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Assessing Long-Term Trends In Vegetation Productivity Change Over the Bani River Basin in Mali (West Africa)

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Abstract

Using time series of Normalized Difference Vegetation Index (NDVI) and rainfall data, we investigated historical vegetation productivity trends from 1982 to 2011 over the Bani River Basin in Mali. Statistical agreements between long-term trends in vegetation productivty, corresponding rainfall and rate of land cover change from Landsat time-series imagery was used to discern climate versus human-induced vegetation cover change. Spearman correlation was used to investigate the relationship between metrics of vegetation, rainfall trends and land cover change categories. The results show there is a positive correlation between increases in rainfall and some land cover classes, while some classes such as settlements were negatively correlated with vegetation productivity trends. Croplands and Natural Vegetation were positively correlated (r=0.89) with rainfall while settlements have a negative correlation with NDVI time series trend (r=-057). Despite the fact that rainfall is the major determinant of vegetation cover dynamics in the study area, it appears that other human-induced factors such as urbanization have negatively influenced the change in vegetation cover in the study area. The results show that a combined analysis of NDVI, rainfall and spatially explicit land cover change provides a comprehensive insight into the drivers of vegetation cover change in semi-arid Africa.

Keywords: NDVI trends, global change, land cover change, Mali

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Introduction

Vegetation vitality or chlorophyll activity indices from low to moderate resolution remote sensing are widely used to study large scale changes and patterns in vegetation productivity. The greatest challenge in vegetation productivity analysis and interpretation is the differentiation between climate and human-induced change (Wessels et al., 2012). Understanding vegetation patterns, trends and rate of change is essential for understanding human effects on ecosystems and underpinning natural resource management practices including where possible rehabilitation measures can be effectively employed for preservation and may help for effectiveness of different management approaches (Prakasam, 2010).

The Normalized Difference Vegetation Index (NDVI is computed using the Red (RED) and the near Infrared (NIR) reflectance wavebands, as (NIR-RED)/NIR+RED), and can be considered the most commonly used remote sensing based index to map vegetation productivity (or 'greeness') and density (Tucker, 1979) as well as vegetation dynamics in various ecosystems worldwide (Belone et al., 2009). As reported by Bai et al., 2008, Beck et al., 1990; the relationship between NDVI and vegetation productivity is well established; the NDVI has been shown to be related to biophysical variables that control vegetation productivity, such as the Leaf Area Index (LAI), the fraction of photo-synthetically-active radiation absorbed by vegetation and Net Primary Productivity (NPP). NDVI is also very useful to detect and measure land degradation processes, that may be defined as a long-term loss of ecosystem function and land productivity (Bai et al., 2008). The long time-series of the Advance Very High Resolution Radiometer (AVHRR) data, since 1981, are reliable source in identifying long-term changes in vegetation productivity (Rigina et al., 2003)

Among the wide range of satellite systems providing NDVI time-series data, the Global Inventory Modelling and Mapping System (GIMMS) provided the most extended time series available so far. The GIMMS datasets are 15-day composites at 8-km geometric pixel resolution (Dardel et al., 2014) Maximum NDVI value compositing was performed to correct for 'noise' artifacts such as cloud cover and cloud shadow, assumed to have a low NDVI in the time series data. The data is derived daily from AVHRR data streams on board of the National Oceanic and Atmospheric Administration NOAA) polar orbiting satellite series.

The GIMMS data has been pre-processed by the GIMMS Group at National Aeronautic and Space Administration's (NASA) Goddard Space Flight Centre and corrected for residual sensor degradation and sensor inter calibration differences, effects of changing solar zenith and viewing angles, volcanic aerosols, atmospheric water vapour and cloud cover, using nonlinear empirical mode decomposition methods (Pinzon et al., 2004, Tucker et al., 2005). The Satellite Pour l'Observation de la Terre (SPOT) VEGETATION (VGT) is one of the recent sensors providing datasets to characterize the Earth's surface from 1998 to present. SPOT VGT data is a 1-km and 10-day composite (S10) data set that is radiometrically calibrated to top of the atmosphere radiance, precisely georeferenced and corrected for atmospheric effect (Zhao et al., 2012; Fenshold et al., 2006).

