Driving forces of recent vegetation changes in the Sahel: lessons learned from regional and local level analyses

Louise Leroux, Agnès Bégué, Danny Lo Seen, Audrey Jolivot, Francois Kayitakire

Driving forces of recent vegetation changes in the Sahel: lessons learned from regional and local level analyses

Louise Leroux[a*], Agnès Bégué[b], Danny Lo Seen[b], Audrey Jolivot[b], Francois Kayitakire[c]

[a] CIRAD, UR AÏDA, Avenue Agropolis, 34938, Montpellier, France
[b] CIRAD, UMR TETIS, 500 rue Jean-François Breton, 34093, Montpellier, France
[c] European Commission, Joint Research Centre, Institute for Environment and Sustainability, Via E. Fermi 2749, I-21027 Ispra, VA, Italy

[*] Corresponding author: Louise Leroux, louise.leroux@cirad.fr, +33467617128
E-mail addresses: louise.leroux@cirad.fr (Louise Leroux), agnes.begue@cirad.fr (Agnès Bégué), danny.lo_seen@cirad.fr (Danny Lo Seen), francois.kayitakire@jrc.ec.europa.eu (François Kayitakire)

Abstract

A wide range of environmental and societal issues such as food security policy implementation requires accurate information on biomass productivity and its underlying drivers at both regional and local scales. While many studies in West Africa are conducted with coarse resolution earth observation data, few have tried to relate vegetation trends to explanatory factors, as is generally done in land use and land cover change (LULCC) studies at finer scales. In this study we proposed to make a bridge between vegetation trend analysis and LULCC studies to improve the understanding of the various factors that influence the biomass production changes observed in satellite time series (using integrated Normalized Difference Vegetation Index [NDVI] as a proxy). The study was conducted in two steps. In the first step we analyzed MODIS NDVI linear trends together with TRMM growing season rainfall over the Sahel region from 2000–2015. A classification scheme was proposed that enables better specification of the relative role of the main drivers of biomass production dynamics. We found that 16% of the Sahel is re-greening—but found strong evidence that rainfall is not the only important driver of biomass increase. Moreover, a decrease found in 5% of the Sahel can be chiefly attributed to factors other than rainfall (88%). In the second step, we focused on the "Degré Carré de Niamey" site in Niger. Here, the observed biomass trends were analyzed in relation to land cover changes and a set of potential drivers of LULCC using the Random Forest algorithm. We observed negative trends (29% of the Niger site area) mainly in tiger bush areas located on lateritic plateaus, which are particularly prone to pressures from overgrazing and overlogging. The significant role of accessibility factors in biomass production trends was also highlighted. Our methodological

framework may be used to highlight changing areas and their major drivers to identify target areas for more detailed studies. Finer-scale assessments of the long-term vulnerability of populations can then be made to substantiate food security management policies.

Keywords: Sahel, NDVI time series, trend, drivers of change, food security, land cover changes

1. Introduction

While the population of Africa is set to exceed 3 billion by 2050 (United Nations, 2013), increasing climate variability, as expressed by extreme climatic events (e.g., droughts or floods) threatens agricultural production and enhances household vulnerability and food insecurity. Schlenker and Lobell (2010) estimated that climate change would be responsible for yield declines of up to 22% in major food staples. However, the dynamics of agricultural production are not solely a result of climatic factors; they depend on many factors, including agricultural practices, population density and environmental and social constraints (type of soil, land accessibility, *etc.*). In the context of increasing food demand, the identification of areas particularly prone to degradation in agricultural production conditions, and a better understanding of the underlying drivers is increasingly important for long-term mitigation and adaptation strategies (Pricope et al., 2013).

The Sahel belt, a transition zone between the Sahara Desert and the tropical savannas, is characterized by substantial rainfall variability and is particularly prone to food insecurity because most of the agropastoralist local population rely on low productivity rainfed agriculture (mainly millet and sorghum) for their livelihoods. Food crises caused by severe droughts are recurrent, some amounting to extreme starvation of the populations (e.g., in the late 1960s and 1980s; Hulme, 2001; Nicholson et al., 1998). Since the late 1990s, however, the Sahel region has seen a general increase in rainfall (Ali and Lebel, 2009; Nicholson, 2005), and the ensuing vegetation recovery, as viewed from space, has been termed a “re-greening” of the region (Eklundh and Olsson, 2003; Olsson et al., 2005; Prince et al., 2007, 1998). Most studies on the re-greening of the Sahel are founded on the Normalized Difference Vegetation Index (NDVI), a spectral ratio index based on the red and infrared bands (Tucker, 1979) and closely linked to vegetation productivity (Asrar et al., 1984; Pettorelli et al., 2005).

The relationship between the Above Net Primary Production (ANPP) and NDVI relies, on one hand, on the close relationship between the fraction of Absorbed Photosynthetically Active Radiation (fAPAR) integrated over a time period and the growing season ANPP (Prince, 1991) and, on the other hand, on the linear correlation between NDVI and fAPAR, due to their similar functional responses to leaf orientation, solar zenith angle and atmospheric optical depth (Myneni and Williams, 1994). Thus, NDVI trends integrated over a time period have been widely used as a proxy to monitor changes in vegetation productivity. To date, the most frequently utilized NDVI dataset is the Advanced Very High Resolution Radiometer (AVHRR) dataset from the National Oceanic and Atmospheric Administration (NOAA) satellite due to its high temporal resolution and its availability since the beginning of the 1980s. This technology has enabled the monitoring of vegetation trends over nearly thirty-five years at a spatial resolution of 8 km (e.g., Anyamba et al., 2014; Dardel et al., 2014b; Herrmann et al., 2005; Huber et al., 2011). Most of these studies reported an increase in the greenness of vegetation over the whole Sahel since the 1980s and helped to fuel the debate on the "irreversible" desertification of the Sahel. However, recent studies based on Moderate Resolution Imagery Spectroradiometer (MODIS) data, which have supported vegetation monitoring at a 250 m spatial resolution since 2000, have highlighted the spatial heterogeneity of trends, with some areas showing negative trends or non-significant trends (Leroux et al., 2014; Rasmussen et al., 2014).

Currently, one of the main challenges in analyzing biomass productivity dynamics is to document the underlying drivers consistently. On a global scale, it has recently been shown that the main driver of the greening of Earth may be increases in CO_2, which augments photosynthesis and, consequently, increases the water use efficiency in water limited environments (Donohue et al., 2013; Zhu et al., 2016). At the Sahelian scale, however, although it is generally acknowledged that variations in vegetation depend on rainfall, several studies have indicated that local NDVI trends might not be fully explained by global drivers such as rainfall and have suggested other causal local factors (Boschetti et al., 2013; Fensholt et al., 2013; Helldén and Tottrup, 2008; Herrmann and Hutchinson, 2005; Hoscilo et al., 2014; Huber et al., 2011; Rasmussen et al., 2014) such as shifts in land use, as shown in Mali by Bégué et al. (2011) or many non-anthropogenic factors (e.g. intra-annual distribution of rainfall events, humidity or temperature) as recently shown in Rishmawi et al. (2016). Characterization of the main drivers of vegetation dynamics therefore relies mainly on the distinction between climate-induced biomass changes and changes induced by other factors (both anthropogenic and natural) (Knauer et al., 2014; Mbow et al., 2015). For instance, Hickler et al. (2005) and Seaquist et al. (2009) used a process-based vegetation model in which vegetation dynamics predicted by the model without any human influence were compared to vegetation trends observed by remote sensing. The climate contribution can also be assessed with the Rain Use Efficiency (RUE) measure; however, the RUE has been widely questioned due to several limitations (Dardel et al., 2014a; Hein and Ridder, 2006; Hein et al., 2011; Prince et al., 2007). For regions where rainfall is the main limiting factor of vegetation growth, another method, considered robust and more widely accepted, is the residuals method (also called the RESTREND; Wessels et al., 2007) proposed by Evans and Geerken (2004), which is based on the trend analysis of the residuals between the observed NDVI and precipitation-normalized NDVI. While RUE is often considered as the relationship between rainfall and NDVI, RESTREND in turn is simply a rearrangement of RUE into a temporal sequence (Rishmawi and Prince, 2016). Trends in the residuals indicate deviations of NDVI from the NDVI-rainfall relationship and express land improvements or degradations greater than those that can be explained by rainfall alone. Thus, such changes are a potential effect of human activities. Several studies have tested the RESTREND method to identify potential changes in ecosystem conditions over Africa (Dardel et al., 2014a; Huber et al., 2011; Ibrahim et al., 2015; Kaptué Tchuenté et al., 2015; Wessels et al., 2007). However, an important but often ignored conceptual limitation of using the RESTREND method is that the biophysical relationship between NDVI-based vegetation productivity and rainfall is supposed to be constant over the time. Yet, Hein et al. (2011) showed that in the Sahelian semi-arid areas, this relationship is far from being linear. In addition, RESTREND will not be able to account for other processes, such as changes in Water Use Efficiency induced by increases in CO_2 that also have impacts on vegetation productivity (Donohue et al., 2013). Finally, in addition to the use of NDVI trends to understand vegetation dynamics, new opportunities are appearing in the understanding of vegetation dynamics in drylands by jointly using NDVI and Vegetation Optical Depth (VOD) trends, as attested by Andela et al. (2013) and more recently by Tian et al. (2016) in the Sahel. In particular, it has been shown that

NDVI is more sensitive to herbaceous vegetation, while VOD can be used as a proxy for woody vegetation (Andela et al., 2013).

Due to the scarcity of reliable long-term ground observations to validate and interpret the low-resolution vegetation index trends, analyses of the underlying processes other than climate are rare. Dardel et al. (2014b) related GIMMS-3g NDVI trends with *in situ* observations of aboveground herbaceous biomass over the Fakara region in Niger and Gourma region in Mali and found a good agreement between the two datasets. By relating these vegetation trends to ground observations, the authors concluded that soil types and soil depth significantly impacted biomass production in Gourma, while no clear pattern could be found for the Fakara site. In Senegal, based on ground-based biomass estimation and a botanical inventory of woody vegetation species, Brandt et al. (2015) assumed that the greening trends come from an increase in tree density.

Meanwhile, in line with the emergence of “Land Change Science” (Verburg et al., 2013a) aims at understanding the land system change as resulting from dynamic interplay of the sociological and ecological systems, a myriad of research on Land Use/Land Cover changes (LULCC) and their related drivers has been undertaken in Africa (e.g., Brinkmann et al., 2012; Estes et al., 2012; Kindu et al., 2015; Nutini et al., 2013; Pricope et al., 2013; Teferi et al., 2013). These studies make use of different sources of data such as LULCC maps derived from remote sensing data, statistics, surveys or other geospatial data related to accessibility, biophysical or demographic factors (Brinkmann et al., 2012; Kindu et al., 2015; Mutoko et al., 2014; Teferi et al., 2013). While it is acknowledged in the literature that land system changes result from changes occurring in biophysical, social and economic systems across various spatial and temporal scales (van Asselen and Verburg, 2013; Verburg et al., 2013b), the incorporation of long-term vegetation trends observed at regional scale as a way to characterize LULCC has rarely been made in LULCC studies (e.g. Nutini et al., 2013).

2. Objectives and overall approach

In line with previous studies on the driving forces of vegetation changes in the Sahel, the overall aim of this study was to gain a better understanding of the factors involved in biomass production dynamics (using NDVI as a proxy) between 2000 and 2015, on both a regional (western Sahel) and local (degree square in southwestern Niger) levels, using a combination of remote sensing and various existing geospatial datasets. The specific objectives of this paper are to:

(1) Identify areas of significant recent monotonic NDVI trends in the western Sahel zone.
(2) Further specify the relative role of rainfall and human factors in NDVI changes on a regional level.
(3) Further explore the importance of various types of potential climatic- and LULCC-related drivers of NDVI changes on a local level.

Few analyses have been conducted combining regional and local approaches to disentangle the main drivers of biomass production trends at the level of the Sahel. Among them, we can mention the recent study of Brandt et al. (2016), which aimed to assess and understand the woody vegetation trends over the Sahelian belt. Here, we proposed an analysis of biomass production trends on a regional level based on NDVI data together with a more detailed analysis on a local level of the underlying processes by relating vegetation trends with rainfall and the related drivers of LULCC. However, while the Brandt et al. (2016) study focused on the woody vegetation cover during the dry season, the present study focuses on the green herbaceous layer and provides a more extensive analysis at the local level.
Figure 1 presents the overall approach developed in this study. We have first analyzed the biomass production trends over a 16-year period (2000–2015) in the western Sahel using growing season integrated NDVI (MOD13Q1 collection 6) time series (iNDVI; Figure 1-1). Then, to assess the role of rainfall and human factors, a classification scheme based on (i) the iNDVI trends, (ii) the correlation between iNDVI and growing season rainfall (iRAIN; hereafter merely referred as rainfall) derived from the TRMM3B43 product, and (iii) the iNDVI residual trend was proposed (Figure 1-2). While it is acknowledged that vegetation productivity may be affected by climate variables other than rainfall, over the Sahel, growing season rainfall, however, remains the primary factor as recently evidenced in Rishmawi et al. (2016) among others. Thus, we chose to restrict our analysis to the study of the relationship between NDVI and growing season rainfall alone. After the main drivers of iNDVI trends were identified over the western Sahel, we conducted a local analysis over a southwestern Niger site to

explain the observed iNDVI trends through detailed environmental (rainfall, topography and soil), human (demography, physical accessibility), and land cover change variable analysis using the Random Forest (Breiman, 2001) algorithm.

