Modelling vegetation trends using biophysical and demographic datasets in the savanna of Burkina Faso

Benewindé Jean-Bosco ZOUNGRANA[1]

Abstract

Savanna represents an important vegetation biome in West Africa, providing food and services to people, and habitat for large amount of vegetation and animal species. However, this biome knows a rapid degradation of its vegetation cover driven by anthropogenic and climatic stressors. Monitoring and modelling vegetation change are relevant to safeguarding forest and combat land degradation. This study explored the use of biophysical and demographic datasets to model vegetation trends in the savanna of Burkina Faso. For that, vegetation trends were detected from 2001 to 2020 with the Mann-Kendall's trend test. Random Forest (RF), Super Vector Machine (SVM) and Artificial Neural Network (ANN) algorithms were used to model vegetation trends driven by biophysical and demographic variables. The result revealed that non-significant vegetation trends were prominent (73%) in the study area during 2001-2020, while greening and degradation trends characterised 13% and 14% of the pixels, respectively. RF was found superior to SVM and ANN in the modelling of vegetation trends categories with overall accuracy (Kappa index) above 0.80 (0.70). The study provided sound information that can support the development of efficient strategies to combat land degradation.

Key words: Vegetation trends; Modelling; Savanna; Burkina Faso

Modélisation des tendances de la végétation à l'aide de données biophysiques et démographiques dans la savane du Burkina Faso

Résumé

La savane représente un important biome en Afrique de l'Ouest, fournissant de la nourriture et des services aux populations, et un habitat à une grande quantité d'espèces végétales et animales. Cependant, ce biome connaît une dégradation rapide de sa couverture végétale due aux pressions anthropiques et climatiques. Le suivi et la modélisation des tendances de la végétation sont nécessaires pour la sauvegarde des forêts et la lutte contre la dégradation des terres. Cette étude a exploré l'utilisation d'ensembles de données biophysiques et démographiques pour modéliser les tendances de la végétation dans la savane du Burkina Faso. Pour cela, les tendances de la végétation ont été détectées de 2001 à 2020 avec le test de tendance de Mann-Kendall. Les algorithmes Random Forest (RF), Super Vector Machine (SVM) et Artificial Neural Network (ANN) ont été utilisés pour modéliser les tendances de la

[1] Ecole doctoral WASCAL, informatique et changement climatique, Université Joseph KI-ZERBO, 03 BP 7021 Ouagadougou, Burkina Faso

végétation induites par des variables biophysiques et démographiques. Le résultat a révélé que des tendances non significatives étaient prédominantes (73 %) dans la végétation de la zone d'étude au cours de la période 2001-2020, tandis que les tendances de verdissement et de dégradation caractérisaient respectivement 13 % et 14 % des pixels. RF s'est avéré supérieure à SVM et à ANN dans la modélisation des catégories de tendances de la végétation avec une précision globale (indice Kappa) supérieure à 0,80 (0,70). L'étude a fourni des informations qui peuvent soutenir le développement de stratégies efficaces pour lutter contre la dégradation des terres.

Mots clés : Tendances de la végétation ; Modélisation ; Savane ; Burkina Faso

Introduction

Vegetation constitutes a key element in the interaction of the geosphere, biosphere and atmosphere (MENNIS, 2001). It is among the first elements to be altered in terrestrial ecosystems degradation (STAVI AND LAL, 2015), and it is thus perceived as an indicator of global change (Peng et al., 2015). Indeed, any change in vegetation cover can affect the environment at any scale (AMRI *et al*., 2011). Nowadays, the problem of vegetation change has become a worldwide issue, part of a global agenda, since it is related to climatic and anthropogenic pressure (LUKAS *et al*., 2023).

