantly correlates with population growth (p-value = 0.04), whereas the decrease in wooded savannah correlates with the increase in settlements (p-value = 0.005) and the increase in grassland (p-value = 0.03). Moreover, a conversion of shrub savannah into grassland has also been recorded (p-value = 0.05). Degraded wooded savannah has been mainly converted into settlement and grassland savannah. Within the time frame, more villages were established and more pastoralists migrated to the area because of its natural vegetation and grassland cover.

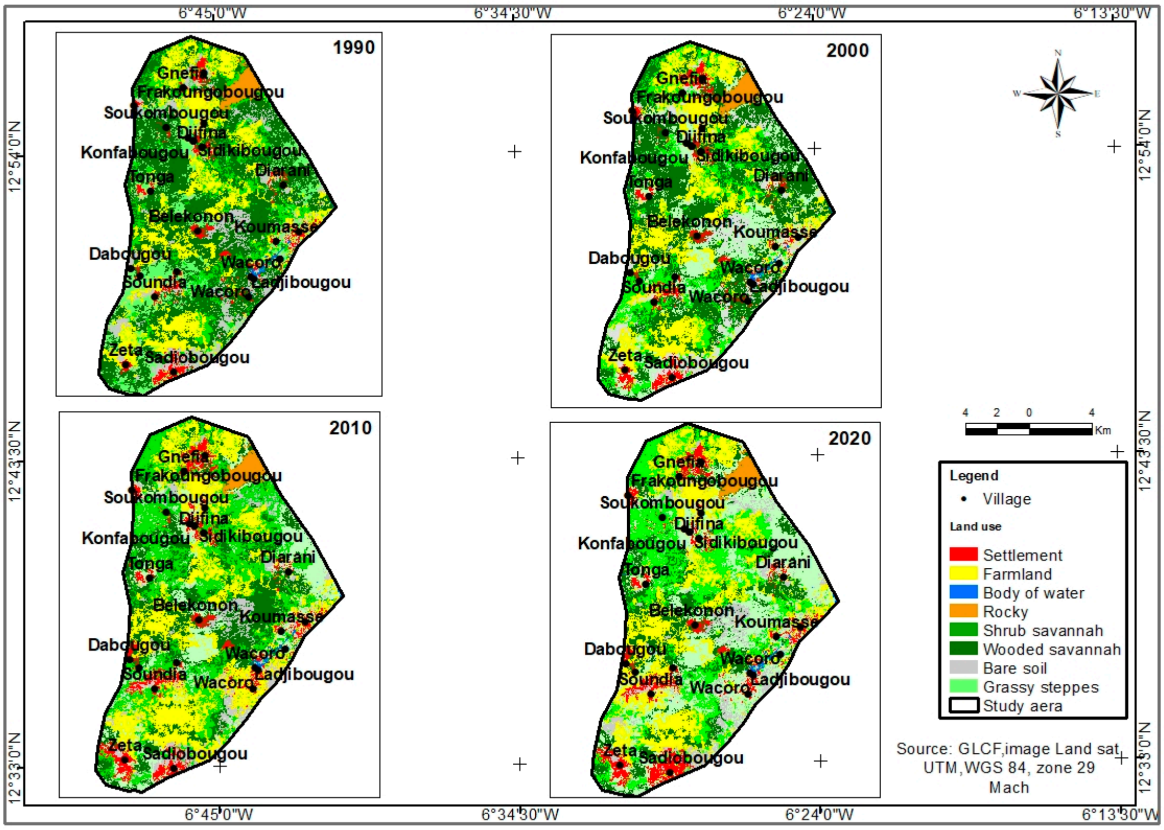

Figure 3. Land cover change maps between 1990 and 2020 in Wacoro, Mali.