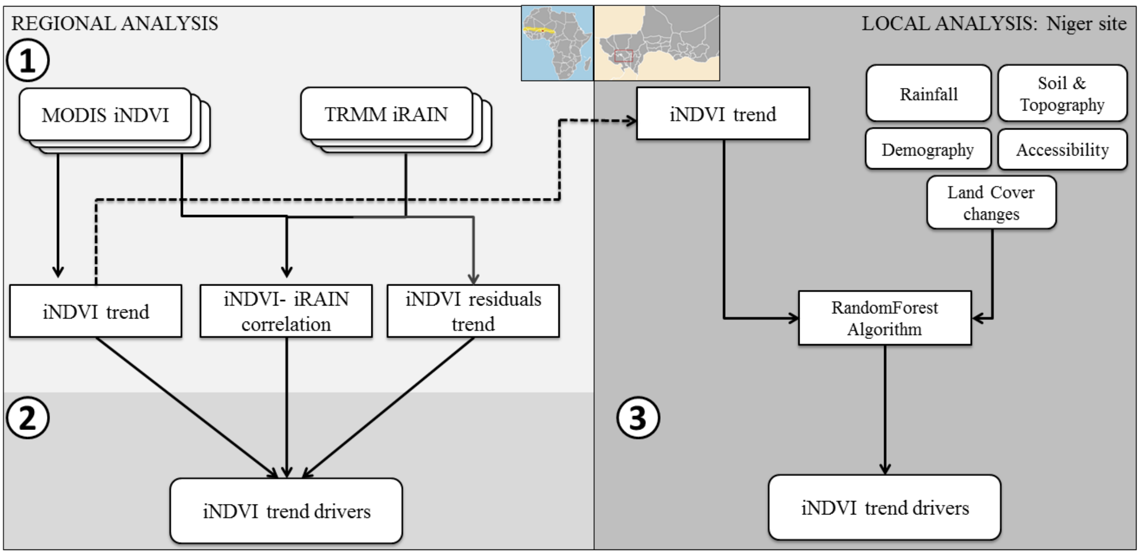


Figure 1. Flowchart of the approach adopted in the study: links between the regional and local analyses. The first part (labeled ①) corresponds to the first objective of the study, which is the iNDVI trend analysis over the western Sahel. The second part (labelled ②) corresponds to the second objective: the identification of the main drivers of iNDVI trends over the western Sahel. The third part (labelled ③) corresponds to the identification of the main drivers of iNDVI trends over the Niger site.

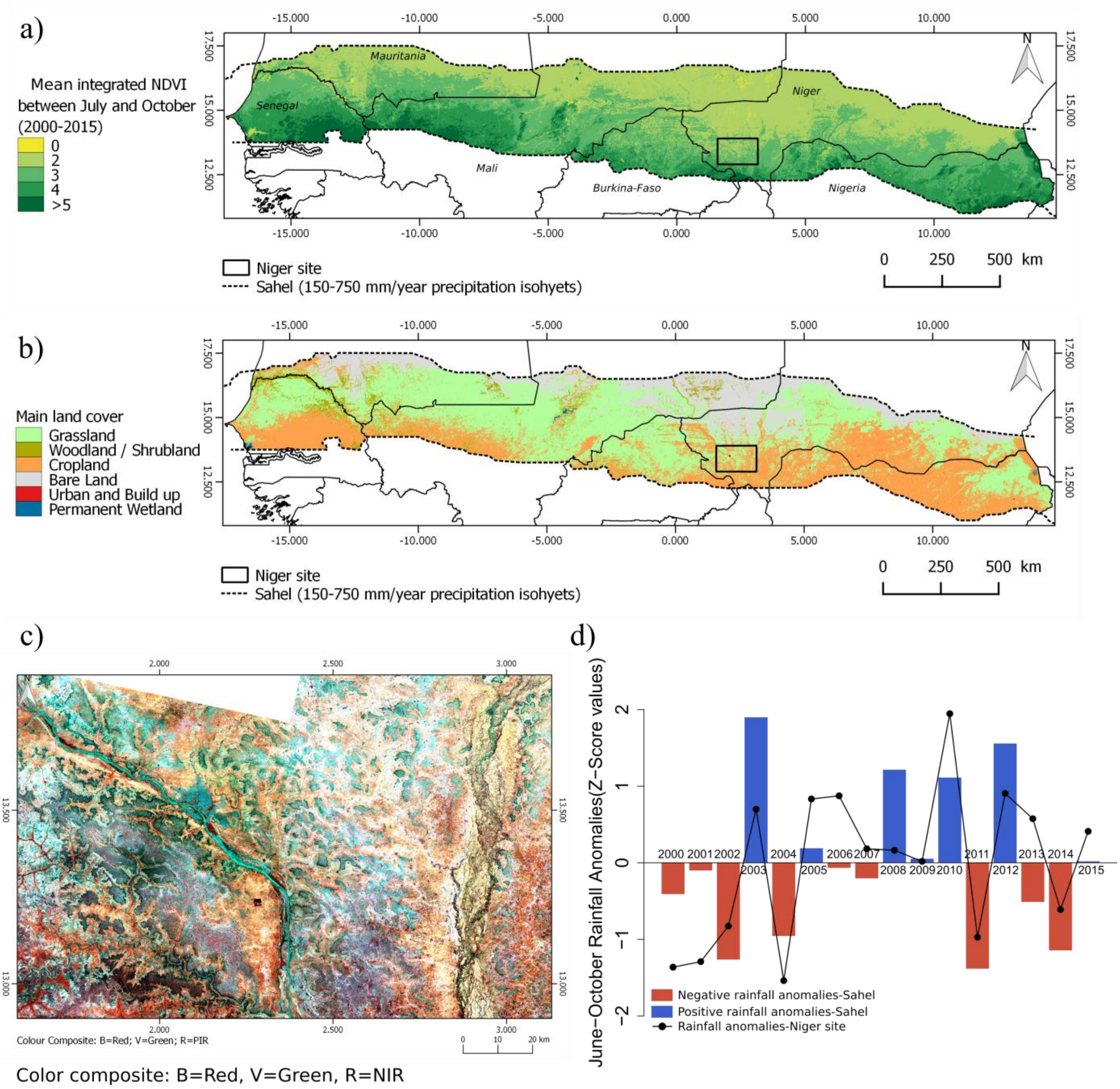
3. Study site and material

3.1. Study site

We focused our study on two spatial levels: the regional level, the western Sahel zone, which is defined as the area receiving an annual rainfall ranging from 150 to 750 mm/year, and the local level, southwestern Niger (Figure 2).

The western Sahel is characterized by marked seasonality with a long dry season and a short wet season lasting from 1–4 months depending on the latitude. The climate is mainly controlled by the timing, amount, and distribution of rainfall by the progression of the Intertropical Convergence Zone during the well-known West African Monsoon (Lebel and Ali, 2009). Consequently, the vegetation pattern over the Western Sahel area closely follows the rainfall gradient: the northern parts of the western Sahel are dominated by sparse vegetation cover (open sparse grassland and shrubland), and the land is used primarily for grazing, while the southern parts are characterized by a larger amount of vegetation cover with woodland and savanna. Rainfed agriculture and grazing are the main land uses observed in the area (Tucker, 1985). Over the whole western Sahel area, the climatic constraint (i.e., annual rainfall and its spatio-temporal variability) is considered as the most important controlling ecosystem driver.

At the local level, we focused on an agropastoral site located in southwestern Niger (12.9°-13.6°N; 1.6°-3.1°N), namely, the “Degré Carré de Niamey” (hereafter referred to as the DCN site), which covers an area of approximately 18,000 km^2. Niger was chosen as a study site because it appears as “a Sahelian exception.” While, overall, greening has been observed over the western Sahel, southwestern Niger has been marked by significant browning trends despite an increase in rainfall (e.g., Anyamba et al., 2014; Dardel et al., 2014b; Fensholt and Rasmussen, 2011a). In addition, between 2000 and 2015, Niger has suffered six major food crises. Thus, a better understanding of the role played by the underlying drivers of biomass productivity changes is essential for such a country for managing food security over the long term. The climate over the DCN site is typically Sahelian and is marked by a high latitudinal gradient with an average annual rainfall ranging from 480 to 630 mm/year despite the area's narrow ranges in latitude and longitude (about 160 km x 110 km). According to D’Herbès and Valentin (1997), the vegetation cover is highly fragmented and composed of three main units: tiger bush on the lateritic plateaus, fallow savanna, and crop fields on the sandy soils. The agricultural production system is dominated by rainfed pearl millet. The area is particularly vulnerable to climate variability because of its strong dependence on rainfall for both livestock and farming. In addition, because of rural population increases in recent decades, most of the arable land is already under cultivation (Hiernaux et al., 2009).



Color composite: B=Red, V=Green, R=NIR

Figure 2. The study sites. a) Mean integrated NDVI between July and October over the western Sahel zone; b) Main land cover classes (MODIS Land Cover Product, MCD12Q1), c) Landsat 8 image of the DCN site in September 2013 (red-green-NIR color composition), and d) anomalies of cumulated rainfall between June and October (deviation from the mean values over the 2000–2015 period) from the TRMM3B43 product over the western Sahel (bar) and the DCN site (line).

3.2. Data sources and pre-processing

3.2.1. MODIS NDVI 16-day composite collection 6 data

A set of 16-day images of NDVI from the new MODIS products available at 250 m (MOD13Q1 collection 6; Didan, 2015) was downloaded. The images cover a period from 2000 to 2015 over the western Sahel zone. These images were used to analyze the NDVI trends as a proxy for biomass productivity changes. The MODIS product is corrected for atmospheric effects, including cirrus clouds and aerosols (Vermote et al., 2002) and preprocessed with the CV-MVC (Constrained View angle-Maximum Value Composites) algorithm to retain the best observations during each 16-day period using pre-composited (8-day) surface reflectance data (Didan, 2015). However, in areas with a marked rainy season such as the Sahel, residual noise can still be present due to remnant cloud cover, which tends to decrease NDVI values. Thus, in addition to the abovementioned preprocessing, a Savitzky-Golay filter was applied to reduce the noise in the NDVI time series(Chen et al., 2004) which allowed matching the upper envelope of the NDVI time series. Finally, the temporal resolution of the NDVI time series was reduced by cumulating the 16-day NDVI values on an annual basis to focus on vegetation growth and avoid noise related to non-vegetated areas or soil moisture contamination. Several methods have been proposed to compute “annual” NDVI values (e.g., Mbow et al., 2013) including NDVI annual sum (Brandt et al., 2015; Nicholson et al., 1998), the maximum growing season NDVI values (Eklundh and Olsson, 2003; Hickler et al., 2005) and the NDVI cumulated over the growing season after removing the dry season NDVI values (Anyamba and Tucker, 2005; Dardel et al., 2014a; Fensholt and Rasmussen, 2011; Tian et al., 2016). To minimize the potential impacts of woody cover (particularly evergreen species) on the NDVI trend analysis (Brandt et al., 2015; Mbow et al., 2013), we restrict our analysis to the annual herbaceous growth season (both rangelands and croplands dominant in the Sahel; including also deciduous trees and shrubs). Thus, NDVI was integrated over the growing season (iNDVI), which takes place in the Sahel between July and October (Anyamba et al., 2014; Anyamba and Tucker, 2005; Dardel et al., 2014a; Fensholt and Rasmussen, 2011; Huber et al., 2011).

3.2.2. TRMM3B43 rainfall data

In the absence of a dense rain gauge network in the study area, a satellite rainfall estimation product was used in this study as a proxy for rainfall (Herrmann et al., 2005), namely, the merged TRMM (Tropical Rainfall Measuring Mission) 3B43v7 dataset, which delivers rainfall estimates at monthly intervals and with 25 km spatial resolution. It combines infrared and microwave information from different sources and is calibrated with monthly rain gauge data to adjust for bias (Huffman et al., 2007). The TRMM data were downloaded from 2000 to 2015 and cumulated over 5 months (iRAIN, June-October) to take the time lag between rainfall and vegetative response into account (Fensholt and Rasmussen, 2011; Helldén and Tottrup, 2008). To allow the comparison between iNDVI and iRAIN, the nearest neighbor resampling method was applied to the TRMM3B43 data to match the spatial resolution of the MODIS NDVI data.

3.2.3. Other geospatial data

As mentioned in the introduction, apart from the climate factors, land use and land cover changes (LULCC) are also considered as change factors in biomass productivity at the local scale. Thus, based on a literature analysis regarding the main drivers of LULCC changes in semi-arid areas (e.g., Brinkmann et al., 2012; Lambin et al., 2001; Teferi et al., 2013) and the availability of data, a set of nine variables was selected that covered three categories (Table 1): (1) natural constraints (slope, toposequence, and type of soil), (2) accessibility (Euclidean distances from roads, rivers, and villages, and traveling time to market), and (3) demography (mean population density for the 2000–2015 period and the change in population density between 2000 and 2015). Among natural constraints, slope is a determinant of soil erosion because it leads to soil fertility loss and chemical soil degradation (e.g., Okou et al., 2016), which, in turn, has an impact on vegetation growth. Slope and toposequence together act as a constraint for land management for cropland expansion in particular, because gentle slopes and low elevations are generally more suitable for agricultural activities (e.g., Teferi et al., 2013; van Asselen and Verburg, 2012). Lastly, soil type is recognized as one of the most important factors for vegetation growth and crop production due to nutrient availability, water retention capability or root conditions. Thus, soil type determines the probability of agricultural use.

All the variables related to accessibility are considered as drivers of agricultural expansion or intensification, with (1) transportation cost and physical accessibility to a piece of parcel (distance from roads), (2) suitability of land for agricultural use through water availability (distance from rivers), and (3) proximities of farms to markets, which determine the availability of farming inputs and the possibility of selling harvest products (distance from a city and travelling time to market; e.g., Brinkmann et al., 2012; Geist and Lambin, 2002, 2004; van Asselen and Verburg, 2012). Lastly, population density and changes in population density can be considered as proxies for potential pressures on natural resources induced by a growing need to increase food production or fuelwood (e.g., Geist and Lambin, 2002; Kindu et al., 2015; Lambin et al., 2001).

In addition to these variables, two climatic variables were also considered: trends in rainfall between 2000–2015 growing periods and mean rainfall for the 2000–2015 growing periods. These variables can have a direct impact on biomass productivity because they determine the type and the development of natural and cropped vegetation. They can give rise to LULCC due to a potential shift in land management (e.g., adaptation of cropping practices and strategies). When persistent changes in rainfall patterns occur (e.g., Keys and McConnell, 2005; Nutini et al., 2013; van Asselen and Verburg, 2012), changes in biomass productivity may also be the result.

Table 1. Variables used as possible drivers of biomass productivity changes over the DCN site.