Changes in vegetation cover or productivity derived from time series based satellite images vegetation index (NDVI) have been widely used to map, quantify and analyse vegetation change and degradation (Deering et al., 1975; Landmann et al., 2014; Le et al., 2012; Propastin et al., 2008; Walker et al., 2014; Wessels et al., 2004; 2007, Zhang et al., 2014). Most of the studies done in West Africa (WA) were focussing on the Sahel zone. The longest NDVI time series data set produced thus far has been 26 years (1981-2006) archives developed by the GIMMS group. Therefore, there is a need to further extend monitoring data on vegetation productivity changes so that climate and human-induced effects can be accurately disentangled and more robust conclusions can be made as to how and where productivity changes occur over decades. This study aimed at using a unique combination of multi sensor remote sensing data to investigate the historical trends using 30 years NDVI time series data and rainfall data from time-series passive radar observations. We further attempted to determine if the mapped change is rather human and/or climate influenced by exploring the relationship between NDVI, rainfall and land cover change, derived from 30-meter Landsat data, over the Bani river Basin in Mali, West Africa. The integrative mapping results allowed for the interpretation of change and change factors within the Bani river basin in the past 30 years.

Study area

The study area (Figure 1) covers the Sahelian (300-700 mm), Soudanian (700-1200 mm) and the Soudano-Guinean (1200-1600 mm) eco-climatic zones.

The spatial distribution of vegetation in the study region is largely related to cumulative (annual) rainfall and the length of the rainy season, which varies along the eco-climatic gradient. Vegetation patterns on a landscape scale are determined by localized climatic variations and human activities such as bush clearing and deforestation for agricultural or energy purposes and overgrazing. Smallholder farming is the most common agricultural practice in the region. Millet, sorghum and cotton are primarily cultivated, whilst pastoralism (bovines, goats and sheep) is practiced throughout the study area. Woody savannas and forests are largely being exploited for wood and charcoal production. These activities have been intensifying over the last 40 years in line with increasing fuel wood demand due to population increases (Ruelland et al., 2008).