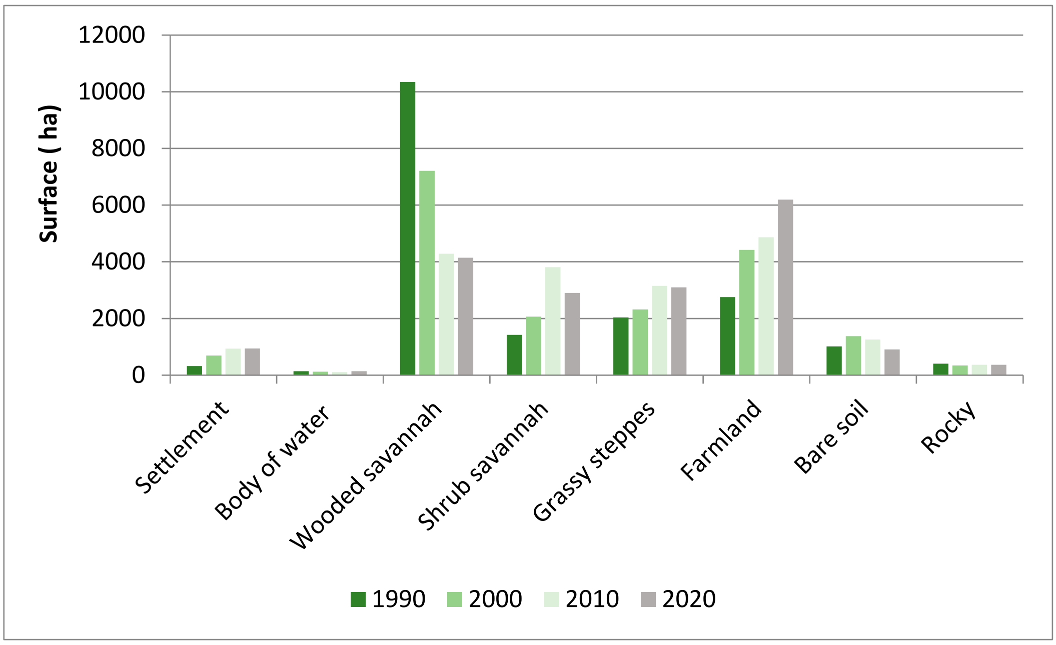

Figure 4. Land cover dynamics between 1990 and 2020.

Table 3. Correlation matrix between different land covers and population growth from 1990 to 2020.

Person's Correlations		**Pop**	**Settlement**	**Water Bodies**	**Wooded Savannah**	**Shrub Savannah**	**Grassy Steppes**	**Farmland**	**Bare Soil**	**Rocky**
Pop	Pearson's r									
	p-value									
Settlement	Pearson's r	0,865								
	p-value	0,135								
Body of water	Pearson's r	0,091	−0,402							
	p-value	0,909	0,598							
Wooded savannah	Pearson's r	−0,893	−0,995 **	0,365						
	p-value	0,107	0,005	0,635						
Shrub savannah	Pearson's r	0,692	0,896	−0,619	−0,912					
	p-value	0,308	0,104	0,381	0,088					
Grassy steppes	Pearson's r	0,888	0,94	−0,333	−0,968 *	0,944				
	p-value	0,112	0,06	0,667	0,032	0,056				
Farmland	Pearson's r	0,960 *	0,927	−0,042	−0,927	0,695	0,857			
	p-value	0,04	0,073	0,958	0,073	0,305	0,143			
Bare soil	Pearson's r	−0,405	0,092	−0,808	−0,011	0,138	−0,135	−0,167		
	p-value	0,595	0,908	0,192	0,989	0,862	0,865	0,833		
Rocky	Pearson's r	−0,417	−0,7	0,438	0,626	−0,437	−0,416	−0,655	0,578	
	p-value	0,583	0,3	0,562	0,374	0,563	0,584	0,345	0,422	

Note: * $p < 0.05$, ** $p < 0.01$.

3.2. Local People's Perception of the Main driving Factors of LULCC

According to the local communities, the main driving factors of decreasing wooded savannah are related to the increase in cotton price inducing agricultural expansion as well as drought, population growth and settlement expansion (Figure 5). Cotton price increase, agricultural expansion and settlements have been scored particularly high by respondents for the period 2010 to 2020. This is somewhat contrasting to our findings from remote sensing (Section 3.1), which indicated that farmland expansion during these years has mainly come from the conversion of shrub savannah, not wooded savannah. Moreover, firewood and charcoal exploitation have also contributed significantly to the loss of wooded savannah. All of these were exacerbated by recurrent poverty and low environmental law enforcement in rural areas during the past 30 years. Most driving factors, such as firewood and charcoal exploitation, timber extraction, bushfires, wind erosion and poverty, recorded their peak from 2000 to 2010 during which severe droughts affected communities. These are the years where much of the wooded savannah decreased, while shrub savannah increased (Figure 4), indicating a loss of woody biomass and degradation. In order to cope with droughts that threaten livelihoods, people put pressure on natural resources as alternative income sources to combat poverty, thus contributing extensively to degradation and deforestation. The period between 2010 and 2020 is considered as a recovering period from drought due to the favorable weather conditions and rural development project interventions supporting natural resources management. Although challenges remained serious, these conditions and the increase in cotton price contributed to agricultural land expansion.