Variable class	Variable name	Definition and units	Data source	Spatial resolution
Climatic	RAIN_M	Mean growing period rainfall 2000-2015 (mm/year)	TRMM3B43	25 km
	RAIN_TREND	Growing period rainfall trend (OLS) 2000-2015	TRMM3B43	25 km
Natural constraints	SLOPE	Slope (degree)	SRTM DEM 30+	30 m
	TOPO	Toposequence	SRTM DEM 30+	
	SOIL	Type of soil	Harmonized World Soil Database-IIASA [1]	1 km
Accessibility	DIST_RIV	Euclidean distance from river (meters)	SRTM DEM 30+	vector
	DIST_CIT	Euclidean distance from villages with more than 1000 habitants (meters)	National Institute of Statistics, Niger	vector
	DIST_ROAD	Euclidean distance from road (meters)	GIST Portal [2]	vector
	MARKET	Traveling time from city market with a population > 20,000 (hours)	HarvestChoice [3]	1 km
Demography	POP_DENS	Mean population density for the 2000-2015 period	AfriPop[4]	1 km
	POP_DIFF	Population density difference between 2000 and 2015	AfriPop[4]	1 km
Land Cover Changes	LAND_COV	Land Cover Changes between 2001 and 2013 (10 classes)	Landsat 5 and Landsat 8	30 m

[1] http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/
[2] https://gistdata.itos.uga.edu/
[3] http://harvestchoice.org/data/tt_20k
[4] http://www.worldpop.org.uk/

Finally, a map of land cover change between 2001 and 2013 was used to analyze the hypothetical link between the iNDVI trends and the land cover change types. Classes of land cover change acquired from this map were also considered as a possible direct explanatory variable of biomass productivity changes (Figure 3). The land cover change map was obtained by using a post-classification comparison approach of two land cover classifications derived from Landsat images. The images were classified using a supervised object-based expert classification, and the resulting land cover maps (2001 and 2013) were validated against a set of 1200 independent validation objects randomly selected over the DCN site. The observed land cover classes of each object were manually labelled through visual interpretations of Google Earth® high resolution satellite images and Landsat images for each date. An overall accuracy of 88% for 2001 and 82% for 2013 was obtained assuming that the validation dataset obtained by photo interpretations was free of error. The resulting land cover change map was composed of six land cover classes characterized by no change between 2001 and 2013 (plateaus, waterbodies, cropland—both fallow and grassland—degraded hillslopes, bare soil and natural vegetation) and three classes characterized by changes: areas of cropland loss (cropland in 2001 and degraded hillslopes, bare soil or natural vegetation in 2013), areas with natural vegetation expansion (degraded hillslopes or bare soil in 2001 but natural vegetation in 2013), and areas of cropland expansion (degraded hillslopes, bare soils or natural vegetation in 2001 and cropland in 2013).

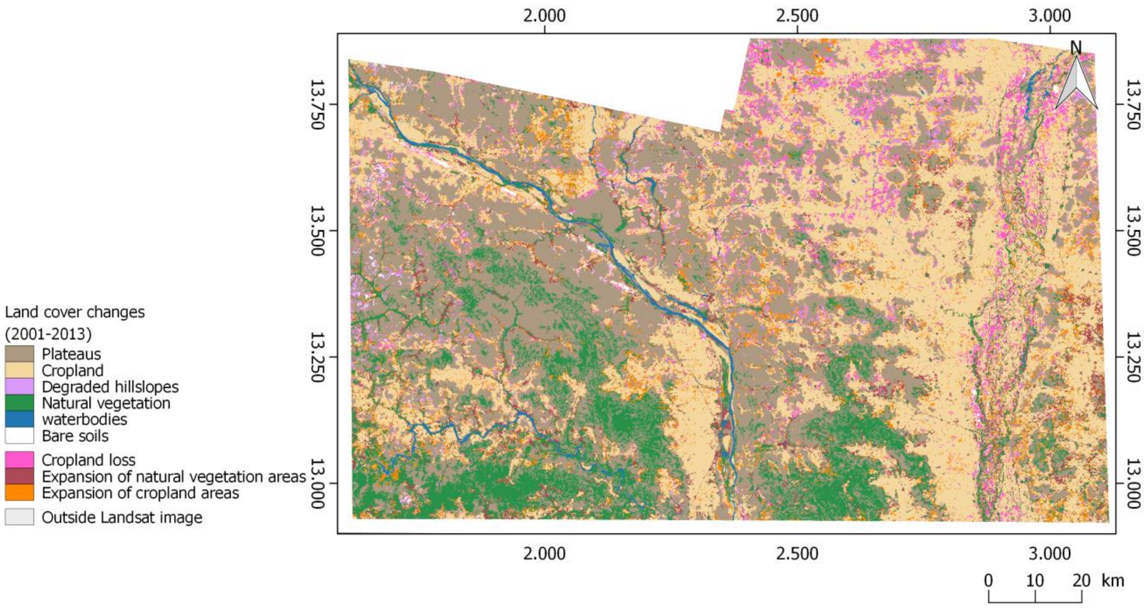


Figure 3. Map of the land cover changes over the DCN site between 2001 and 2013 derived from Landsat images.

4. Methods

4.1. NDVI trends

To investigate the NDVI changes, pixel-wise temporal trends (iNDVI) were computed over the western Sahel zone during the 2000-2015 period using an Ordinary Least Squares (OLS) regression. OLS is considered as a simple but robust way to detect long-term trends in NDVI time series (e.g., Anyamba et al., 2014; Helldén and Tottrup, 2008; Ibrahim et al., 2015). OLS measures the relationship between the iNDVI as a dependent variable and time (i.e., in the present case 16 years) as an independent variable and is represented by the following equation:

Linear model $$\mathrm{iNDVI} = \alpha + \beta \mathrm{Time} \quad (1)$$

where α is the y-intercept, which gives iNDVI values at the start of the observed period, and β is the slope coefficient, which measures the rate of change of iNDVI per unit of Time.

By using Ordinary Least Squares regression as a means to measure change in iNDVI, we assumed in this study that changes in biomass productivity occur as gradual and linear processes through time. However, this approach cannot detect abrupt breaks in the time series and will necessarily obscure the existence of short-term trends as previously mentioned by Jamali et al. (2014).

To examine the consistency of trends over time, the p-values of two-sided Student's t-tests were computed for the slope coefficients (β). While it has recently been suggested by Colquhoun (2014) to consider at least a p-value < 0.001 to make conclusions concerning the significance of obtained results, to be consistent with most of studies on NDVI trend analysis, all trends at the 95% confidence level (p-value<0.05) or higher were considered statistically significant (i.e., null hypothesis $H0: \beta = 0$). Nonetheless, different classes of significance ($0.01<$p-value<0.05, $0.001<$p-value<0.01 and p-value<0.001) are also presented. The direction of change (an increase or decrease in biomass production) was determined by analyzing the sign of the slope coefficient.

4.2. Drivers of NDVI trends at the regional level

4.2.1. NDVI-rainfall correlation

In semi-arid areas such as in the Sahel, the biomass production, and thus NDVI, is known to be highly dependent on rainfall, both the inter-annual rainfall variability as well as the timing and intra-seasonnal distribution of rainfall events. Since annual rainfall is usually considered as the main driver of biomass production, we focused this study only on the growing season rainfall. The pixel-wise Pearson correlation coefficient (r) between iNDVI (July–October NDVI) and iRAIN (June–October RAIN) over the 2000–2015 period was calculated for each pixel to evaluate the nature and strength of the NDVI-rainfall relationship. The iNDVI-iRAIN relationship was considered statistically significant at the 95% level (p-value<0.05, corresponding to r =0.49). The predicted values of iNDVI for each year and each pixel from the observed iRAIN were then computed.

4.2.2. Residual NDVI trends (RESTREND)

Because biomass production is greatly controlled by inter-annual rainfall variability in semi-arid environments, the trends in iNDVI contain a significant rainfall signal. As suggested by Evans and Geerken (2004), to distinguish rainfall-induced changes from changes induced by other factors, the rainfall component must be removed from the iNDVI signal. To isolate the iNDVI trends not explained by rainfall, we computed the pixel-wise iNDVI residuals (RESTREND; Wessels et al., 2007)—the difference between the observed iNDVI and the predicted iNDVI. However, while it has been suggested that RESTREND is a useful method for detecting vegetation changes independent of rainfall (e.g. Wessels et al., 2007), it is not without inherent limitations and its validity is subjected to several requirements owing to its dependence to RUE, as recently discussed in Rishmawi and Prince (2016). Particularly, the use of RESTREND is relevant only in cases where significant linear relationships between iNDVI and iRAIN are observed (Fensholt et al., 2013; Fensholt and Rasmussen, 2011; Wessels et al., 2012). For cases with high levels of changes, the relationship between iNDVI and iRAIN sometimes becomes weak, thus making the RESTREND method unreliable (Wessels et al., 2012). In the present study, pixels with no significant vegetation productivity to rainfall correlation (r<0.49) were excluded from the residual analysis. Any trend in the iNDVI residuals could then be interpreted as a change in biomass production independent of growing seasonal rainfall, assuming other causative factors such as land cover or land use changes. Trends in the iNDVI residuals were computed following the approach used for the iNDVI and assuming that the MODIS NDVI and TRMM3B43 measurements were error-free thus not affecting the significance of the RESTREND regression line. However, if rainfall data are accompanied by a measure of errors, a correction can be applied in the process to test the significance of RESTREND values as in Rishmawi and Prince (2016).

4.2.3. Mapping the main drivers of NDVI trends over the Sahel

The conceptual approach developed in this study relies on the fact that biomass productivity dynamics (using iNDVI trends as a proxy) on a per-pixel basis result mainly from interactions with climate (i.e. rainfall) and human factors. Thus, we postulated that if we could isolate the climatic factors from the human factors, the relative roles of both factors in NDVI trends could be assessed and mapped.

While most studies isolate rainfall-driven biomass production changes from changes induced by human factors (hereafter referred to as "other factors") using either RUE or RESTREND analyses (e.g. Evans and Geerken, 2004; Ibrahim et al., 2015; Prince et al., 2007; Wessels et al., 2007), this study proposes a classification scheme to assign relative roles to rainfall and other causative factors in NDVI changes.

This classification scheme results in a set of 6 possible decision rules based on the slope of the iNDVI trend, the iNDVI-iRAIN coefficient of correlation and the slope of the iNDVI residual trend (Table 2). It reflects the assumption that biomass production could be driven (i) only by rainfall, (ii) only by factors other than rainfall, or (iii) by a combination of both factors (rainfall and other factors). The combination case was not taken into account when considering the first two methods. The impact of other factors is assessed using the slope of the iNDVI trend corrected from the rainfall effect (i.e., NDVI residual trend), for which a positive trend (slope >0) means that vegetation productivity increases more than can be explained by rainfall alone, and a negative trend (slope < 0) means that vegetation productivity decreases more than can be explained by rainfall alone (Table 2). Thus, a positive iNDVI trend (i.e., an increase in biomass productivity) associated with a significant iNDVI-iRAIN correlation ($r > 0.49$) and a significant positive trend in iNDVI residual (slope > 0) indicates that the vegetation growth benefits both from rainfall and from other factors because—after removing the rainfall effect—a positive trend can still be observed in iNDVI (Table 2). In contrast, if a significant iNDVI-iRAIN correlation is observed together with an iNDVI residual negative (slope <0) or non-significant trend (p-value <0.05), the observed vegetation growth is due mainly to the rainfall factor. Finally, when there is no iNDVI-iRAIN correlation, it means that vegetation growth benefits only from factors other than rainfall (Table 2). The same reasoning is followed to interpret a negative iNDVI trend.

The results of the iNDVI trends main drivers' map over the Sahel are then illustrated through different case studies extracted from the literature.

Table 2. Classification rules to disentangle rainfall-driven NDVI changes from changes induced by other factors.

iNDVI trend (p-value<0.05)	Coefficient of correlation iNDVI-iRAIN	iNDVI residual trend (p-value<0.05)	Interpretation of the iNDVI trend
Positive iNDVI trend (slope>0)	r>0.49	Slope>0	Rainfall factor and other factors
	r>0.49	Slope<0 or Slope (p-value>0.05)	Rainfall factor
	r<0.49		Other factors
Negative iNDVI trend (slope <0)	r>0.49	Slope<0	Rainfall factor and other factors
	r>0.49	Slope>0 or Slope (p-value>0.05)	Rainfall factor
	r<0.49		Other factors

4.3. Drivers of NDVI trends over the DCN site

To extend the analysis of the underlying factors of the iNDVI trends, a Random Forest algorithm (RF) was used to classify and identify the most important factors at the local level. To accomplish this, the previous two classes (i.e., "rainfall factor" and "other factor" used at the regional level) were disaggregated into 14 potential drivers and used as explanatory variables in RF (Table 1), while iNDVI trend classes (negative, positive, or no significant trends) were treated as the variables to be explained. RF is an ensemble learning method based on bagging (repeated selecting of random sampling with replacement) and used for classification. It combines large numbers of classification trees to optimize classification accuracy (Breiman, 2001). RF fits several small classification trees based on random samples of observations and a random sample of variables. These small classification trees are then aggregated, and the resulting class is elected by a majority vote (Breiman, 2001). Here, first and foremost, we were interested in identifying the drivers with the most important contributions in distinguishing the different iNDVI trend classes. Thus, we benefited from the capacity of RF to determine variable importance in a classification process using the RF internal variable importance measures. In the present study, we focused on the mean decrease in accuracy. The mean decrease in accuracy consists of a random permutation of explanatory variables in the construction of the classification trees. It then measures the difference in the accuracy (named Out-Of-the-Bag error and computed internally on the samples not used during tree construction) before and after the switching process (Cutler et al., 2007). Thus, in our case study, the larger the decrease in accuracy is, the higher the importance of the drivers is in explaining iNDVI trends. In this study, the RF algorithm was implemented using the RandomForest package available in R (Liaw and Wiener, 2002).

5. Results

5.1. NDVI trends analysis

We found that 79% of the pixels of the western Sahel zone are characterized by no significant iNDVI trend (Table 3; Figure 4a) and that most of the significant trends were positive (16%). Among these, 20% were highly significant (p-value < 0.001; Table 4; Figure 4a). When analyzing the spatial pattern of the iNDVI trends (Figure 4a), we observed that the changes in iNDVI across the western Sahel zone are spatially heterogeneous. The iNDVI trends were positive over the western Sahel (mainly in Mali, Mauritania and Burkina Faso, < 2°W) while the eastern part of the western Sahel (> 0°, mainly Niger and Nigeria) is predominantly characterized by a strong reduction in iNDVI over the period 2000–2015 (p-value< 0.001 or p-value <0.01; Table 4). This spatial distribution of iNDVI trends appears to be the result of a recent process because it is generally observed only in studies conducted from approximately 2011 or later (e.g., Dardel et al., 2014b) and not in older studies (those conducted before 2007) (e.g., Herrmann et al., 2005; Huber et al., 2011). It is also in agreement with a study (Brandt et al., 2016) that covers the same period (2000–2014) but focuses on woody vegetation land cover changes. When analyzing the DCN site level, the spatial distribution of trends differed from those at the western Sahel level (Figure 5a; Table 3). While the western Sahel zone exhibits mainly linear positive trends (i.e., a greening trend), the distribution of linear trends was reversed for the DCN site, where negative linear trends accounted for 29% of the study area. Among these, 31% were highly significant (p-value < 0.001; Table 4; Figure 6a) meaning that the last 16 years (2000–2015) have been marked by a reduction in biomass productivity (i.e., a “browning” trend).