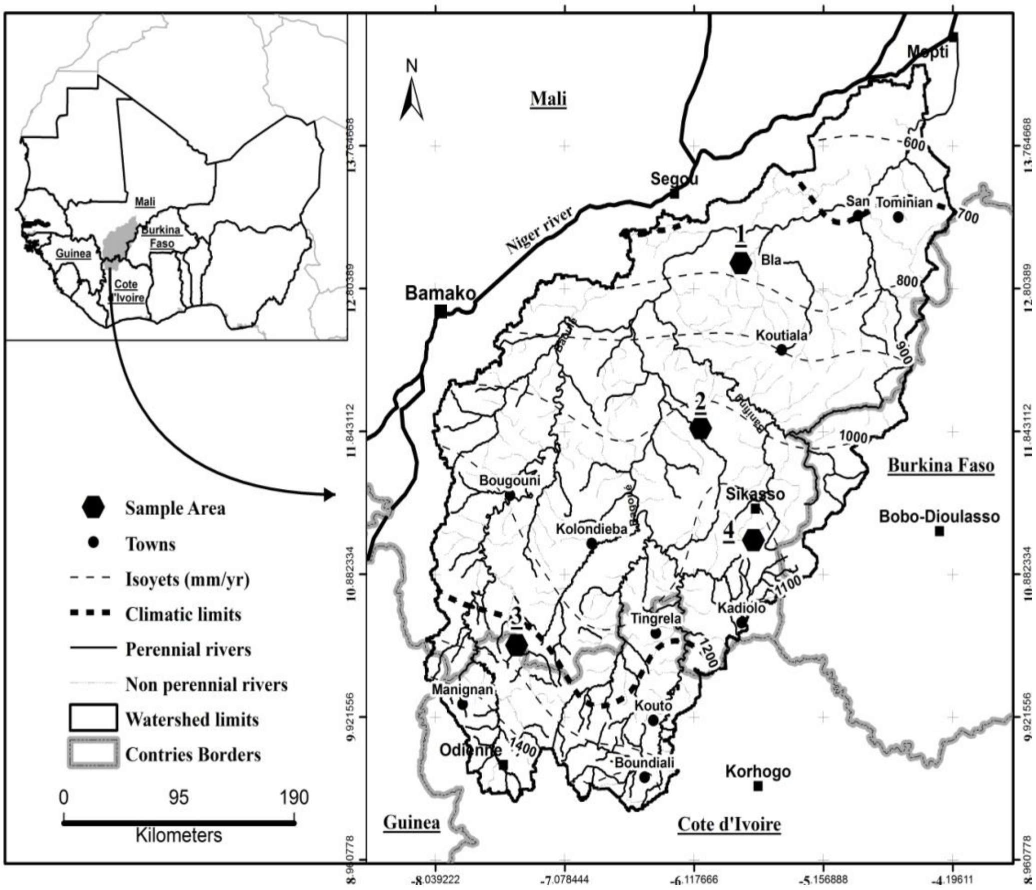


Figure 1: Map Showing the Study area and the four References areas, Numbered Accordingly

Methods

NDVI Time Series Data

Monthly 8-km Normalized Difference Vegetation Index (NDVI) time-series data from 1982 to 2011 used in this analysis was created using a 10-day SPOT Vegetation 1-km (1998~2011) and 15-day GIMMS 8km reference data (1982~2006). The maximum value compositing technique (Holben, 1986) was used to firstly generate monthly time series data metrics for the two datasets. In a second processing step we resampled the SPOT VGT time series to match the coarser 8 km of GIMMS by spatial averaging (Fensholt et al., 2009). Lastly we applied a linear correlation between the two dataset using their overlapping period and then generated a new 8-km time-series data for the 30 years observation period using GIMMS data from 1982 to 2000 and VGT data from 2001 to 2011 (Zhang et al., 2013).

Rainfall Time Series Data

Since consistent and seamless rain-gauge data sets were not available for key stations in the study area, passive radar satellite rainfall estimates from 1998 to current from 25 kilometer Tropical Rainfall Measurement Mission (TRMM) were used to complement ground based gauge measures. As such monthly TRMM rainfall (mm) measures (product 3B43) were statistically compared with rain-gauge data for the overlapping period (1998~2002) using a t-test. The gauge rainfall data for the period from 1982 to 2002 was available for 40 meteorological stations. The newly and much improved monthly rainfall time-series data for the missing period from 2002 to 2011 were essentially generated using a regression equation developed by Almazroui (2011). Using the regressions equations and inverse distance weighted (IDW) interpolation of monthly data from 40 meteorological stations contained within the basin, a 30-year rainfall time-series dataset at an 8-km grid resolution was created.

Trend Calculation

Long-terms per-pixel trends are a good indicator to assess the existence of any changes in vegetation productivity time-series data. A wide range of approaches have been developed by scientific communities to extract phonological metrics form time series data (Jönsson & Eklundh 2004; Reed & Brown 2005; Walker et al., 2014).

This study used Mann-Kendall (MK) monotonic trend tests, which have been applied in a few previous studies on remote sensing time series data (De Beurs & Henebry, 2004a; De Beurs & Henebry, 2004b; De Beurs & Henebry, 2005a; De Beurs & Henebry, 2005b). Since NDVI time series often do not meet parametric assumptions the MK test was deemed suitable for this analysis (Tabari et al., 2011). The MK test quantifies the strength and the direction of the relationship between two variables. Kendall tau rank correlation coefficient is the range [-1; +1] expressing direct (inverse) proportionality for positive or negative tau values. The output of the analysis is a map of tau (t) values which are significant at the 90% level. Besides the MK tau, the test delivers the p-value of the trend analysis. A p-value less than 0.07 were used as a threshold of strongly significance trend in this study.