The observed increase in farmland is attributed with high relevance mainly to the rapid population growth, increase in cotton price, low soil fertility, access to agricultural inputs for cotton farming (Figure 6). Moreover, remittances, family labor force availability and low law enforcement contributed but with medium relevance. The results also show that although agricultural land expansion is related to the above driving factors, their effects differ from one period to another. Most of the driving factors recorded their peak between 2010 and 2020, for which we found a strong decrease in shrub savannah but not in wooded savannah (Section 3.1). This phenomenon is mainly due to the high demand of agricultural products for livelihood support (income and subsistence food) caused by population growth. In addition, the cotton price had its peak from 2010 to 2020 compared to the period 1990 to 2010. This finding supports the hypothesis of socio-economic activities' contribution to the land use changes.

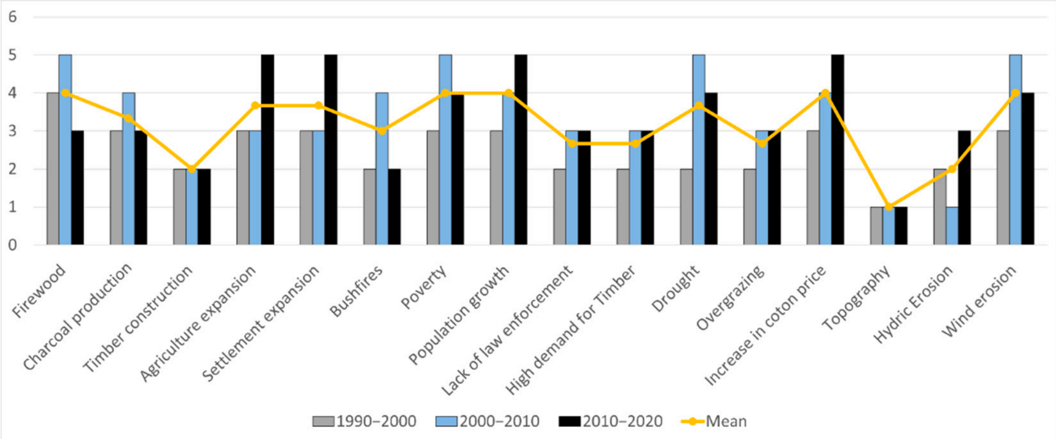

Figure 5. Driving factors of wooded savannah area decrease in Wacoro municipality between 1990 and 2020.

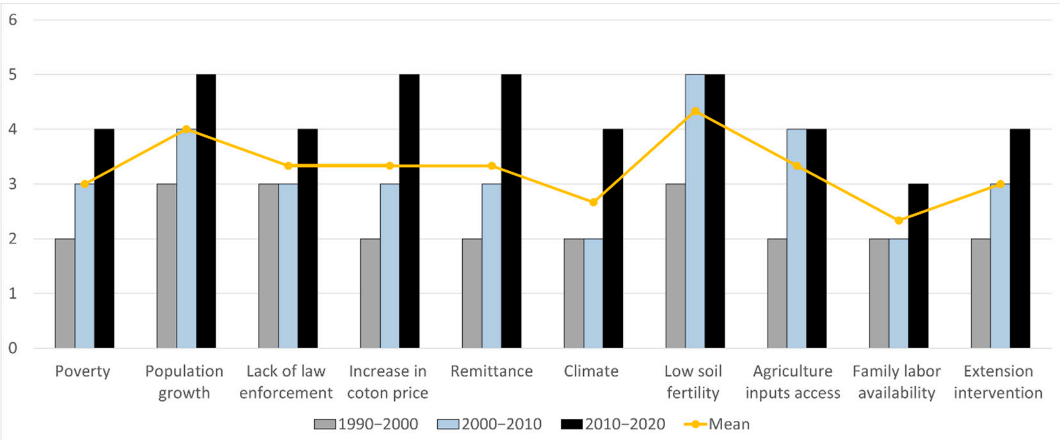

Figure 6. Driving factors of farmland area increase in Wacoro municipality between 1990 and 2020.