Table 3. Distribution of the iNDVI and iNDVI Residual trends (p-value < 0.05) over the western Sahel region and the DCN site obtained using MODIS NDVI and TRMM3B43 time series images between 2000 and 2015.

		Trend types (p-value < 0.05)		
		Linear Negative	*Linear Positive*	*No trend*
western Sahel	*NDVI trend (%)*	5	16	79
	*Residual trend (%)**	2	13	85
DCN site	*NDVI trend (%)*	29	4	67
	*Residual trend (%)***	10	5	85

* Among the 56% of pixels with a significant NDVI-rainfall correlation over the western Sahel
** Among the 7.6% of pixels with a significant NDVI-rainfall correlation over the DCN site

Table 4. Distribution of the iNDVI trends types according to their significance level over the western Sahel region and the DCN site using MODIS NDVI time series between 2000 and 2015.

	Trend types (p-value < 0.05)					
	Linear Negative			*Linear Positive*		
	p-value<0.001	0.001<p-value<0.01	0.01<p-value<0.05	p-value<0.001	0.001<p-value<0.01	0.01<p-value<0.05
western Sahel NDVI trend (%)	20	30	50	11	29	60
DCN site NDVI trend (%)	31	32	37	14	30	57

5.2. Drivers of NDVI trends at the regional level

5.2.1. The NDVI-rainfall relationships

Slightly over half (56%) of the Sahelian belt exhibited significant iNDVI-iRAIN linear relationships, but this proportion fell to 7.6% for the DCN site. The spatial pattern of the iNDVI-iRAIN correlation showed that the area with low correlation seemed to be associated with highly significant negative changes (p-value < 0.001 and $\beta < 0$) in biomass production. This is particularly visible in Niger, as already noted by Fensholt and Rasmussen (2011) (Figure 5a and Figure 5b).

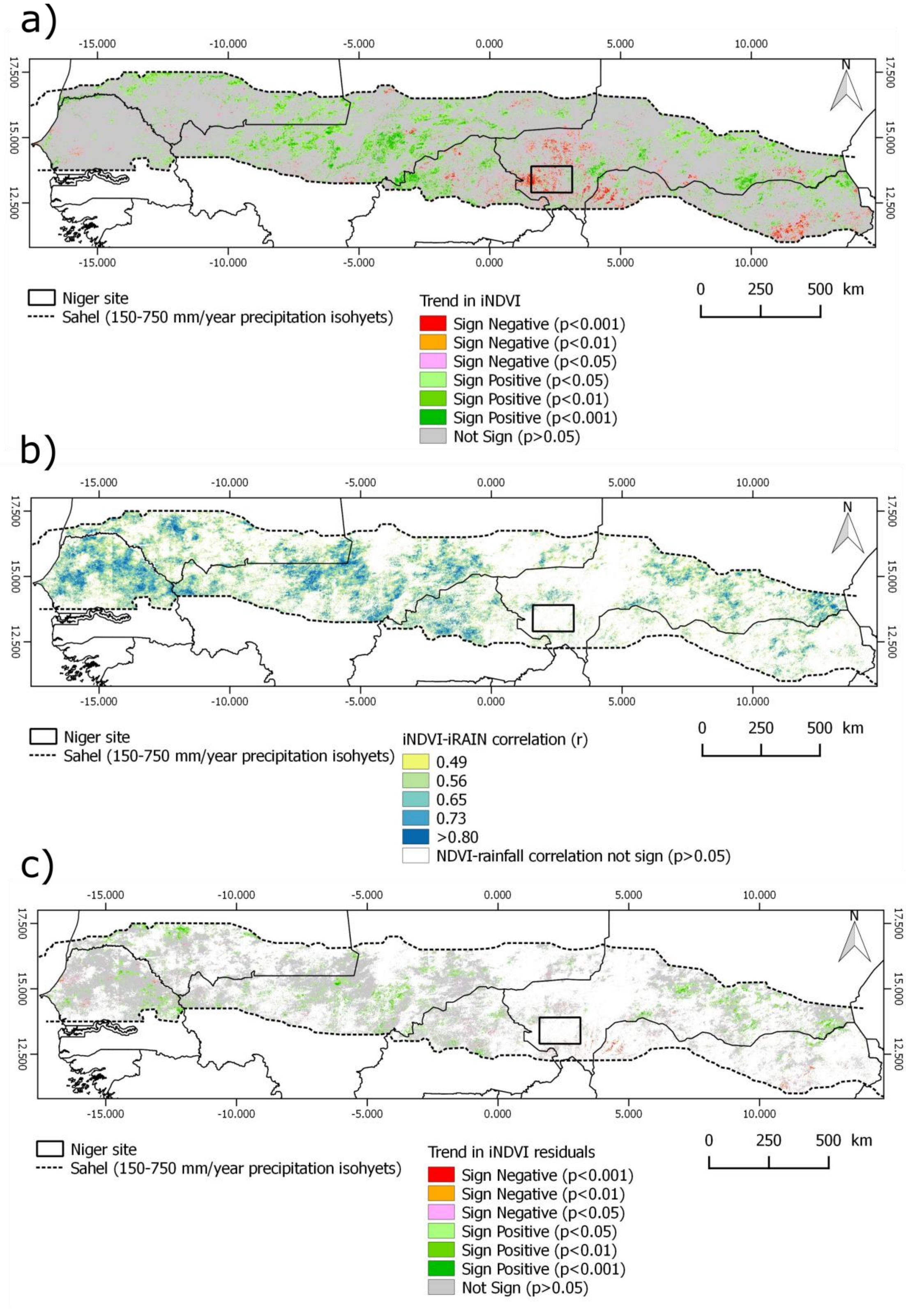


Figure 4. Spatial distribution over the western Sahel of a) the MODIS iNDVI trends; b) the correlation coefficient between MODIS iNDVI and TRMM3B43 June–October rainfall (significant at the 5% level for r=0.49); c) the iNDVI residual trends obtained for pixels with a significant linear NDVI-rainfall relationship during the 2000–2015 period.

5.2.2. NDVI residual trends analysis

For pixels marked by a significant vegetation productivity-rainfall relationship, the iNDVI residuals represent the part of herbaceous biomass production that is not fully explained by rainfall variability during the growing season. Figure 4c shows the geographical distribution of trends in the iNDVI residuals throughout the western Sahel; Figure 5c shows the same trends for the DCN site, and Table 3 lists the distribution of the trend types. Large areas without significant trends were detected (85%); however, some areas (e.g., east of Senegal or central part of Mali) displayed highly positive trends in the iNDVI residuals (13% of the residual trends). These correspond to spatially consistent areas where the herbaceous biomass production increased more than could be explained by rainfall only. When looking at the distribution of iNDVI residual trend types over the DCN site (Table 3), only 15% consisted of significant trends, of which approximately two-thirds were highly negative. Some authors have suggested that this NDVI decline trend may be due to land use or land cover changes around the city of Niamey (Anyamba et al., 2014; Kaptué Tchuenté et al., 2015), an assumption explored hereafter.

5.2.3. Mapping the main drivers of NDVI over the Sahel

The respective roles of rainfall and other factors of change in iNDVI changes were assessed following the rule sets presented in Table 2. Figure 6a shows that half the increase in biomass production over the 2000–2015 period is explained by factors other than rainfall only (52%; Figure 6b), and the other half is explained by rainfall alone or rainfall combined with other factors. The rainfall factor-driven trends occurred over a specific area: from the south of Mauritania to the north of Burkina Faso. The decrease in biomass production was mainly explained by the impacts of factors other than rainfall (88%), while the combination of both rainfall and other factors accounted for 11% of the negative iNDVI trends and could be pinpointed in the north of Nigeria. Figure 5c shows a zoomed area of the DCN site, making it clear that both increases and decreases in biomass production seemed to be mainly driven by factors other than rainfall only (90% and 98%, respectively). However, increases in biomass production occurred in only a few areas—mainly in the eastern portion of the site—while the rest of the DCN site was dominated by a degradation in vegetation conditions.

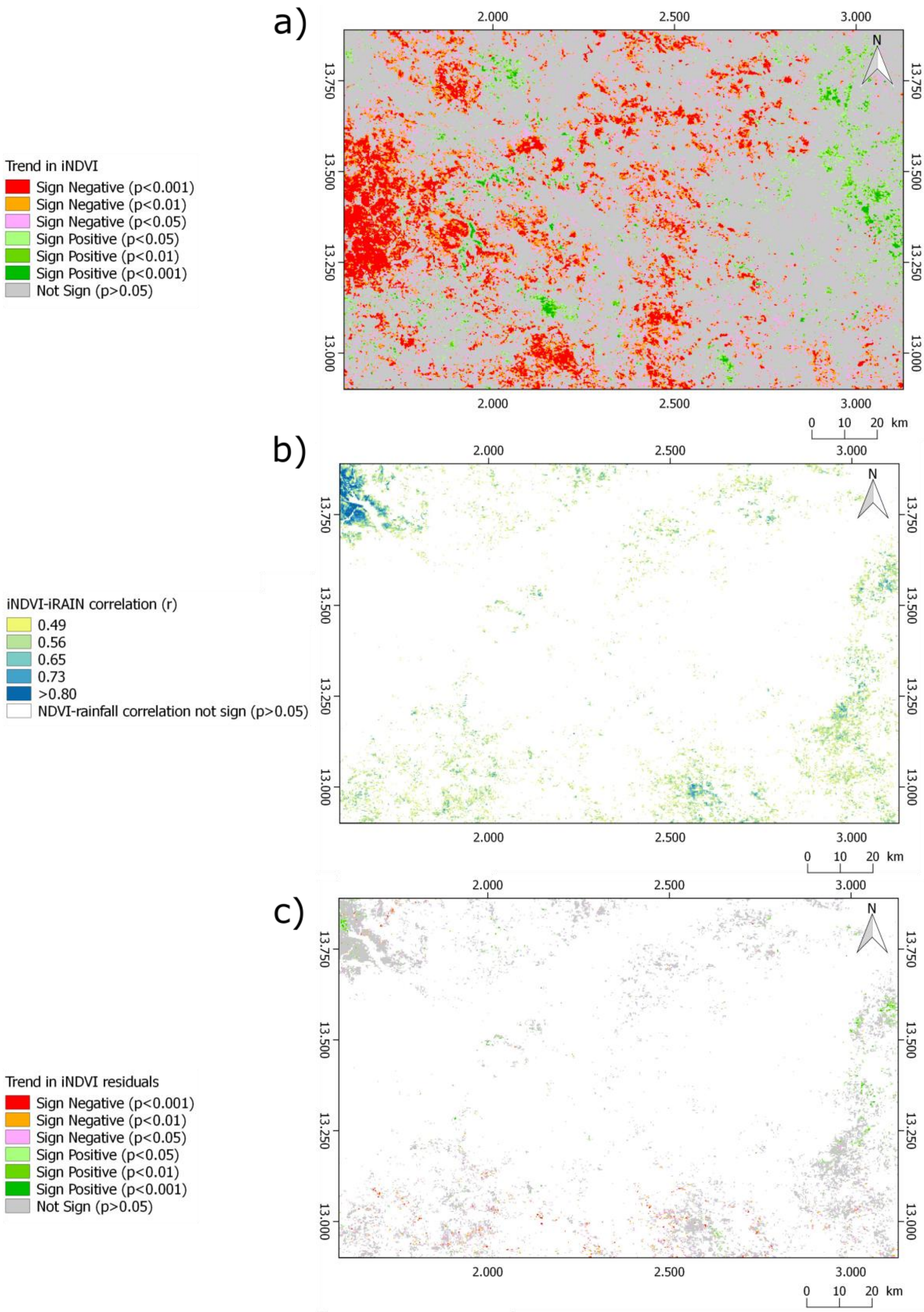


Figure 5. Spatial distribution over the DCN site of a) the MODIS iNDVI trends; b) the correlation between MODIS iNDVI and TRMM3B43 June–October rainfall (significant at the 5% level for r=0.49); and c) the iNDVI residual trends obtained for pixels with a significant NDVI-rainfall linear relationship during the 2000–2015 period.