Extracting reference Land Use and Land Cover (LULC) information from Landsat data

Several pixels with the same general trend (positive or negative) can be identified from the MK trend map. Land cover change data, derived from multi-temporal 30-meter Landsat data sets, was used to explain and cross verify representative areas that exhibit either entirely negative MK-trends or entirely positive MK-trends over the monitoring period. Two positive trend areas and two negative trend areas were used in the cross verification (Figure 1). Essentially, the selection criteria were: negative NDVI and RF trend (area 1), positive NDVI and negative RF trend (area 2), negative NDVI and positive RF trend (area 3) and lastly positive NDVI and positive RF trend (area 4). Cloud-free Landsat Thematic Mapper (TM) images with 30-meter of resolution were acquired for the four reference areas for the following years; 1984 and 1986, 1999 and 2000 and 2009 and 2010. In all cases end of the growing season (October to December) images were used because the contrast between cropland and natural environment is most marked (Ruelland et al., 2009). The Landsat image datasets were obtained from the USGS data archives (http://glovis.usgs.gov). The acquired images were geometrically corrected using a polynomial order with ~30 Ground Control Points (GCPs) and classified using the maximum likelihood algorithm. The most recent images were classified first and validated using ground trust data for classification collected during the field trip conducted in the area in January 2014. Further training data was collected using very high resolution imagery in Google Earth. Moreover ground data on land cover and land use (from 1990) collected in the context of the Project Inventories of Ligneous Resources (PIRL) was also used.

The accuracy of the Landsat-based classifications was assessed using an error matrix, which is one of the most widely used for accuracy assessment (Lu & Weng, 2007). A post-classification comparison change detection algorithm was used to determine changes in Land Use and Land Cover (LULC). This approach provides ''from–to'' change information, for which LULC transformations can be easily calculated. Cross tabulation analysis was carried out to analyse the spatial distribution of different LULC classes and LULC changes. The rate of land conversion was computed using this formula (Manandhar et al., 2009):

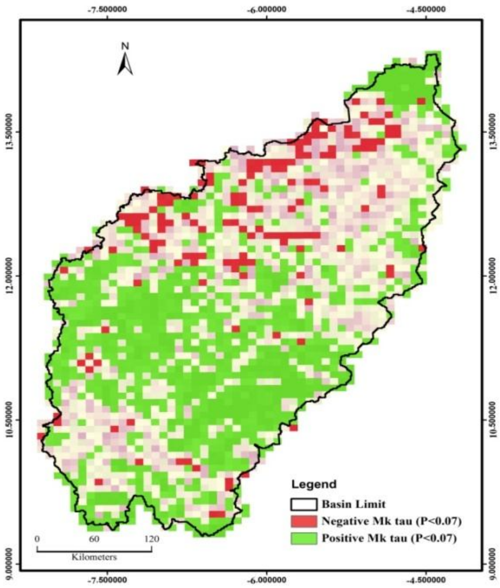
$$Change(\%) = \frac{AreaD2 - AreaD1}{AreaD1} * 100 \quad (1)$$

Change area = D2 –D1, where D1and D2 are the area of the target vegetation cover type at the beginning and the end of the study period, respectively.

Results and Discussion

Trend in Vegetation and Rainfall

The MK long-term trend analysis results using monthly NDVI and rainfall trends for the period 1982 to 2011 are shown in Figures 2 and 3 respectively. The NDVI trend showed areas with decreasing and increasing NDVI. The total pixels affected by significant decreases in monotonic trend at p-value less than 0.07 was 155 (8% of the total area) while 934 pixels (49% of the total area) showed a significant positive trend using the same p-value threshold.