Increases in settlement area, which we found mainly between 1990 and 2010 (Section 3.1), were mainly attributed to population growth, easy access to construction materials (tree-based products), remittances from internal and external migrants, and income from cotton production (Figure 7). Labor force availability and construction knowhow are also contributing factors but with low relevant effects. While local people's technical capacities, labor availability and good topographical conditions have also contributed, all these factors are directly or indirectly related to the rapid population growth that the area has seen during the last three decades. In addition, external supports of migrants, income from cotton and access to the construction material contributed to increased settlements. These drivers recorded their peak between 2010 to 2020, which coincides with the period when cotton prices increased. More remittances were received as a consequence, more pressure was put on the shrub savannah as well as on grasslands, and even agricultural land was often converted into settlements.

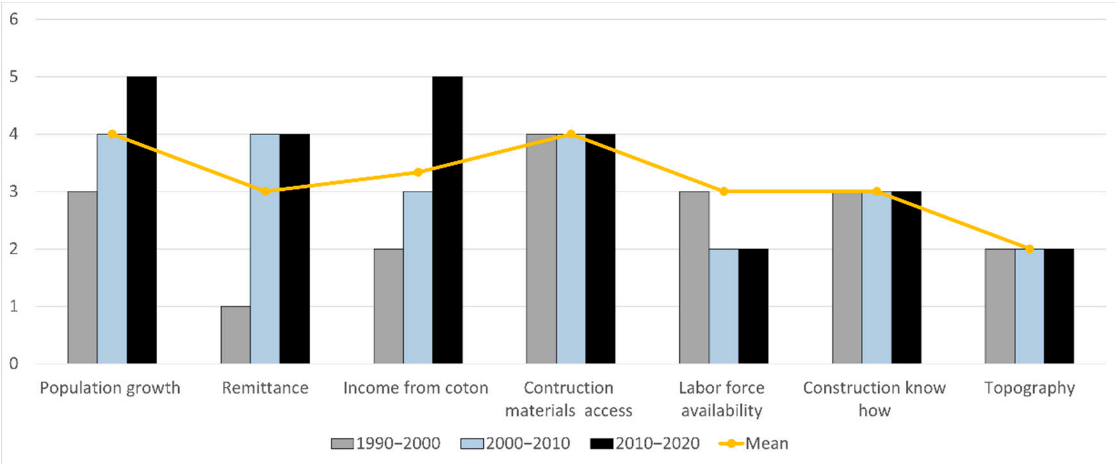

Figure 7. Driving factors of settlement area increase in Wacoro between 1990 and 2020.

The increase in grass and shrub land area over the last 30 years has been mainly attributed to the decrease in wooded savannah. We found that grassland cover is negatively correlated with wooded savannah cover (Table 3). This means that part of the already degraded wooded savannah became grass and shrub savannah in time. This finding confirms local communities' perception of grassland and shrub savannah cover increase due to the severe destruction of the wooded savannah for livelihood needs from 2000 to 2010, when drought caused damages on livelihood (Figure 8). Moreover, annual rainfall distribution affected grassland and shrubland cover and, consequently, feed availability over the study period. To cope with this, transhumance was used as a local strategy to counteract the drought stress affecting agropastoralists between 2000 and 2010. The approach consisted of migrating most of the livestock (both big and small ruminants) to humid areas for a long period of time before the drought effects negatively affected the landscape. In the meantime, between 2007 and 2010, although climatic conditions were not as expected, livestock pressure reduced the grassland and shrub savannah. According to local communities, from 2010 onwards, all livestock was brought back without any further measure. From 2010 onwards, the pressure on the regreened grassland and shrub land increased again.