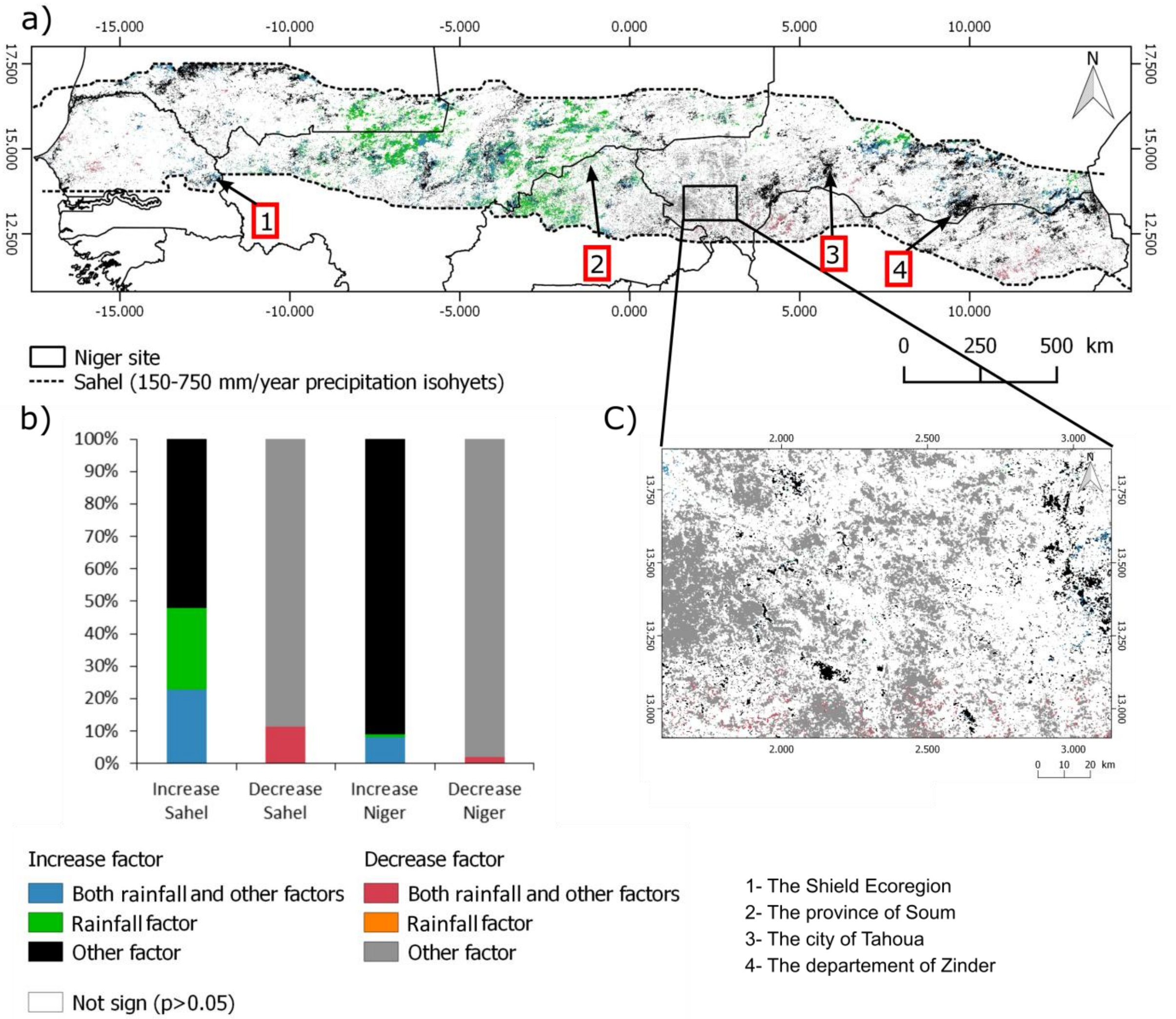


Figure 6. a) Spatial distribution of the main drivers of the biomass production changes over the western Sahel; b) distribution of driver types according to the direction of changes (increase or decrease) for western Sahel and the DCN site; and c) zoomed area of the DCN site.

5.3. Drivers of NDVI trends at the local level

As noted previously, the DCN site presented large areas of negative iNDVI trends for which rainfall did not appear to be the main driver (Figure 6c). A local analysis was conducted to explore the interpretation of potential underlying causes more deeply.

As a first overview, we analyzed the distribution of trend types on the basis of land cover changes. From Table 5, it can be observed that lateritic plateaus, degraded hillslopes, natural vegetation and, to a lesser extent, cropland loss (Figure 3) are land cover classes where a clear pattern in the distribution of trend types is particularly notable. Specifically, these classes experienced a strong decrease in biomass production between 2000 and 2015 (47% for plateaus, 38% for degraded hillslopes, 29% for natural vegetation and 25% for cropland loss). For the other types of land cover classes, no clear trend patterns were observed.

Then, a RF algorithm was employed to identify the most important drivers of iNDVI changes based on the importance variable measures provided. The importance variables were used for both the general model (i.e., for all types of trend) and for each trend class separately, allowing a specific assessment of drivers. The overall accuracy of the final RF model was estimated at 80%. Figure 7 shows the relative importance of the contribution of the five most important variables to the RF classification model generated by considering rainfall, natural constraints, accessibility, demography and land cover data. For trend types or for the overall RF model, the three most contributions are, in order of importance, the mean growing period rainfall, the distance from villages, and the type of soils. Other contributing variables are the travel time from markets and the distance of farms from rivers, except for linear negative trends for which land cover changes and topography are the most important variables, in accordance with the results shown in Table 5.

Table 5. Distribution of trend types according to land cover and land cover changes* between 2001 and 2013.

		Linear Negative (29%)	*Linear Positive (4%)*	*No trend (67%)*	*Total*
No change	**Plateaus (34.45%)**	47	2	51	*100*
	Cropland (35.40%)	14	5	81	*100*
	Degraded hillslopes (2.05%)	38	2	60	*100*
	Natural vegetation (12%)	29	6	65	*100*
Changes	**Cropland loss (3.82%)**	25	4	71	*100*
	Natural vegetation expansion (5.35%)	20	9	71	*100*
	Cropland expansion (5.13%)	21	5	74	*100*

* *Waterbodies and bare soil classes were excluded from the analysis because they represent a non-significant area (less than 1%).*

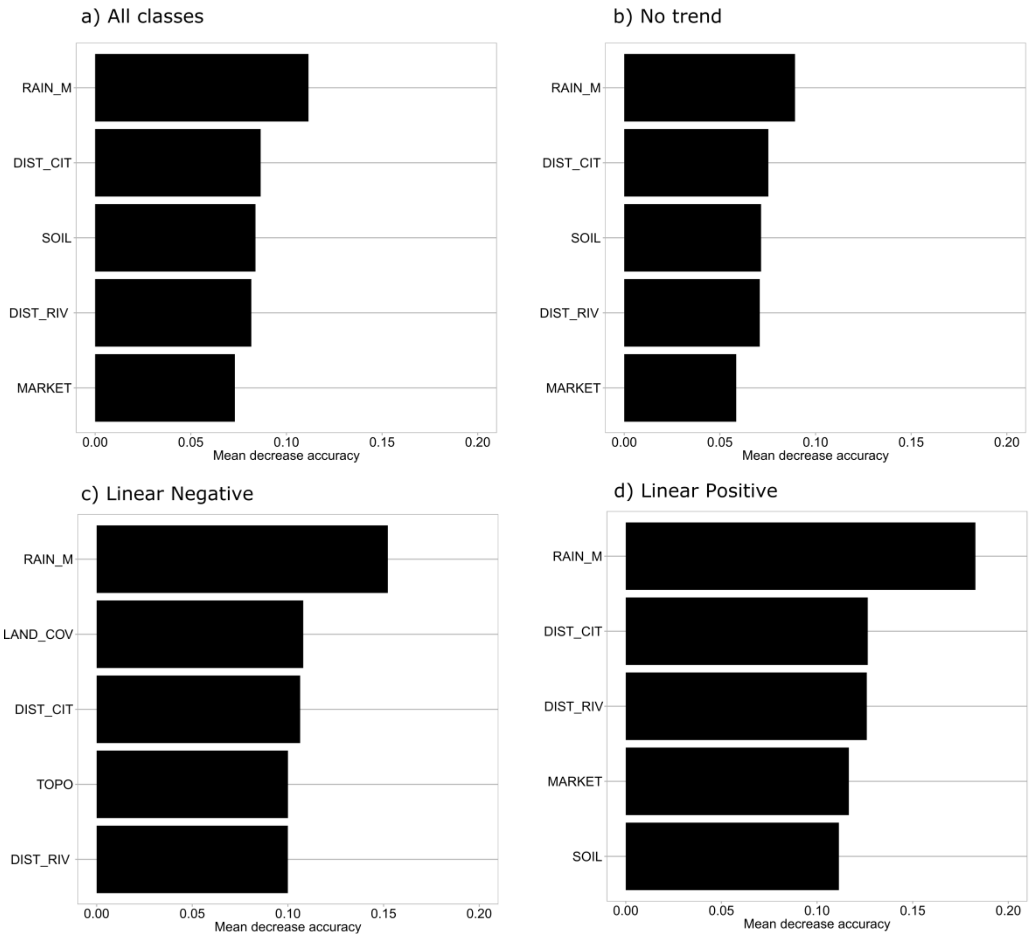


Figure 7. Importance of variables in the Random Forest model according to NDVI trend classes over the DCN site: a) all classes; b) no trend; c) linear negative trend; and d) positive linear trend. Only the first five variables are displayed. Their importance is given in the "Mean decrease in accuracy". See Table 1 for variable abbreviations.

The analysis of the distribution of trend types for the five RF most important variables (Figure 8) indicates that areas far from villages (> 6 km), from rivers (> 8 km) and from markets (> 2 h) were more prone to undergo decreases in biomass production (i.e., a linear negative trend). In contrast, the areas with increased biomass production (i.e., a linear positive trend) generally occurred around villages (<6 km) and close to rivers (< 8 km) and markets (< 2 h).

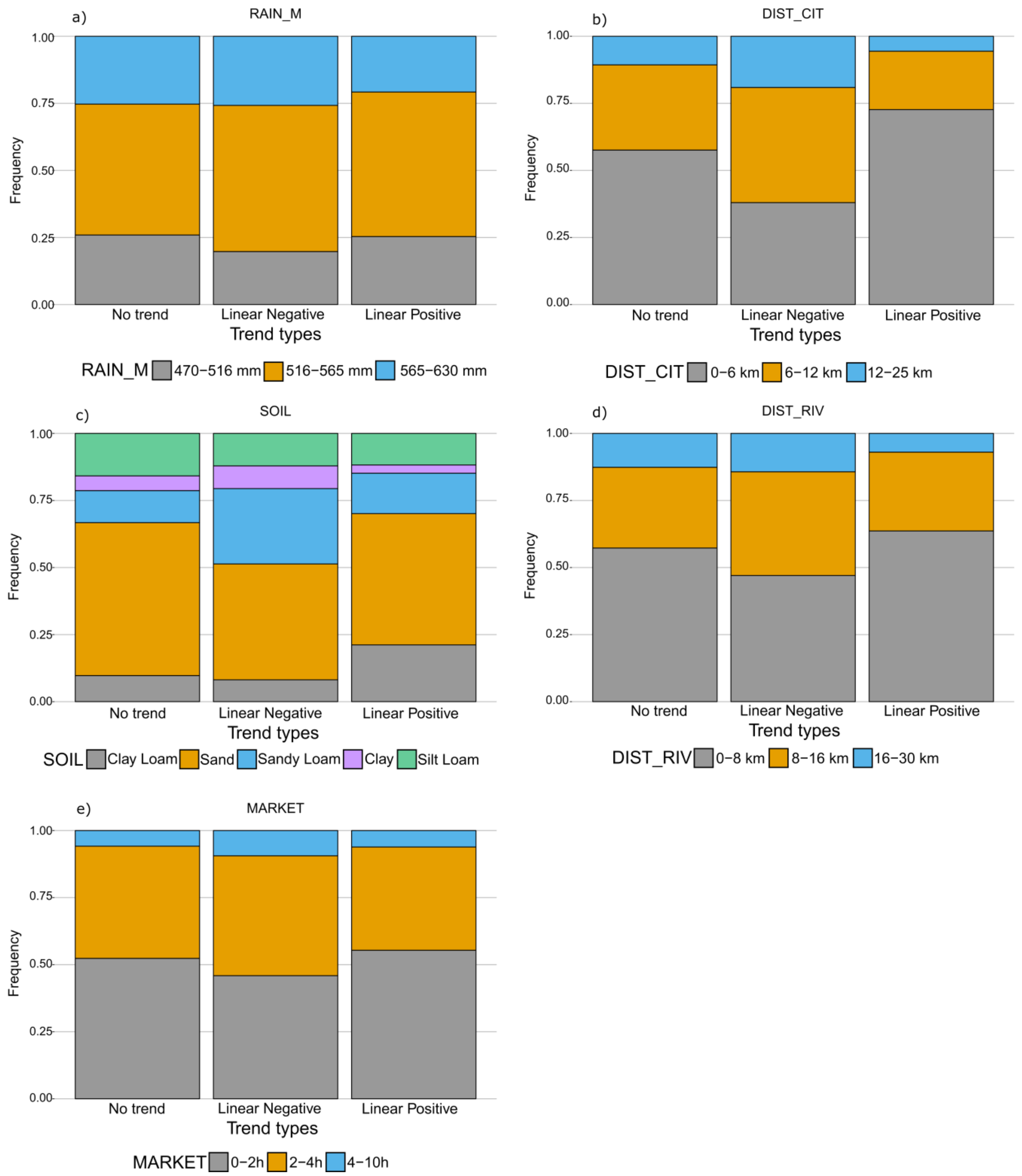


Figure 8. Distribution of trend types for the five most important Random Forest variables a) mean growing period rainfall; b) Euclidean distance from villages; c) type of soil; d) Euclidean distance from rivers; and e) travelling time from city market; for the DCN site.

6. Discussion

6.1. NDVI trends between 2000 and 2015

For the period 2000–2015, our results revealed that linear positive iNDVI trends occurred mainly in the central part of Mali or southern portion of Mauritania. These results correspond with recent greenness trends reported by Hoscilo et al. (2014), who considered the 2001–2010 period based on

SPOT-VGT NDVI time series, and with Cho et al. (2015), based on MODIS EVI acquired between 2000 and 2009. Our results also agreed with previous regional-scale findings that analyzed NDVI trends over longer time periods based on GIMMS NDVI data (Anyamba et al., 2014; Dardel et al., 2014b; Herrmann et al., 2005; Huber et al., 2011; Seaquist et al., 2009), thus verifying a longer-term process.

In contrast, hotspots of highly significant negative iNDVI trends were highlighted along the western Niger and the Niger-Nigeria border. In this area, regardless of what period is considered, what data is used, or which analysis techniques were employed, western Niger (corresponding to the Tillaberi province) has been recognized as an area of consistent degradation in biomass production since at least the beginning of the 21st century, according to the works of Boschetti et al. (2013) over the 1998–2010 period, or Hoscilo et al. (2014) over the 2001–2010 period. More generally, however, this browning trend has been observed since the 1980s (e.g., Huber et al., 2011 over the 1982–2007 period or Dardel et al., 2014b over the 1982–2011 period).

One salient point of difference between this study and previous studies concerned Senegal. This country has been considered as a hotspot of greening trends regardless of which period is considered (e.g., Brandt et al., 2014; Fensholt and Rasmussen, 2011; Huber et al., 2011), but we found mainly non-significant iNDVI trends. Based on the findings of a recent study, conducted over the same period but focusing on woody cover changes during the dry season (Brandt et al., 2016), we can assume that the generally observed greening trend in Senegal is probably more closely linked to a positive trend in vegetation productivity of long-living woody cover (evergreen species), while annual herbaceous layer (including also some deciduous trees and shrubs) has probably had inter-annual variations (i.e., no trend) as shown in our study. This assumption is supported by the studies of Brandt et al. (2015), which are based on ground-based herb biomass estimations, and of Kaptué Tchuenté et al. (2015).