In West Africa, savanna represents an important vegetation biome, providing food and services to people, and habitat for large amount of vegetation and animal species. However, this biome knows a rapid degradation of its vegetation cover driven by human and climatic stressors (RASMUSSEN *et al.,* 2014; ZOUNGRANA AND DIMOBE, 2023). In this regard, it drew the attention of several researchers and scholars. Many of the previous investigations used earth observation data to monitor the spatiotemporal change of vegetation cover. Land use/cover dynamics analysis is one of the largely adopted methods to detect spots of vegetation conversions by anthropogenic land use (BRAIMOH, 2004; OUEDRAOGO *et al*., 2010; HOUESSOU *et al*., 2013; DIMOBE *et al*., 2015). Other authors have rather focused on vegetation trends analysis using long time series of vegetation index, like NDVI (Normalized Difference Vegetation Index), to assess greening or browning trend areas (LI *et al*., 2010; TRAORE *et al*., 2014). The underlying driving factors of vegetation trends were also matter of investigation, and the climatic-driven effects and anthropogenic pressures are pointed out as the main causes of the savanna vegetation change in West Africa (HERRMANN *et al*., 2005; OLSSON *et al*., 2005; LEROUX et *al*., 2017; ZOUNGRANA AND DIMOBE, 2023).

Despite the previous investigations, in the savanna of West Africa, the link of vegetation dynamics with biophysical and anthropogenic variables still needs to be documented to efficiently combat land degradation. For that, the accuracies of vegetation change modelling must be improved to set up appropriate safeguarding and mitigation measures. Commonly, logistic regression models were used to model and assess drivers of vegetation change among biophysical and anthropogenic variables (BRAIMOH AND VLEK, 2005; DIMOBE et al., 2015). Recently, studies have shown the strength of non-parametric algorithms, such as Random Forest (RF), Super Vector Machine (SVM) and Artificial Neural Network (ANN), to relate vegetation change to biophysical (climatic, topographic, edaphic, accessibility data) and anthropogenic variables (ZOUNGRANA AND DIMOBÉ, 2023; LEROUX et al., 2017). Those algorithms are presented as potential modelling tools, because of their performance and high predictive capacity (FORKUOR et al., 2017; LEROUX et al., 2017). However, their potentials to model vegetation trends using biophysical and demographic predictors have not been fully explored in the West African savanna zone.

In Burkina Faso, the savanna biome is of paramount importance, since it provides food and vital ecosystem services to local populations which depend largely on it for their livelihood. However, several spots of this biome have shown alarming signals of land degradation driven by climatic pressure as well as by the rapid population growth with the unsustainable use of land (YANGOULIBA et al., 2023; ZOUNGRANA AND DIMOBÉ, 2023). If this dynamic maintains, it is likely to increase land degradation, and loss of soil fertility and biodiversity, which can affect food security in the country. It is therefore important to monitor and model vegetation dynamics in line with anthropogenic and biophysical factors in order to provide sound information to combat vegetation degradation in the savanna biome of Burkina Faso.

The objective of the present study was to explored the use of biophysical and demographic datasets to model vegetation trends in the savanna of Burkina Faso. Specifically, the study aimed to: (i) detect vegetation trend categories in the study area from 2001to 2021; and (ii) assess the performance of Random Forest, Super Vector Machine and Artificial Neural Network algorithms to model vegetation trend categories in the savanna of Burkina Faso.

I. Materials and methods

I.1. Study area

The study area covers 44,685 km^2 and is located in Burkina Faso approximately between latitudes 11º0´0´´N to 13º0´0´´N and longitudes 0º15´0´´W to 3º0´0´´W (Figure1). The study area has a tropical climate, and it belongs to the Sudanian phytogeographical domain, which is divided into the North and South Sudanian sectors (FONTES AND GUINKO, 1995). Savanna vegetation, from tree savanna to grassy savanna, dominates in the study area, with key species such as *Vitellaria paradoxa, Parkia biglobosa, Pterocarpus erinaceus, Terminalia laxiflora, Afzelia africana, Anogeisus leiocarpa,* etc. (THIOMBIANO AND KAMPMANN, 2010). There are also gallery forests encountered along the rivers. The population is dynamic with high fertility rates. Agriculture is the principal economic activity, representing the main source of livelihood for the local population, as in the whole country where 85.5% of the labour are involved in the agriculture sector (SANFO, 2010; INSD, 2022). Small-scale agricultural practices are common with a rudimentary character. The main crop grown are cereals, such as sorghum, millet, maize and rice. The expansion of cropland coupled with population growth and climate vagaries increase pressure on the natural vegetation of the study area.