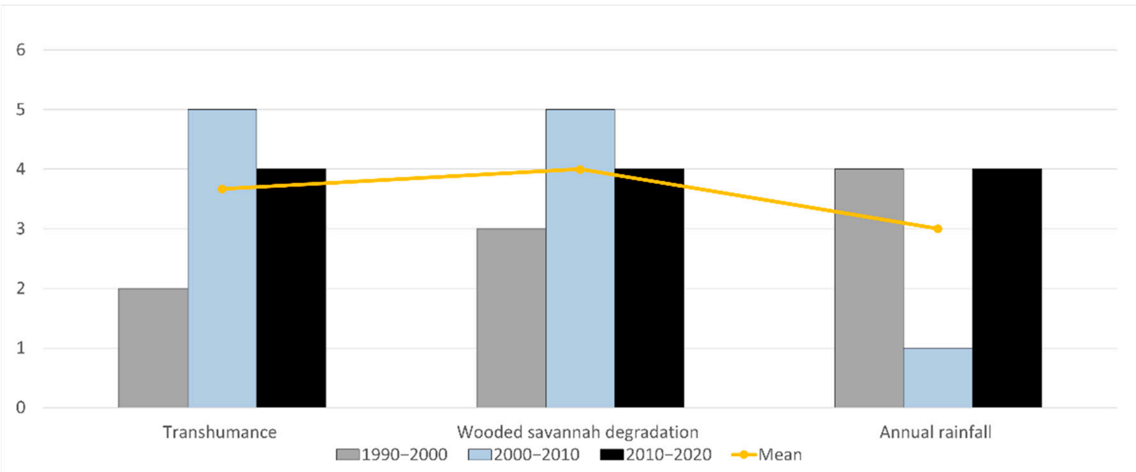

Figure 8. Driving factors of slight increases in shrub and grass savannah area from 1990 to 2020.

4. Discussion

In general, we found a decline in wooded savannah area with an increase in settlement, farmland, and shrub savannah areas, which is in line with similar studies in the

Sahel [36,37,39]. This was mainly driven by smallholder agricultural expansion, recurrent droughts, overgrazing, population growth, increases in cotton price and high needs of tree-based energy products. Other land use change happened primarily due to the unsustainable exploitation of trees. Thereby, more research on integrated farming practices considering vegetation conservation and restoration needs to be conducted and respective recommendations added to the National Agriculture orientation law called LOA in French and Pastoral Charter ("Charte Pastorale") for the purpose of ensuring sustainable land use strategies for livelihood security for the local people. Agroforestry technologies promotion could be one of the strategies to support farmers' livelihoods in the long term.

While our study focused on Mali, it has contributed to the understanding of wider land change drivers relevant to the Sahel region as a whole. Similar to the results of our current study, other authors also reported that climate change in general and increasing drought periods in particular negatively affect the livelihoods of rural communities in Sahelian West Africa [43–45] and that this pushes them towards expansion of cropland and alternative livelihoods (firewood, charcoal and timber), ultimately driving land cover change (e.g., loss of wooded savannah). Thereby, land management strategies need to consider climate friendly energy and timber sources for livelihood improvement in the Sahel [46].

Keeping more livestock through transhumance to meet the high meat and milk demand leads to overgrazing which has been considered as contributing factor to the decline of wooded, shrub and grass savannah by the majority of local communities [7,47,48]. Overgrazing, combined with trampling by livestock hooves and subsequent soil compaction, leaves bare land which is subsequently exposed to the hot sun during the dry period and, ultimately, leads to soil [49] and wind erosion [50]. Unsustainable land use practices are attributed to the insufficient level of enfo rcement of the national pastoral charter and natural resources management policy. Few people are conscious of these policies and their implications for future land-based resources preservation for the next generation. This scenario was a lesson learned by the community that transhumance is not a long-term solution for grassland and shrub land restoration if it is not adapted to the carrying capacity of the ecosystem, as it may cause unexpected damage. The perception on transhumance is consistent with [35], who found that drought across Mali's north seriously affected transhumant populations, forcing pastoralists to remain near permanent water sources and leading to considerable overgrazing in 2004. There is a need for grazing land to be restored through a combination of fodder trees, grass and shrub planting, as well as controlled livestock populations for sustainable livelihoods in the pastoral communities in the Sahel.