6.2. Drivers of NDVI at the regional level

6.2.1. The mitigating impact of rainfall on NDVI trends

As expected, iNDVI in the Sahel was found to be correlated with iRAIN over a large part of the study area. Nevertheless, this dependence on growing season rainfall is not general, because areas of low correlation (i.e., r <0.49) were found in Niger and in northern Mali, among others. For those areas, observed changes in biomass production are due to factors other than rainfall (e.g., temperature) or human factors (e.g., LULCC) that could have a stronger influence than rainfall variability. In the northern part of the western Sahel (the arid zone), this low correlation could be explained by the very patchy distribution of vegetation as well as the low annual rainfall: both are factors that are not correctly captured by satellite sensors. For the remaining portion of the western Sahel, when considering water availability as the sole driver ignoring, for now, other potential drivers, the low iNDVI-iRAIN correlation could be explained by: (i) greater dependence of herbaceous biomass production on intra-annual rainfall distribution and its timing rather than the total amount of annual growing season rainfall or (ii) a possible water supply other than rainfall. For the latter case, for areas such as the inner Niger delta (Mali) or along the river in southwest Niger, we can assume that vegetation production is less rainfall-limited due to exogenous stream flows, as already mentioned by Huber et al. (2011). In any case, this is valid only if water availability is the single determinant of vegetation growth, which is rarely the case at local scales where vegetation growth is determined by complex interactions between multiple drivers. By focusing our study on the 2000–2015 period, we provided a new insight on the impact of rainfall on vegetation over recent years. In contrast to studies conducted over earlier periods that generally showed an overall positive NDVI-rainfall correlation (e.g., Fensholt et al., 2012; Herrmann et al., 2005), this study showed that in recent years, only 56% of the area has a significant NDVI-rainfall correlation, meaning that for a large part of the Sahelian areas, the broadly accepted predominance of annual rainfall variability on vegetation growth and dynamics is now challenged by other factors.

This is reinforced by the analysis of the NDVI residual trends that were used to detect trends in biomass production induced by factors other than rainfall such as land use changes or population pressure. Our study revealed mainly areas of positive iNDVI residual trends in the eastern part of the western Sahel (e.g., Senegal or Mali) meaning that biomass production has increased more than can be explained by rainfall. This result was also consistent with the findings of Fensholt and Rasmussen (2011), who found positive trends in the western part of the Sahel based on a RUE linear trend analysis using residual NDVI estimates (which can be considered equivalent to the RESTREND method) for the 1982–2007 period. For these areas, this suggests that iNDVI positive trends are temporally and spatially constant. The iNDVI residual trends obtained in this study were also spatially consistent with the study of Kaptué Tchuenté et al. (2015) and Ibrahim et al. (2015) who found areas of positive residual trends located mainly in Senegal and Mali over two 30-year periods (1983–2012 and 1982–2012, respectively).

6.2.2. Case study analyses of NDVI trends from the literature

A classification scheme based on iNDVI trend, the iNDVI/iRAIN correlation and iNDVI residual trend was proposed as an original contribution to the existing literature on the underlying drivers of vegetation changes over the Sahelian zone. Here, we illustrate our results in the light of available independent knowledge. Four specific sites (numbered from 1 to 4 in Figure 6a) where studies have previously been carried out were identified in the literature and used here.

In Senegal (zone 1, Figure 6a), we found some areas that were characterized by an increase in biomass production due to a combination of rainfall and other factors. In this study, these other factors were found to be dominant for biomass production increases in the western part of the Sahel. However, in some areas (close to where Senegal, Mauritania and Mali meet), rainfall and other-induced factors all played a significant role. For the Senegalese part, according to Tappan et al. (2004), this corresponds to the Shield ecoregion, which is characterized by low human population density and low environmental pressures, leading to a high degree of biodiversity for both fauna and flora. Thus, we could assume that the relatively high rainfall and the relative stability of summer rainfall since the 2000s (Funk et al., 2012) have favored the growth of woody and crop vegetation.

The second site we identified is situated in Soum province in northern Burkina Faso (zone 2, Figure 6a) for which we found a predominance of negative iNDVI trends explained by other factors. This corresponded to the area studied by Rasmussen et al. (2014), according to whom the NDVI trends observed in the northern part of their study area were closely linked to landscape elements (plateaus and slopes). They suggested that a possible explanation was a loss of woody cover, possibly induced by increased grazing.

Third, near the city of Tahoua in Niger (zone 3, Figure 6a), we found a small area of increase in biomass production due to other factors. This corresponded to the area of the “Keita Project,” which was launched in 1982 with the objective of increasing food security while combating desertification by promoting soil and water conservation, natural resource management, and reforestation (Tarchiani et al., 2008), as mentioned previously by Herrmann et al. (2005).

Finally, the region of Zinder in south Niger (zone 4, Figure 6a) also displayed a significant increase in biomass production induced by other factors. Since the late 1980s, farmers from the Zinder region have been encouraged to reforest their fields through the Farmer-Managed Natural Regeneration (FMNR) project, which concentrates on protecting and managing the regeneration of small trees and shrubs among cropped fields (Reij et al., 2009). In the mid-2000s, it was estimated that nearly 1 million ha have been affected by FMNR, with a tree density ranging between 20–120 trees/ha (Larwanou et al., 2006). Thus, by increasing the density of the woody cover, one impact of FMNR is, among others, the improvement of soil fertility through the decomposition of plant litter, added nutrient supply from animals due to the integration of livestock in cropping systems, and the conservation of nitrogen-fixing species such as *Faidherbia Albida* (Reij et al., 2009). As a consequence of this improvement in soil fertility, crop productivity increased; thus, positive iNDVI trends were observed.

Apart from these specific case studies, where possible explanations can be found in the literature, the method developed here can only help localize and identify the main drivers of biomass production dynamics. Exact causes of the observed trends must be determined by more detailed analyses at a finer scale.

6.3. Drivers of NDVI trends in the DCN site

6.3.1. Explaining the overall trends

Even though biomass production dynamics result from complex interactions between different factors, in arid environments such the western Sahel, rainfall is considered as an overriding factor. Thus, we expected that variables related to rainfall would be the most important factors of discrimination between all trend type classes. Our assumptions were verified by the RF model because overall, as well as for each of the four trend type classes, the rainfall averaged over all growing seasons, not the individual 16 years, from 2000–2015 was identified as the most important driver for the classification. This means that iNDVI trends were, above all, sensitive to the spatial distribution of rainfall (latitudinal variations probably lead to variations in vegetation types) rather than its inter-annual distribution. This is in agreement with previous studies such as Cutler et al. (2007), who stated that the most important factor selected by the RF model should correspond to our knowledge of biophysical principles. However, we can note that the other four drivers were not linked to rainfall. They included distance from villages, distance from rivers, travel time to markets and soil type. These results strengthened the idea that human activities as well as environmental conditions (potential water availability or soil fertility) are important for biomass production. This also made it possible to confirm the relevance of the approach developed on a regional level as an initial approach to assess the relative role of rainfall and other factors in biomass production changes.

6.3.2. Linear negative trends

We found that linear negative trends were mainly related to the lateritic plateaus and, in general, to less accessible areas. In our study area, as in the whole Sahel, lateritic plateaus and degraded hillslopes (corresponding to plateaus edge areas) are covered by tiger bush, a typically banded vegetation pattern consisting of trees and bushes in alternating strips of dense vegetation separated by bare soils or low herbaceous cover. In previous studies (e.g. Brinkmann et al., 2012; Leblanc et al., 2008), a decrease in the tiger bush vegetation cover on lateritic plateaus around Niamey has been observed since the 1960s. A possible cause for this tiger bush degradation is overexploitation to satisfy the demand of the city of Niamey for fuelwood and extraction of certain tree species for traditional medicine. Thus, the expected growth in population, estimated at 66 million by 2050 for Niger (FEWS NET, 2014), together with an increase in urban population, will probably lead to increasing pressures on these woodlands. In addition to the overexploitation of wood, tiger bush is also prone to overgrazing from livestock increases because formerly pastoral lands are being converted into cropped areas (Hiernaux et al., 2009). According to the National Institute of Niger (INS, 2014) the livestock population in the Tillaberi region was estimated at 4,791,000 head in 2006 and nearly 5,800,000 head in 2011. The decrease in woody coverage induced by wood harvesting and pasture is a common concern for many Sahel regions (van Vliet et al., 2013) such as those around Sikasso in Mali (Brinkmann et al., 2012) or in the Ferlo in Senegal (Brandt et al., 2014a). The same explanations for degradation may hold for areas with natural vegetation because most of them (particularly in the south of the DCN site) likely correspond to vegetation on lateritic plateaus misclassified as natural vegetation.

Areas that experienced crop loss (i.e. crop abandonment) were also prone to biomass production degradation (Table 5). As Bégué et al. (2011) and Leroux et al. (2014) highlighted, in the Sahel, cropped vegetation tends in some cases to have a higher NDVI value than natural vegetation, particularly degraded savannahs with sparse vegetation, suggesting that a decrease in iNDVI should be expected when croplands are abandoned. In addition, cropland (which includes fallow land and grassland) was also prone to grazing pressure, meaning that high stocking rates, soil trampling and changes in the species composition may have contributed to a decrease in biomass production (Hiernaux et al., 2016).

6.3.3. Linear positive trends

The analysis of Table 5 shows that 10% of cropped areas in 2013 (cropland and cropland expansion) displayed an increase in biomass production. The importance of accessibility factors in linear positive trends (Figure 7) highlights the fact that they are key variables for agricultural expansion or intensification because they reduce transportation costs and allow better accessibility to markets for both seed purchasing and harvest selling. Another potential explanation for the increase in biomass production for both croplands and natural vegetation might be a direct consequence of the degradation of tiger bushes, because such degradation certainly leads to more runoff due to an increase in bare areas (Galle et al., 1999) and, thus, leads to more water being available for vegetation growth in the valleys. Moreover, San-Emeterio et al. (2013) also referred to a densification of ligneous vegetation cover in lowlands between 1965 and 2010 that was linked to the development of irrigated vegetable gardens, thus positively affecting biomass production.

6.3.4. No significant trends

Finally, it is interesting to note that a large share of cropland (81%) did not change significantly in terms of biomass production between 2000 and 2015. This lack of change can be considered an important issue in the context of a growing population, because food requirements increase accordingly. In the area of the Niamey Square Degree, land use was characterized by an increase in the length of the cropping period and a reduction in fallow periods, resulting in frequent shifts between cropping and fallowing periods since the 1950s (Hiernaux et al., 2009; Loireau, 1998). In our land cover classification, we considered the crop domain (both crop and fallow areas). Thus, shifting cultivation practices can influence year-to-year biomass production and be considered as displaying no significant trends.

6.4. General discussion

6.4.1. Interpretation, methodological and validation issues

In this study, iNDVI is considered as an indicator of biological productivity and thus of land degradation or greening. Still, some studies have highlighted that changes in biodiversity or species composition may lead to a greening trend while not inducing environmental improvements (Brandt et al., 2014; Herrmann and Tappan, 2013). For example, based on ground measurements in Senegal, Herrmann and Tappan (2013) found a reduction in woody species richness despite a greening trend observed in NOAA AVHRR data. This type of change can have great importance for the assessment of livestock fodder availability, particularly when it results in an increase in unpalatable species (e.g., Mbow et al., 2013; Olsen et al., 2015). Care must thus be taken when associating variables such as iNDVI with food availability.

For both our analysis at regional and local levels, the relevance of our approach can be challenged by the use of an inconsistent dataset in terms of spatial and temporal resolutions and geospatial properties (e.g., point data, continuous data, from 30 m to 25 km spatial resolution). This is particularly true for complex environments characterized by high spatial heterogeneity in processes. For instance, the best resolution used here is 30 m, but most of the processes certainly occurred at a finer scale. In addition, it has been shown that the results of the Random Forest variable importance measures from the R

RandomForest package can be biased by an artificial variable selection when data of varying types and scales are used (Strobl et al., 2007). In particular, the coarse resolution of the TRMM data (25 km), which is associated with a strong latitudinal gradient, leads to a simplified patterned image composed of East-West bands following the gradient that can have an effect on the bootstrap sampling replacement and lead to a higher selection probability in each individual classification tree. The importance of the mean growing period rainfall (RAIN_M) in the RF model might be a result of this algorithm weakness.

Finally, as pointed out previously (e.g., Herrmann et al., 2005; Nutini et al., 2013; Brandt et al., 2014b; Rasmussen et al., 2014), ground information is needed to validate trend analyses and to check whether observed trends are truly due to the drivers identified. This is also a major concern for LULCC studies, as previously highlighted by van Vliet et al. (2013) in their meta-analysis of cropland changes. Nevertheless, the validation of trends requires time-series of biomass data with a spatial and temporal scale suitable for comparison with remote sensing time series. For instance, to check whether degradation trends in tiger bush areas are caused by the overexploitation of woody vegetation for firewood and overgrazing, spatialized and quantitative information on livestock and firewood trading is required. In addition, local knowledge (both expert and traditional) might be a valuable source of information for interpreting trends and is still largely underused in remote sensing studies (Mbow et al., 2015).

6.4.2. Perspectives for food security policies

A specific application of the findings of our study can be considered in the framework of food security monitoring systems. Currently, the food security monitoring is mostly a result of Early Warning Systems (EWS), which primarily focus on food production by monitoring agricultural production and agroclimatic events. EWS have both a warning role when crises occur and a monitoring role from a long-term perspective. In most existing EWS, time-series vegetation indices are used to assess current vegetation conditions and phenology through the production of anomaly maps. Thus, they act only on food insecurity situations due to particular circumstances (e.g., adverse climatic events, pests or diseases) and focus on short-term quick fixes. However, for some countries (such as Niger), food insecurity has become endemic; for such cases, the scientific community agrees that there is a need for long-term structural solutions (The World Bank, 2013). By focusing more specifically on agricultural and pasture lands, the approach developed here could not only help to assess the vulnerability of populations and to delineate areas with decreases in crop and grassland production but also to target zones with good potential where long-term food security planning policies can be implemented. In addition, for countries in the Sahel, long-term monitoring of natural vegetation areas is also of great importance because, for example, harvesting and selling timber are among the proven coping strategies used during times of food shortages. Finally, because food security is not exclusively reliant on agricultural production, the whole food system must be considered to provide efficient food insecurity mitigation (Ericksen, 2008; Verburg et al., 2013b). In that way, by contextualizing regional land changes with local studies, our study contributes to a better understanding of the land system changes which, in turn, are considered as key drivers of the food system. Thus, our study can help by supporting proposals for context-specific food security policies (Ericksen, 2008).