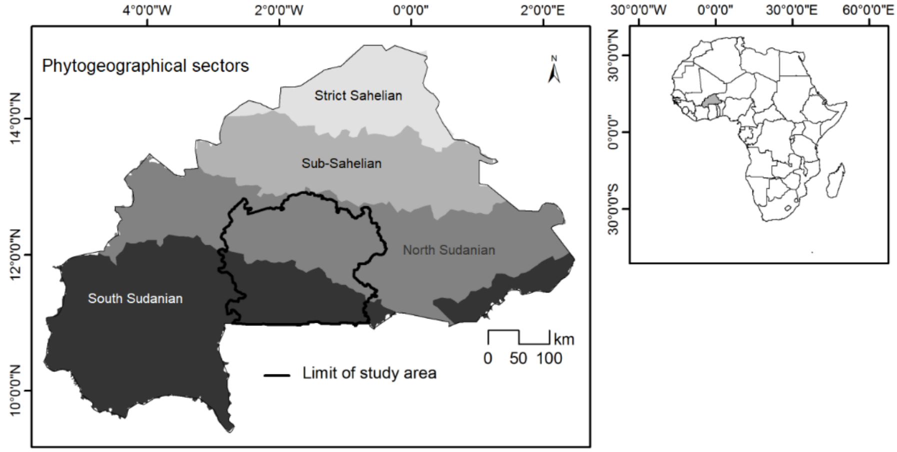

Figure 1. Location of the study area; the insets show the phytogeographical sectors of Burkina Faso, and Burkina Faso in Africa

I.2. Data collection

I.2.1. Vegetation data: 250 m MODIS NDVI data from 2001 to 2020

NDVI trends was employed as proxy to assess vegetation change. Time series of NDVI 16-day composites of MODIS Terra MOD13Q1 product, with a spatial resolution of 250 m and spanning from 2001 to 2020, were obtained from Google Earth Engine (GEE) cloud platform. The MOD13Q1 product was widely used for vegetation change monitoring, and it have already been successfully applied in the West African Sudanian savanna to analyse vegetation dynamics (ZOUNGRANA AND DIMOBE, 2023). Based on the pixel-level data quality indicators provided by MOD13Q1 product, quality assurance mask was applied to the dataset in order to obtain a high-quality MODIS NDVI time series. Annual mean NDVI time series were derived for the 2001-2020 period and used for trend analysis in the GEE platform.

I.2.2. Biophysical and demographic datasets

Various biophysical and demographic related data were gathered to model vegetation trends (Table 1). Annual rainfall data (gridded) were collected from TAMSAT (MAIDMENT *et al*., 2014; TARNAVSKY *et al*., 2014) for the period 2001-2020. These datasets are based on Meteosat thermal infra-red (TIR) imagery provided by EUMETSAT, and the TIR is calibrated against an extensive ground-based rain gauge data archive. Three indicators of rainfall were computed: coefficient of variation, rainfall trend and mean annual rainfall. Elevation above mean sea level was derived from the 30 m SRTM (Shuttle Radar Topography Mission) (https://earthexplorer.usgs.gov/), and soil type data were collected from the national soil office of Burkina Faso (BUNASOL). Accessibility data (distance to river) were derived from data collected at the Geographical Institute of Burkina Faso (IGB). Population growth between 2000 and 2020 was computed (equation 1) using the Gridded Population of the World version 4 (GPWv4) dataset produced by the Center for International Earth Science Information Network. All the environmental data were projected to UTM WGS 84 zone 30 with spatial resolution of 250 m to match the pixel size and the projection of the MODIS NDVI data.

$$P_{Gr} = \frac{p_{2020} - p_{2000}}{p_{2000}} x100 \qquad (1)$$

where, P_{Gr} indicates population growth

Table I. Set of predictors selected to model vegetation trends

Types	Variables	Sources	Spatial resolution
Climatic	Coefficient of variation of annual rainfall (%)	TAMSAT	~ 4 km
	Mean annual rainfall (mm)		
	Rainfall trend		
Topographic	Elevation (m)	SRTM	30 m
Edaphic	Soil types units	BUNASOL BF	Vector data
Accessibility	Euclidean distance from river (m)	IGB	Vector data
Demographic	Population growth (2000-2020 in %)	GPWv4	1 km

I.3. Evaluation of modelling performance

The process of vegetation trends modelling includes three steps:

- Step 1: detection of vegetation trend classes;
- Step2: fitting modelling algorithms with biophysical and anthropogenic predictors;
- Step 3: assessing the performance of the modelling algorithms.