In line with our findings, evidence suggests that increasing population density is one of the most important factors behind the declining use of fallows and increased land fragmentation in Burkina Faso [51]. Population pressure on resources could rise in the coming years and could threaten the survival of plant and animal species and ecosystems in addition to human well-being in Mali and beyond, especially in the current context of climate change [52]. This finding suggests a competing scenario between land uses without a proper landscape-level strategy. A good balance is needed between population growth and settlement cover through sustainable territorial planning which is sometimes conditioned by political will. Thereby, sustainable land management strategies should consider population projections in the short, mid- and long term for future stable and resilient natural resources and livelihoods for local communities.

Agriculture, through its related policies, is recognized as one of the major drivers of forest cover loss [53]. In our research, we found that in addition to the rapid population growth (and settlement), cotton price incentives contributed significantly to agricultural land expansion and reduced vegetation cover. This phenomenon was exacerbated by the national policy facilitating access to agriculture inputs for cotton farming [54]. Similar results were observed in neighboring countries, Burkina Faso [44] and Senegal [55]. We therefore advocate that any new agriculture development policy or strategy (such as cotton price incentives) should always be accompanied by an assessment of their potential environmental impacts and the design of adequate mitigation measures to ensure sustainable land use. One existing opportunity to ensure implementation of such measures in the field is that the cotton sector in Mali and in other cotton-farming countries in the Sahel (for instance Burkina Faso) has generally a well-structured extension system with extension agents closely monitoring individual farms to ensure productivity. A remaining challenge is the design of a joint environmental standard to be enforced by extension agents at subregional level.

Our research showed that population growth, energy demand, drought and cotton price incentives were the main driving factors of land cover changes—factors that could potentially be persistent in a business-as-usual scenario. This could exacerbate the prevailing severe food insecurity and malnutrition in the area and conflict, terrorism and jihadism may be expanded [16]. Security is the priority of the current Government of Mali, but this might be hampered if due attention is not paid to secure livelihoods for vulnerable populations, as emphasized by [56], who stated that "Where hunger rules peace cannot prevail". Sustainable land management policies which consider the driving factors (population growth, incentive cotton price, fuelwood extraction and drought) are urgently needed.

While our research was limited to a certain study area, period (30 years) and context, we were, nonetheless, able to advance the knowledge on land change drivers that can be relevant for the Sahel region as a whole. Other limitations linked to our research include the lack of a clear distinction between underlying and direct drivers, which is often a challenge when comparing remote sensing and GIS analyses with local perceptions; the non-inclusion of climate modelling data; and the level of detail in assessing each land use and specific change drivers that would enable more concrete recommendations for policymakers. All of these pose opportunities for further research.

In the current study, our approach of using mixed methods has supported the understanding of how the dynamics of land cover changes could be explained by communities' perceptions of potential drivers. In the prevailing context of climate change, future studies could endeavor to evaluate to which extent such dynamics could be explained by specific climate factors through climate-impact-modeling approaches. Moreover, it would be interesting, beyond communities' perceptions on the potential drivers, to explore what—in their view—constitutes alternative environmentally friendly livelihood options given the circumstances.

5. Conclusions

In general, a conversion and competition were noticed between land use and land cover types (wooded savannah, grass and shrub savannah, settlement, and farmland) although the change rate differed from one land cover class to another. The purpose of this study was to analyze LULCC and related driving factors in the Sahel using the municipality of Wacoro in the Koulikoro region of Mali as the study site. We applied a mixed-methods approach by (a) using remote sensing and GIS with satellite images for the years 1990, 2000, 2010 and 2020 and (b) facilitating focus group discussions with knowledgeable resource persons in rural communities on the potential drivers of the observed changes during the same years. Our study revealed that natural vegetation cover (wooded savannah) has diminished, while anthropogenic land use (farmland and settlement) has increased from 1990 to 2020 mainly due to rapid population growth, agriculture land expansion for cash crop (cotton) production, high energy demand and drought and related factors. Importantly, all driving factors are directly or indirectly related to severe poverty. One particular finding worth emphasizing was that cotton price incentives have been a motivating factor to agricultural land expansion in the study area. Over the selected 30-year time frame, the decade 2000–2010 showed a noticeable LULCC which the communities attributed to continuous drought in the region that severely threatened their livelihoods. Our results contribute to suggestions for more sustainable land uses and accompanying policies which might include designing environmental standards for cotton farming and ensuring enforcement through the well-established extension system of Mali's cotton sector.

The recommended interesting future research areas include climate impact modeling and investigation of alternative livelihood options in the Sahel region.

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