7. Conclusion

This study contributes to the burgeoning scientific literature on the “re-greening” of the Sahel by further exploring the factors that have contributed to vegetation changes over the last 16 years and by considering both regional and local drivers. A bridge between vegetation trend analysis and LULCC studies is thus proposed. Our study showed clear spatial patterns of increasing/decreasing trends in biomass production over the western Sahel for the period 2000—2015. Within the areas of increasing trends, about half could be related to a combination of rainfall and other factors, whereas only the other factors were necessary for to explain the other half. Within the areas of decreasing trends, factors other than rainfall were predominant. At local level over the DCN site, biomass production trends were estimated from different potential drivers using a Random Forest algorithm. Here, we found that biomass production degradation was linked to specific land cover classes such as lateritic plateaus as well as to accessibility factors. By focusing on herbaceous vegetation, our study is complementary to the study of Brandt et al. (2016), which focused on woody vegetation. Taken together, these two studies form the most “up-to-date” analysis of the recent vegetation cover changes in the Sahel.

While most studies to date have relied mainly on coarse spatial resolution data such as MODIS or NOAA-AHRR, in the future, the study of complex and spatially variable processes underlying vegetation changes will benefit from the availability of high resolution satellite Sentinel-2, which has been active since June 2015. This satellite offers new prospects for both long- and short-term monitoring of Sahelian ecosystems. In particular, by providing time series of frequent high quality observations, we expect detailed analyses of LULCC covering the entire Sahel, allowing a better interpretation of NDVI changes at regional levels. For example, although it is still a challenge today to link changes in agricultural production to intensification of agricultural practices or expansion of agricultural lands, we hope that this information will become more accessible in the near future and thus able to benefit a wide range of issues such as food security.

Acknowledgments

Louise Leroux is supported by CIRAD and by the Centre National d'Etudes Spatiales (CNES-TOSCA "Dynafrique" Project). This research was also conducted as part of the SIGMA European Collaborative Project (FP7-ENV-2013 SIGMA - Stimulating Innovation for Global Monitoring of Agriculture and its Impact on the Environment in support of GEOGLAM project http://www.geoglam-sigma.info/Pages/default.aspx) funded by the European Commission. The authors are thankful to the four anonymous reviewers for their critical comments and suggestions to improve the manuscript.

References

Ali, A., Lebel, T., 2009. The Sahelian standardized rainfall index revisited. Int. J. Climatol. 29, 1705–1714. doi:10.1002/joc

Andela, N., Liu, Y.Y., M. Van Dijk, A.I.J., De Jeu, R.A.M., McVicar, T.R., 2013. Global changes in dryland vegetation dynamics (1988-2008) assessed by satellite remote sensing: Comparing a new passive microwave vegetation density record with reflective greenness data. Biogeosciences 10, 6657–6676. doi:10.5194/bg-10-6657-2013

Anyamba, A., Small, J., Tucker, C.J., Pak, E., 2014. Thirty-two Years of Sahelian Zone Growing Season Non-Stationary NDVI3g Patterns and Trends. Remote Sens. 6, 3101–3122. doi:10.3390/rs6043101

Anyamba, A., Tucker, C.J., 2005. Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981 – 2003. J. Arid Environ. 63, 596–614. doi:10.1016/j.jaridenv.2005.03.007

Asrar, G., Fushs, M., Kanemasu, E.T., Hatfield, J.L., 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in Wheat. Agron. J. 76, 300–306.

Bégué, A., Vintrou, E., Ruelland, D., Claden, M., Dessay, N., 2011. Can a 25-year trend in Soudano-Sahelian vegetation dynamics be interpreted in terms of land use change? A remote sensing approach. Glob. Environ. Chang. 21, 413–420. doi:10.1016/j.gloenvcha.2011.02.002

Boschetti, M., Nutini, F., Brivio, P.A., Bartholomé, E., Stroppiana, D., Hoscilo, A., 2013. Identification of environmental anomaly hot spots in West Africa from time series of NDVI and rainfall. ISPRS J. Photogramm. Remote Sens. 78, 26–40. doi:10.1016/j.isprsjprs.2013.01.003

Brandt, M., Hiernaux, P., Rasmussen, K., Mbow, C., Kergoat, L., Tagesson, T., Ibrahim, Y.Z., Wélé, A., Tucker, C.J., Fensholt, R., 2016. Assessing woody vegetation trends in Sahelian drylands using MODIS based seasonal metrics. Remote Sens. Environ. 183, 215–225. doi:10.1016/j.rse.2016.05.027

Brandt, M., Mbow, C., Diouf, A.A., Verger, A., Samimi, C., Fensholt, R., 2015. Ground- and satellite-based evidence of the biophysical mechanisms behind the greening Sahel. Glob. Chang. Biol. 21, 1610–1620.

Brandt, M., Romankiewicz, C., Spiekermann, R., Samimi, C., 2014a. Environmental change in time series – An interdisciplinary study in the Sahel of Mali and Senegal. J. Arid Environ. 105, 52–63. doi:10.1016/j.jaridenv.2014.02.019

Brandt, M., Verger, A., Diouf, A., Baret, F., Samimi, C., 2014b. Local Vegetation Trends in the Sahel of Mali and Senegal Using Long Time Series FAPAR Satellite Products and Field Measurement (1982–2010). Remote Sens. 6, 2408–2434. doi:10.3390/rs6032408

Breiman, 2001. Random Forest. Mach. Learn. 45, 5–32.

Brinkmann, K., Schumacher, J., Dittrich, A., Kadaore, I., Buerkert, A., 2012. Analysis of landscape transformation processes in and around four West African cities over the last 50 years. Landsc. Urban Plan. 105, 94–105. doi:10.1016/j.landurbplan.2011.12.003

Chen, J., Jönsson, P., Tamura, M., Gu, Z., Matsushita, B., Eklundh, L., 2004. A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. Remote Sens. Environ. 91, 332–344. doi:10.1016/j.rse.2004.03.014

Cho, J., Lee, Y.-W., Lee, H.-S., 2015. The effect of precipitation and air temperature on land-cover change in the Sahel. Water Environ. J. 29, 439–445. doi:10.1111/wej.12118

Colquhoun, D., 2014. An investigation of the false discovery rate and the misinterpretation of p-values. R. Soc. 1, 1–16. doi:10.1371/journal.pmed.0020124

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J., 2007. Random forests for classification in ecology. Ecology 88, 2783–2792. doi:10.1890/07-0539.1

D'Herbès, J.M., Valentin, C., 1997. Land surface conditions of the Niamey region : ecological and hydrological implications. J. Hydrol. 188–189, 18–42.

Dardel, C., Kergoat, L., Hiernaux, P., Grippa, M., Mougin, E., Ciais, P., Nguyen, C.C., 2014a. Rain-Use-Efficiency: What it Tells us about the Conflicting Sahel Greening and Sahelian Paradox. Remote Sens. 6, 3446–3474. doi:10.3390/rs6043446

Dardel, C., Kergoat, L., Hiernaux, P., Mougin, E., Grippa, M., Tucker, C.J., 2014b. Re-greening Sahel: 30years of remote sensing data and field observations (Mali, Niger). Remote Sens. Environ. 140, 350–364. doi:10.1016/j.rse.2013.09.011

Didan, K., 2015. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. NASA EOSDIS Land Processes DAAC. http://doi.org/10.5067/MODIS/MOD13Q1.006.

Donohue, R.J., Roderick, M.L., McVicar, T.R., Farquhar, G.D., 2013. Impact of CO2 fertilization on maximum foliage cover across the globe's warm, arid environments. Geophys. Res. Lett. 40, 3031–3035. doi:10.1002/grl.50563

Eklundh, L., Olsson, L., 2003. Vegetation index trends for the African Sahel 1982–1999. Geophys. Res. Lett. 30, 1–4. doi:10.1029/2002GL016772

Ericksen, P.J., 2008. Conceptualizing food systems for global environmental change research. Glob. Environ. Chang. 18, 234–245. doi:10.1016/j.gloenvcha.2007.09.002

Estes, A.B., Kuemmerle, T., Kushnir, H., Radeloff, V.C., Shugart, H.H., 2012. Land-cover change and human population trends in the greater Serengeti ecosystem from 1984-2003. Biol. Conserv. 147, 255–263. doi:10.1016/j.biocon.2012.01.010

Evans, J., Geerken, R., 2004. Discrimination between climate and human-induced dryland degradation. J. Arid Environ. 57, 535–554. doi:10.1016/S0140-1963(03)00121-6

Fensholt, R., Langanke, T., Rasmussen, K., Reenberg, A., Prince, S.D., Tucker, C.J., Scholes, R.J., Le, Q.B., Bondeau, A., Eastman, R., Epstein, H., Gaughan, A.E., Hellden, U., Mbow, C., Olsson, L., Paruelo, J., Schweitzer, C., Seaquist, J., Wessels, K., 2012. Greenness in semi-arid areas across the globe 1981-2007 - an Earth Observing Satellite based analysis of trends and drivers. Remote Sens. Environ. 121, 144–158. doi:10.1016/j.rse.2012.01.017

Fensholt, R., Rasmussen, K., 2011. Analysis of trends in the Sahelian " rain-use efficiency " using GIMMS NDVI , RFE and GPCP rainfall data. Remote Sens. Environ. 115, 438–451. doi:10.1016/j.rse.2010.09.014

Fensholt, R., Rasmussen, K., Kaspersen, P., Huber, S., Horion, S., Swinnen, E., 2013. Assessing Land Degradation/Recovery in the African Sahel from Long-Term Earth Observation Based Primary Productivity and Precipitation Relationships. Remote Sens. 5, 664–686. doi:10.3390/rs5020664

FEWS NET, 2014. NIGER FOOD SECURITY BRIEF.

Funk, C., Rowland, J., Adoum, A., Eilerts, G., Verdin, J., White, L., 2012. A Climate Trend Analysis of Senegal. U.S. Geological Survey Fact Sheet 2012–3123.

Galle, S., Ehrmann, M., Peugeot, C., 1999. Water balance in a banded vegetation pattern. Catena 37, 197–216. doi:10.1016/S0341-8162(98)90060-1

Geist, H.., Lambin, E.F., 2002. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. Bioscience 52, 143. doi:10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2

Geist, H.J., Lambin, E.F., 2004. Dynamic Causal Patterns of Desertification. Bioscience 54, 817–829. doi:10.1641/0006-3568(2004)054[0817:DCPOD]2.0.CO;2

Hein, L., Ridder, N. De, 2006. Desertification in the Sahel : a reinterpretation. Glob. Chang. Biol. 12, 751–758. doi:10.1111/j.1365-2486.2006.01135.x

Hein, L., Ridder, N. De, Hiernaux, P., Leemans, R., Wit, A. De, Schaepman, M.E., 2011. Desertification in the Sahel : Towards better accounting for ecosystem dynamics in the interpretation of remote sensing images. J. Arid Environ. 75, 1164–1172. doi:10.1016/j.jaridenv.2011.05.002

Helldén, U., Tottrup, C., 2008. Regional desertification : A global synthesis. Glob. Planet. Change 64, 169–176.

Herrmann, S.M., Anyamba, A., Tucker, C.J., 2005. Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. Glob. Environ. Chang. 15, 394–404.

doi:10.1016/j.gloenvcha.2005.08.004

Herrmann, S.M., Hutchinson, C.F., 2005. The changing contexts of the desertification debate. J. Arid Environ. 63, 538–555. doi:10.1016/j.jaridenv.2005.03.003

Herrmann, S.M., Tappan, G.., 2013. Vegetation impoverisment despite greening : A case study from central Senegal. J. Arid Environ. 90, 55–66.

Hickler, T., Eklundh, L., Seaquist, J.W., Smith, B., Ardo, J., Olsson, L., Sykes, M.T., Sjostrom, M., 2005. Precipitation controls Sahel greening trend. Geophys. Res. Lett. 32, 1–4. doi:10.1029/2005GL024370

Hiernaux, P., Ayantunde, A., Kalilou, A., Mougin, E., Gérard, B., Baup, F., Grippa, M., Djaby, B., 2009. Trends in productivity of crops , fallow and rangelands in Southwest Niger : Impact of land use , management and variable rainfall. J. Hydrol. 375, 65–77. doi:10.1016/j.jhydrol.2009.01.032

Hiernaux, P., Dardel, C., Kergoat, L., Mougin, E., 2016. Desertification, Adaptation and Resilience in the Sahel: Lessons from Long Term Monitoring of Agro-ecosystems, in: Behnke, R., Mortimore, M. (Eds.), The End of Desertification? Springer Berlin Heidelberg, Berlin, Germany, pp. 147–178. doi:10.1007/978-3-642-16014-1

Hoscilo, A., Balzter, H., Bartholomé, E., Boschetti, M., Brivio, P.A., Brink, A., Clerici, M., Pekel, J.F., 2014. A conceptual model for assessing rainfall and vegetation trends in sub-Saharan Africa from satellite data. Int. J. Climatol. 11. doi:10.1002/joc.4231

Huber, S., Fensholt, R., Rasmussen, K., 2011. Water availability as the driver of vegetation dyamics in the African Sahel from 1982 to 2007. Glob. Planet. Change 76, 186–195.

Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman, K.P., Stocker, E.F., 2007. The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. J. Hydrometeorol. 8, 38–55. doi:10.1175/JHM560.1

Hulme, M., 2001. Climatic perspectives on Sahelian desiccation : 1973 - 1998. Glob. Environ. Chang. 11, 19–29.