I.3.1. Vegetation trends detection

Vegetation trend analysis was conducted over area covered by vegetation, while water bodies were excluded. Vegetation trend classes were detected with the non-parametric Mann-Kendall's trend test that was applied to the annual NDVI time series (2001-2020) using GEE platform. Actually, this trend detection technique computes the correlation between the NDVI time series data (observation data) and time. Two outputs were considered from the Mann-Kendall's trend analysis: the trend significance value (p-value) and the Kendall's tau (τ) which is a correlation coefficient indicating the sign of trends. Positive τ values stand for increasing trend, and negative τ values indicate degradation. A trend is statistically significant if p-value < 0.05, while non-significant trend is attributed to pixels with $p > 0.05$. Three vegetation trend classes were considered based on the results of the trend analysis (Table II). The formula of Mann-Kendall's trend test is given below as described in ZOUNGRANA AND DIMOBE (2023).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sign}(x_j - x_i) \qquad (2)$$

Where n is the numbers of data points. x_i and x_j are annual values in years j and i. j > 1 and Sign (x_i - x_j) calculated using the equation:

$$\mathrm{Sign}(x_j - x_i) = \begin{cases} 1 \text{ if } (x_j - x_i) > 0 \\ 0 \text{ if } (x_j - x_i) = 0 \\ -1 \text{ if } (x_j - x_i) < 0 \end{cases} \qquad (3)$$

The computation of Mann Kendall significance produces a standardized Z (Equation 4) and corresponding probability p (Equation 5).

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S < 0 \end{cases} \qquad (4)$$

$$\text{and } p = 2[1 - \phi(|Z|)] \qquad (5)$$

$$\text{Where } \phi(|Z|) = \frac{2}{\sqrt{\pi}} \int_0^{|Z|} e^{-t^2}\, dt \qquad (6)$$

Table II. Vegetation trend classes considered in this study

Kendall's tau (τ)	P value	Change class
$\tau > 0$	$p < 0.05$	Greening
	$p > 0.05$	Unchanged
$\tau < 0$	$p < 0.05$	Degradation
	$p > 0.05$	Unchanged

I.3.2. Modelling algorithms

Random Forest (RF), Super Vector Machine (SVM) et Artificial Neural Network (ANN) algorithms were used to relate vegetation trends to anthropogenic and biophysical variables due to their high predictive capacity (FORKUOR *et al*., 2017; LEROUX *et al*., 2017). Random Forest (RF), Support Vector Machine (SVM) and Artificial Neural Network (ANN) are among the most popular MLA (LÖW *et al*., 2015; FORKUOR *et al*., 2017; THANH NOI AND KAPPAS, 2017;). RF is an ensemble machine learning algorithm developed by BREIMAN (2001) for classification and regression. It is based on bagging, a technique used for training data creation by randomly resampling the original dataset with replacement (ZOUNGRANA *et al*., 2015). For classification, RF builds several trees with random samples of observations and a random sample of variables, then, the outputs of the classification trees are aggregated, and a class is assigned by majority voting (BREIMAN, 2001). SVM focuses exclusively on the training samples that are closest in the feature space to the optimal boundary between the classes. These samples are called support vectors and give the method its name. SVM aims to find the optimal boundary, which maximizes the separation, or margin, between the support vectors (MAXWELL *et al*., 2018). As for ANN, it is a system based on biological neural networks. It consists of an interconnected group of neurons, and each neuron has a single computation process (ZHOU AND YANG, 2008). The elements of an ANN are neurons (equivalent to biological axons), which are organized in layers. An ANN has minimum input and output layers, with a neuron for each input variable, and a neuron for each output class (MAXWELL *et al*., 2018). These three non-parametric algorithms were found more accurate than the parametric algorithms, particularly when dealing with many predictors and different types of data as well as complex non-linear mappings (PAL, 2005; GHIMIRE *et al*., 2012; MAXWELL *et al*., 2018).