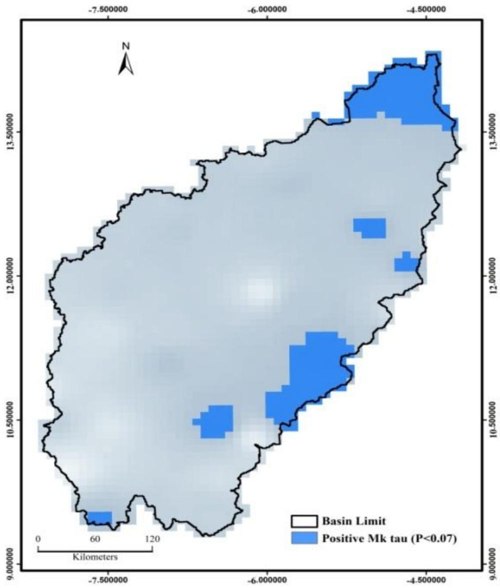


Figure 2: Trends in NDVI from Time-Series for 1982~2011 Figure 3: Trends in Rainfall from Time-Series for 1982~2011

Positive trends were mainly located in Soudano-Sahelian zone; where near to natural vegetation was still well represented. Ruelland et al., 2010 reported that most of these areas were still covered by natural vegetation. The most marked land cover change in the study area was the reduction of closed woodland with an increase in tree parkland agriculture. In contrast, decreasing trends were mostly found across the transitional zone between the Sahel and the Sudanian. The land cover were dominated by cropland (>70 %) which increases from one year to another due to the development of cotton cultivation. The analysis moreover showed that there are no significant changes or trends in seasonal rainfall in almost the whole study area. The analysis showed only a few portions of the total area with significant positive trend at p-value < 0.07. Our observations are in agreement with those of Bégué et al., 2011, who observed a similar no significant rainfall trend in the same area during the period from 1982 to 2005 for almost the whole catchment.

Land Conversion Rate

The reference land cover data from the four sampling area, were grouped in four categories: cropland, natural vegetation, settlement and others.

The cropland class is characterized by scattered trees (canopy coverage from 20% onwards) in spatial arrangement with annual crops (mainly millet and sorghum). Crops are usually harvested between October and November and the cropping season is followed by a fallow period that lasts from December to April. The natural vegetation classes, such as presented, are made up by near to natural woody vegetation and perennial or annual grassland. The categories “others” include bare lands or rural settlement structures. . The table 1 shows the rate of land conversion for the entire study period and all the four reference sites. Generally, decrease of near to natural vegetation could be mapped in all of the Landsat reference sites and temporal sequences. The total near to natural vegetation lost was about 63.47% and 22.83% for area (1) and (2), while it was 8.35% for area (3) and 13.39% for area (4). The ‘cropland’ class increased for 564.86% in area (3); 62.17% in area (4); 35.79% in area (2) and 16.22% in area (1). In area (3) the class “others” decreased by 87.01%, whilst it increased for 791.12% in area (1); 134.15% in area (2) and only 1.39% for area (4).

Table 1: NDVI and Rainfall Trends Associated with Landsat Based Land Cover Change (In Ha) Mapped for the Four Reference Sites

			Land cover change in % (1980s-2000s)			
Sites	**NDVI**	**RF**	**Others**	**Settlement**	**Cropland**	**Vegetation**
Area #1	-2	-2	**791.56**	**501.12**	16.22	**-63.47**
Area #2	2	-2	**134.15**	0	35.79	**-22.82**
Area #3	-2	2	**-87.01**	0	**564.86**	-8.35
Area #4	2	2	1.39	0	**62.17**	**-13.39**

These results are in concordance with Ruelland et al., 2010, who reported the reduction of natural vegetation and simultaneously an increase of farmlands in West Africa agro-ecosystems over the past few decades.