Ibrahim, Y., Balzter, H., Kaduk, J., Tucker, C.J., 2015. Land Degradation Assessment Using Residual Trend Analysis of GIMMS NDVI3g, Soil Moisture and Rainfall in Sub-Saharan West Africa from 1982 to 2012. Remote Sens. 7, 5471–5494. doi:10.3390/rs70505471

INS, 2014. Annuaire statistique du Niger 2008-2012 : Elevage [WWW Document]. URL http://www.stat-niger.org/statistique/file/Annuaires_Statistiques/INS_2012/AS2008-2012ELEVAGE.pdf

Jamali, S., Seaquist, J., Eklundh, L., Ardö, J., 2014. Automated mapping of vegetation trends with polynomials using NDVI imagery over the Sahel. Remote Sens. Environ. 141, 79–89. doi:10.1016/j.rse.2013.10.019

Kaptué Tchuenté, A.T., Prihodko, L., Hanan, N.P., 2015. On regreening and degradation in Sahelian watersheds. Proc. Natl. Acad. Sci. 2015, 1–6. doi:10.1073/pnas.1509645112

Keys, E., McConnell, W.J., 2005. Global change and the intensification of agriculture in the tropics. Glob. Environ. Chang. 15, 320–337. doi:10.1016/j.gloenvcha.2005.04.004

Kindu, M., Schneider, T., Teketay, D., Knoke, T., 2015. Drivers of land use/land cover changes in Munessa-Shashemene landscape of the south-central highlands of Ethiopia. Environ. Monit. Assess. 187, 1–17. doi:10.1007/s10661-015-4671-7

Knauer, K., Gessner, U., Kuenzer, C., Dech, S., 2014. Remote sensing of vegetation dynamics in West Africa – a review. Int. J. Remote Sens. 35, 6357–6396. doi:10.1080/01431161.2014.954062

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., George, P.S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E.F., Mortimore, M., Ramakrishnan, P.S., Richards, J.F., Skånes, H., Steffen, W., Stone, G.D., Svedin, U., Veldkamp, T. a., Vogel, C., Xu, J., 2001. The causes of land-use and land-cover change: moving beyond the myths. Glob. Environ. Chang. 11, 261–269. doi:10.1016/S0959-3780(01)00007-3

Larwanou, M., Abdoulaye, M., Reij, C., 2006. Etude de la Régénération Naturelle Assistée dans la Région de Zinder (Niger).

Lebel, T., Ali, A., 2009. Recent trends in the Central and Western Sahel rainfall regime (1990–2007). J. Hydrol. 375, 52–64. doi:10.1016/j.jhydrol.2008.11.030

Leblanc, M.J., Favreau, G., Massuel, S., Tweed, S.O., Loireau, M., Cappelaere, B., 2008. Land clearance and hydrological change in the Sahel: SW Niger. Glob. Planet. Change 61, 135–150. doi:10.1016/j.gloplacha.2007.08.011

Leroux, L., Bégué, A., Lo Seen, D., 2014. Regional analysis of Crop and Natural Vegetation in West Africa based on NDVI metrics, in: IEEE (Ed.), IEEE International Geoscience & Remote Sensing Symposium. Québec, Canada, pp. 5107–5110.

Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest. R news 2, 18–22. doi:10.1177/154405910408300516

Loireau, M., 1998. Espaces-Ressources-Usages: Spatialisation des interactions dynamiques entre les systèmes sociaux et les systèmes écologiques au Sahel nigérien.

Mbow, C., Brandt, M., Ouedraogo, I., de Leeuw, J., Marshall, M., 2015. What Four Decades of Earth Observation Tell Us about Land Degradation in the Sahel? Remote Sens. 7, 4048–4067. doi:10.3390/rs70404048

Mbow, C., Fensholt, R., Rasmussen, K., Diop, D., 2013. Can vegetation productivity be derived from greenness in a semi-arid environment? Evidence from ground-based measurements. J. Arid Environ. 97, 56–65. doi:10.1016/j.jaridenv.2013.05.011

Mutoko, M.C., Hein, L., Bartholomeus, H., 2014. Integrated analysis of land use changes and their impacts on agrarian livelihoods in the western highlands of Kenya. Agric. Syst. 128, 1–12. doi:10.1016/j.agsy.2014.04.001

Myneni, R.B., Williams, D.L., 1994. On the relationship between FAPAR and NDVI. Remote Sens. Environ. 49, 200–211. doi:10.1016/0034-4257(94)90016-7

Nicholson, S.A., 2005. On the question of the "‘ recovery ’" of the rains in the West African Sahel 63, 615–641. doi:10.1016/j.jaridenv.2005.03.004

Nicholson, S.E., Tucker, C.J., Ba, M.B., 1998. Desertification, Drought, and Surface Vegetation : An Example from the West African Sahel. Bull. Am. Meteorol. Soc. 79, 815–829.

Nutini, F., Boschetti, M., Brivio, P.A., Bocchi, S., Antoninetti, M., 2013. Land-use and land-cover change detection in a semi-arid area of Niger using multi-temporal analysis of Landsat images. Int. J. Remote Sens. 34, 4769–4790.

Okou, F.A.Y., Tente, B., Bachmann, Y., Sinsin, B., 2016. Regional erosion risk mapping for decision support: A case study from West Africa. Land use policy 56, 27–37. doi:10.1016/j.landusepol.2016.04.036

Olsen, J.L., Miehe, S., Ceccato, P., Fensholt, R., 2015. Does EO NDVI seasonal metrics capture variations in species composition and biomass due to grazing in semi-arid grassland savannas? Biogeosciences 12, 4407–4419. doi:10.5194/bg-12-4407-2015

Olsson, L., Eklundh, L., Ardo, J., 2005. A recent greening of the Sahel — trends, patterns and potential causes. J. Arid Environ. 63, 556–566. doi:10.1016/j.jaridenv.2005.03.008

Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J., Tucker, C.J., Stenseth, N.C., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. TRENDS Ecol. Evol. 20, 503–510. doi:10.1016/j.tree.2005.05.011

Pricope, N.G., Husak, G., Lopez-Carr, D., Funk, C., Michaelsen, J., 2013. The climate-population nexus in the East African Horn: Emerging degradation trends in rangeland and pastoral livelihood zones. Glob. Environ. Chang. 23, 1525–1541. doi:10.1016/j.gloenvcha.2013.10.002

Prince, S.D., 1991. Satellite remote sensing of primary production: comparison of results for Sahelian grasslands 1981-1988. Int. J. Remote Sens. 12, 1301–1313.

Prince, S.D., Brown de Colstoun, E., Kravitz, L.L., 1998. Evidence from rain-use efficiencies does not indicate extensive Sahelian desertification. Glob. Chang. Biol. 4, 359–374.

Prince, S.D., Wessels, K., Tucker, C.J., Nicholson, S.E., 2007. Desertification in the Sahel : a reinterpretation of a reinterpretation. Glob. Chang. Biol. 13, 1308–1313. doi:10.1111/j.1365-2486.2007.01356.x

Rasmussen, K., Fensholt, R., Fog, B., Vang Rasmussen, L., Yanogo, I., 2014. Explaining NDVI trends in northern Burkina Faso. Geogr. Tidsskr. J. Geogr. 114, 17–24. doi:10.1080/00167223.2014.890522

Reij, C., Tappan, G., Smale, M., 2009. Agroenvironmental Transformation in the Sahel: Another Kind of “Green Revolution.”

Rishmawi, K., Prince, S., 2016. Environmental and Anthropogenic Degradation of Vegetation in the Sahel from 1982 to 2006. Remote Sens. 8, 948. doi:10.3390/rs8110948

Rishmawi, K., Prince, S., Xue, Y., 2016. Vegetation Responses to Climate Variability in the Northern Arid to Sub-Humid Zones of Sub-Saharan Africa. Remote Sens. 8, 910. doi:10.3390/rs8110910

San-Emeterio, J.L., Alexandre, F., Andrieu, J., Génin, A., Mering, 2013. Changements socio-environnementaux et dynamiques des paysages ruraux le long du gradient bioclimatique nord-sud dans le sud-ouest du Niger (régions de Tillabery et de Dosso). VertigO 13, 1–27.

Schlenker, W., Lobell, D.B., 2010. Robust negative impacts of climate change on African agriculture. Environ. Res. Lett. 5, 14010. doi:10.1088/1748-9326/5/1/014010

Seaquist, J.W., Hickler, T., Eklundh, L., Ardo, J., Heumann, B.W., 2009. Disentangling the effects of climate and people on Sahel vegetation dynamics. Biogeosciences 6, 469–477.

Strobl, C., Boulesteix, A.L., Zeileis, A., Hothorn, T., 2007. Bias in random forest variable importance measures: illustrations, sources and a solution. BMC Bioinformatics 8, 25. doi:10.1186/1471-2105-8-25

Tappan, G.., Sall, M., Wood, E.., Cushing, M., 2004. The West African Land Use and Land Cover project, Ecoregions and land cover trends in Senegal. J. Arid Environ. 59, 427–462. doi:10.1016/j.jaridenv.2004.03.018

Tarchiani, V., Di Vecchia, A., Genesio, L., Sorani, F., 2008. Monitoring drylands ecosystem dynamics for sustainable development policies: the Keita experience, in: Lee, C., Schaaf, T. (Eds.), The

Future of Drylands. Springer Netherlands, Dordrecht, pp. 395–407. doi:10.1007/978-1-4020-6970-3_38

Teferi, E., Bewket, W., Uhlenbrook, S., Wenninger, J., 2013. Understanding recent land use and land cover dynamics in the source region of the Upper Blue Nile, Ethiopia: Spatially explicit statistical modeling of systematic transitions. Agric. Ecosyst. Environ. 165, 98–117. doi:10.1016/j.agee.2012.11.007

The World Bank, 2013. Agricultural sector risk assessment in Niger: Moving from Crisis Response to Long-Term Risk Management.

Tian, F., Brandt, M., Liu, Y.Y., Verger, A., Tagesson, T., Diouf, A.A., Rasmussen, K., Mbow, C., Wang, Y., Fensholt, R., 2016. Remote sensing of vegetation dynamics in drylands: Evaluating vegetation optical depth (VOD) using AVHRR NDVI and in situ green biomass data over West African Sahel. Remote Sens. Environ. 177, 265–276. doi:10.1016/j.rse.2016.02.056

Tucker, C.J., 1985. Satellite Remote Sensing of Total Herbaceous Biomass Production in the Senegalese Sahel : 1980-1984. Remote Sens. Environ. 17, 233–249.

Tucker, C.J., 1979. Red and Photographic Infrared linear Combinations for Monitoring Vegetation. Remote Sens. Environ. 8, 127–150.

United Nations, 2013. World Population Prospects : The 2012 Revision, Highlights and advance tables.

van Asselen, S., Verburg, P.H., 2013. Land cover change or land-use intensification: simulating land system change with a global-scale land change model. Glob. Chang. Biol. 3648–3667. doi:10.1111/gcb.12331

van Asselen, S., Verburg, P.H., 2012. A Land System representation for global assessments and land-use modeling. Glob. Chang. Biol. 18, 3125–3148. doi:10.1111/j.1365-2486.2012.02759.x

van Vliet, N., Reenberg, A., Rasmussen, L.V., 2013. Scientific documentation of crop land changes in the Sahel: A half empty box of knowledge to support policy? J. Arid Environ. 95, 1–13. doi:10.1016/j.jaridenv.2013.03.010

Verburg, P.H., Erb, K.H., Mertz, O., Espindola, G., 2013a. Land System Science: Between global challenges and local realities. Curr. Opin. Environ. Sustain. 5, 433–437. doi:10.1016/j.cosust.2013.08.001

Verburg, P.H., Mertz, O., Erb, K.H., Harberl, H., Wu, W., 2013b. Land system change and food security: towards multiscale land systems solutions. Curr. Opin. Environ. Sustain. 5, 1–9.

Vermote, E.F., El Saleous, N.Z., Justice, C., 2002. Atmospheric correction of MODIS data in the visible to middle infrared: first results. Remote Sens. Environ. 83, 97–111. doi:10.1016/S0034-4257(02)00089-5

Vu, Q.M., Le, Q.B., Vlek, P.L.G., 2014. Hotspots of human-induced biomass productivity decline and their social–ecological types toward supporting national policy and local studies on combating land degradation. Glob. Planet. Change 121, 64–77. doi:10.1016/j.gloplacha.2014.07.007

Wessels, K., Prince, S.D., Malherbe, J., Small, J., Frost, P., VanZyl, D., 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability ? A case study in South Africa. J. Arid Environ. 68, 271–297. doi:10.1016/j.jaridenv.2006.05.015

Wessels, K.J., van den Bergh, F., Scholes, R.J., 2012. Limits to detectability of land degradation by trend analysis of vegetation index data. Remote Sens. Environ. 125, 10–22. doi:10.1016/j.rse.2012.06.022

Zhu, Z., Piao, S., Myneni, R.B., Huang, M., Canadell, J.G., Ciais, P., Sitch, S., Friedlingstein, P., Arneth, A., Stocker, B.D., Poulter, B., Koven, C., 2016. Greening of the Earth and its drivers. Nat. Clim. Chang. 3004, 1–6. doi:10.1038/nclimate3004

List of Figure Captions

Figure 1. Flowchart of the approach adopted in the study: links between the regional and local analyses. The first part (labeled ①) corresponds to the first objective of the study, which is the iNDVI trend analysis over the western Sahel. The second part (labelled ②) corresponds to the second objective: the identification of the main drivers of iNDVI trends over the western Sahel. The third part (labelled ③) corresponds to the identification of the main drivers of iNDVI trends over the Niger site.

Figure 2. The study sites. a) Mean integrated NDVI between July and October over the western Sahel zone; b) Main land cover classes (MODIS Land Cover Product, MCD12Q1), c) Landsat 8 image of the DCN site in September 2013 (red-green-NIR color composition), and d) anomalies of cumulated rainfall between June and October (deviation from the mean values over the 2000–2015 period) from the TRMM3B43 product over the western Sahel (bar) and the DCN site (line).

Figure 3. Map of the land cover changes over the DCN site between 2001 and 2013 derived from Landsat images.

Figure 4. Spatial distribution over the western Sahel of a) the MODIS iNDVI trends; b) the correlation coefficient between MODIS iNDVI and TRMM3B43 June–October rainfall (significant at the 5% level for r=0.49); c) the iNDVI residual trends obtained for pixels with a significant linear NDVI-rainfall relationship during the 2000–2015 period.

Figure 5. Spatial distribution over the DCN site of a) the MODIS iNDVI trends; b) the correlation between MODIS iNDVI and TRMM3B43 June–October rainfall (significant at the 5% level for r=0.49); and c) the iNDVI residual trends obtained for pixels with a significant NDVI-rainfall linear relationship during the 2000–2015 period.

Figure 6. a) Spatial distribution of the main drivers of the biomass production changes over the western Sahel; b) distribution of driver types according to the direction of changes (increase or decrease) for western Sahel and the DCN site; and c) zoomed area of the DCN site.

Figure 7. Importance of variables in the Random Forest model according to NDVI trend classes over the DCN site: a) all classes; b) no trend; c) linear negative trend; and d) positive linear trend. Only the first five variables are displayed. Their importance is given in the "Mean decrease in accuracy". See Table 1 for variable abbreviations.

Figure 8. Distribution of trend types for the five most important Random Forest variables a) mean growing period rainfall; b) Euclidean distance from villages; c) type of soil; d) Euclidean distance from rivers; and e) travelling time from city market; for the DCN site.