I.3.3. Models fitting and validation

The presence of high spatial autocorrelation in the reference dataset can lead to overestimation of modelling accuracy. To avoid high spatial autocorrelation in the reference data, Moran's I-based correlogram was built for the different variables using the Elsa package of the software R. The analysis of the correlograms enabled the selection of a minimum distance between sampling points to reduce spatial autocorrelation. Accordingly, the minimum distance between sampling points was set to 3 km with Moran's I value of 0.4. In all, 1600 reference samples (pixels), shared between the three vegetation trend classes (greening, degradation and unchanged), were randomly selected for the modelling. RF, SVM and ANN classification models were fit using the statistical software R, with vegetation trend classes as categorical response variable, and the climatic, topographic, edaphic, accessibility and demographic variables were considered as predictors.

To ensure an effective comparison of the modelling algorithms, two types of modelling validations were considered: internal 10-fold cross validation with 3 repetitions and external validation with 30% of the reference sample. Overall accuracy and Kappa index were derived to assess the performance of each modelling algorithms. Furthermore, the McNemar's test was used to evaluate the statistical significance of the differences between the performances of each algorithm based on the derived confusion matrices. McNemar's test is a nonparametric test which is based on a pair of confusion matrices of correctly and wrongly classified reference samples (ZOUNGRANA *et al.*, 2015), and it produces a chi-square (χ^2) statistics that is computed by Equation (3).

$$\chi^2 = \frac{(f_{12} - f_{21})^2}{(f_{12} - f_{21})} \qquad (7)$$

Where f_{12} indicates the number of cases correctly classified by classifier 1 but incorrectly classified by classifier 2, and f_{21} represents the number of cases correctly classified by classifier 2 but wrongly classified by classifier 1.

II. Results

II.1. Vegetation trend during 2001-2020

The vegetation trend map revealed consistent patterns of NDVI trends in the study area between 2001 and 2020 (Figure 2). Unchanged vegetation area (grey colour) was particularly prominent (73%) and distributed throughout the study area. Greening trend (green colour) covered 13% of the pixels and was concentrated in the North-Sudanian. Degradation trend, in red colour, characterized 14% of the pixels and occurred mainly in the South-Sudanian. Most of the protected areas had often unchanged vegetation cover (non-significant trend, p value > 0.05) (e.g. Tambi Kaboré national park, Nazinga forest and Sissili forest), and other like the Gonsé forest exhibited dominant patterns of greening vegetation trend. However, spots of declining vegetation were also detected in some protected areas such as the Nakambe forest and Tiogo forest.