Correlation of NDVI trend with cumulative rainfall and rate of land cover change The vegetation index and the rainfall for the reference pixels were scored following their positive or negative trend (table1). Table 2 shows the descriptive statistic distribution of variables used for the correlations.

Table 2: Basic Statistic for Variables Used

Variable	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
NDVI	4	-2.000	2.000	0.000	2.309
RF	4	-2.000	2.000	0.000	2.309
Others	4	-87.010	791.560	210.023	398.203
Settlement	4	0.000	501.120	125.280	250.560
Cropland	4	16.220	564.860	169.761	264.072
Vegetation	4	-63.470	-8.350	-27.007	25.038

Spearman correlation was performed to quantify the relationships between NDVI decline/increase rainfall trend and rate of land cover change.

A negative correlation between vegetation and settlement was found (Table 3), implying that urbanisation induced vegetation decline. Similarly, the positive spearman correlation of 0.89 between cropland, natural vegetation and rainfall illustrates that increases in rainfall trends in some areas were related to increases in semi-natural vegetation cover or cropland.

Table 3: Spearman Correlation Matrix between NDVI, Rainfall and Rate of Land Cover Change

Variables	NDVI	RF
Vegetation Index	**1**	0.000
Rainfall	0.000	**1**
Others (Bare land & Burn Area)	0.000	**-0.894**
Settlement	**-0.577**	**-0.577**
Cropland	0.000	**0.894**
Natural vegetation	0.000	**0.894**

The results of this study showed that trends in NDVI for the period 1982 to 2011 can be explained by both climate, i.e. rainfall variability and human factors such as expansion of croplands, urbanization, and decreases of near to natural vegetation. The Spearman correlation revealed a high correlation coefficient between the trend in NDVI, RF and rate of land cover change. Some authors mentioned linkages between population growth and environmental degradation in Africa (Cleaver & Schreiber, 1994). Other authors, i.e. Charney et al., 1975; Stancioff et al., 1986 cited evidence of negative rainfall trends and frequent droughts in the Sahel, causing soil erosion and vegetation declines.

There is however number of publications arguing the reverse – namely improved land management as a result of growing population e.g. Elmqvist and Khatir, 2006, Hilhorst and Coulibaly, 1998. Indeed, cropland expansion that usually accompanies population growth in rural areas does not necessarily follow a monotonic trend, and subsequent agricultural land management by smallholders encompasses a diversity of practices that are far from being immutably detrimental to the natural resource base. Across Sudano-Sahelian Africa there are numerous examples of increases in fallow land due to livelihood diversification, labor constraints (Elmqvist and Khatir, 2006), indigenous promotion of sustainable natural resource management (Hilhorst and Coulibaly, 1998) and more generally improved land care in conjunction with a growing population (Tappan and McGahuey, 2007).

Conclusion

The 30-year (1982-2011) of NDVI time-series data analysed has provided a good assessment of the vegetation productivity change and its linkage to climate and human activities. The finding of this study can be summarized as follows: the NDVI time-series showed significant increasing and decreasing trends for 49% and 9% of the study area, respectively. The rainfall time-series showed increased trend but significant for only a portion of the study area. The long-term trend in vegetation was correlated with rainfall and rate of land cover conversion. The correlation coefficient provided useful information for land cover dynamics in the area. It has a high relationship between the NDVI and RF long-term trend. The results of this study provide spatially explicit and temporally good and rich information of vegetation productivity dynamic at local scale. This is an important input for assessing the impact of climate change on vegetation for biophysical modelling. It also improves our knowledge of the drivers of vegetation productivity changes. The obtained information can be used for replication since it was based on freely satellite data. The study suggests that NDVI can be useful for general cover monitoring and planning. However it would be good to add to the analysis other landscape components like population density and soil degradation information.

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