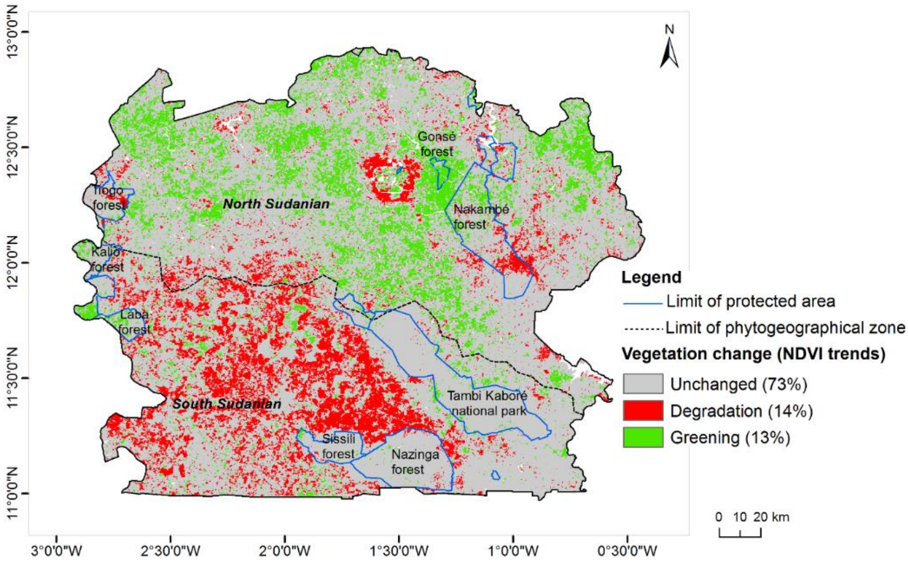

Figure 2. Changes occurred in the vegetation of the study area during 2001-2020

II.2. Performance of the machine learning algorithms

The achieved modelling accuracies for RF, SVM and ANN classifications are presented in Figure 3. RF came out as the best algorithm against SVM and ANN from the two types of modelling validation. RF classifier outperformed SVM and ANN with the highest overall accuracy and kappa index across the 10 folds of the cross validation (Figure 3a-b). The mean overall accuracy (kappa index) of the 10 folds were 0.82(0.73), 0.76(0.63) and 0.59(0.47) for RF, SVM and ANN respectively (Figure 3c). The external validation also showed the superiority of RF (ov. accuracy= 0.81; kappa =0.75) over SVM (ov. accuracy= 0.72; kappa =0.60) and ANN (ov. accuracy= 0.60; kappa =0.46) (Figure 3d).

The McNemar's test indicated that all observed differences in accuracy between the three classifiers predictions were significant at the 0.01 significance level (Table III). Particularly, RF and SVM were the most accurate modelling algorithms, and their performances were significantly different from the one of ANN.

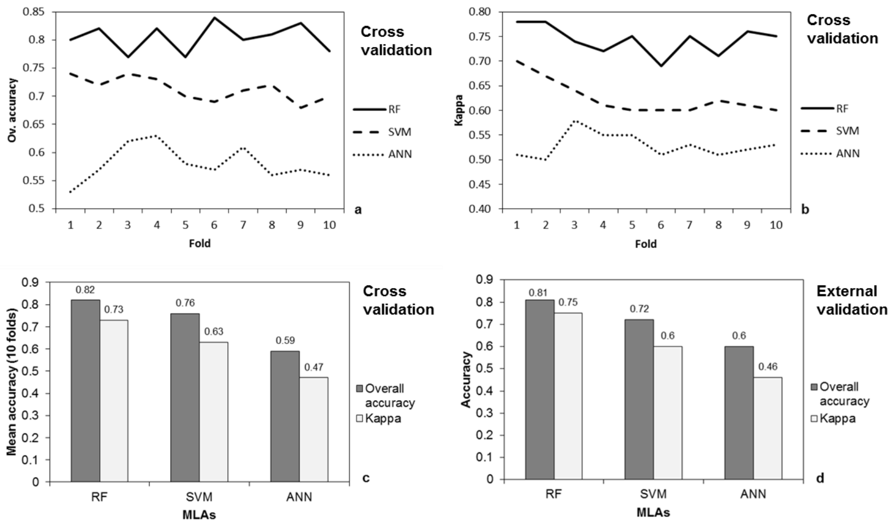

Figure 3. Overall accuracy and kappa index values from the validation methods

Table III. McNemar's test results based on a comparison of the classifiers performance

	F11	F12	F21	F22	Chi-square	p-value
RF-SVM	1327	50	163	260	59.9	<0.001
RF-ANN	1107	0	383	310	383	< 0.001
SVM-ANN	1107	77	220	396	68.9	< 0.001

II.3. Contribution of variables to the modelling

Modelling with RF, SVM and ANN provides the opportunity to assess the predictors contribution through the importance score of variables. The relative importance score of the predictors from the two best algorithms (RF and SVM) are shown in Table IV. According to RF and SVM modelling, rainfall trend, mean annual rainfall and population growth were by order of importance the key contributing variables, followed by the coefficient of variation (CV) of annual rainfall, elevation and distance to river. Soil type was found to be the least important variable with the weakest contribution in RF and SVM modelling.

Table IV: Variable importance score (mean decrease accuracy) derived from RF and SVM modelling

Variables	Relative importance	
	RF	SVM
Rainfall trend	95	90
Mean annual rainfall	89	85.21
Population growth	82	65.07
CV of annual rainfall	63.1	40.11
Elevation	59.55	33.5
Distance to river	32.26	11.75
Soil type	2.36	3.23

III. Discussions

As reported by previous investigations that used NDVI time series (LEROUX *et al.*, 2014; ZOUNGRANA *et al.*, 2018; ZOUNGRANA AND DIMOBE 2023), the vegetation of the West African Sudanian savanna has largely exhibited in the last decades non-significant trends. The same characteristic is also observed in the study area of this investigation between 2001 and 2020. However, the combined effects of climate vagaries and unsustainable anthropogenic land use might explain the occurrence of the detected vegetation trends. Rainfall variables (rainfall trend and mean annual rainfall), that was found as the key contributing variables in machine learning modelling, could have probably guided the greening trend. Indeed, an increase in rainfall was reported in this region since the beginning of the 2000s (LUCIO *et al.*, 2012). Similar conclusions were reached in Niger by LEROUX *et al.* (2017) that found rainfall average with the highest variable importance score in a random forest classification of vegetation trends. In addition to the climatic variables, our findings revealed population growth also as a key variable in the modelling of vegetation trends in the study area. Anthropogenic actions, such as reforestation, might have also contributed to the greening spots in the study area. However, human, through the unsustainable land use, is shown as the key driver of vegetation degradation in the Sudanian savanna, especially at local scale (BRAIMOH, 2004; DIMOBE *et al.*, 2015). At landscape scale, human impact is perceived through built-up and cropland expansion at the detriment of the natural vegetation cover (OUEDRAOGO *et al.*, 2010; HOUESSOU *et al.*, 2013; KNAUER *et al.*, 2017).

It came out from our results that RF has better modelling capacity of vegetation trend classes with climatic, topographic, edaphic, accessibility and demographic variables than SVM and ANN in the Sudanian savanna, at least in the Sudanan savanna of Burkina Faso. This predictive performance of RF was also noticed by LEROUX *et al*. (2017) that used RF to model local vegetation production trends in southwestern Niger and achieved an overall accuracy of 80%. Our results accord with previous studies that found RF efficient in the mapping of vegetation change in the African savannas (FORKUOR, 2014; GESSNER *et al*., 2015; ZOUNGRANA *et al*., 2015). Studies have also found RF outperforming SVM and ANN. For instance, FORKUOR *et al.* (2017) combined remote sensing and biophysical data to predict soil information, and they findings revealed that RF performed better than SVM and multiple linear regression in the prediction of soil properties such as sand, silt, clay, cation exchange capacity, soil organic carbon and nitrogen. Similar conclusions were noted in the modelling of electronic tongue (LIU *et al*., 2013). However, contrasted results were obtained by ABDI (2020) in the classification land use/cover in a boreal landscape using Sentinel-2 data. The author noted the superiority of SVM to RF, gradient boosting and deep learning. The difference of geographical zone might explain the discrepancy of results with the present study. Nevertheless, in the Sudanian savanna, our findings highlight that RF can be preferably used with biophysical and demographic variables to predict directional vegetation change and anticipate future change. It also showed that RF model offers an opportunity to distinguish the influence of environmental variables on vegetation change (KRAKAUER *et al*., 2017).

Our study confirmed the continuity of vegetation degradation in the West African Sudanian savanna despite the presence of greening spots. Climatic and anthropogenic pressures are driving vegetation change in this part of the world. The study showed the superiority of RF algorithm to model vegetation trend classes, which is useful in the context of climate change and can help to combat land degradation in the savanna of Burkina Faso.

Conclusion

Monitoring and modelling vegetation change is of paramount importance, especially in the context of climate change and population growth. The intercomparison of the Random Forest (RF), Super Vector

Machine (SVM) and Artificial Neural Network (ANN) algorithms to model vegetation trends with biophysical and demographic datasets in the savanna of Burkina Faso yielded acceptable accuracies. The findings confirmed the potential of RF and SVM to relate vegetation trends to biophysical and demographic variables, which is motivating in the combat against land degradation. The degradation of vegetation in the Sudanian savanna of Burkina Faso is still ongoing, despite the presence of greening spots. Climatic and anthropogenic pressures are the main threats for vegetation cover in the study area. More efforts towards sustainable land use are needed and safeguarding policies should be reinforced in the country. The study provided sound information that could help to tackle land degradation and improve our understanding of vegetation dynamics in the savanna of Burkina Faso.

Conflicts of interest

No potential conflict of interest was reported by the authors

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