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Vegetation Activity in the Upper Oueme Basin (Benin, Africa) Studied from SPOT-VGT (2002-2012) According to Land Cover

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Abstract

Signs of climate change in West Africa over the last few decades are among the significant observed in the tropics, in particular the decrease in mean annual precipitation. Although such change has brought about new eco-climatic constraints on vegetation forms, it has not proven easy to determine interannual and intra-seasonal variations on a regional scale for major vegetation forms, whether natural or highly artificial as a result of human activities. The present study analyzes vegetation activity via a Normalized Difference Vegetation Index (NDVI) defined from ten-day SPOT-VGT data (one-km resolution, covering the period from 2002 to 2012) in the African Monsoon Multidisciplinary Analysis (AMMA) Program observation zone, located in the Upper Oueme River Basin in Benin. The statistical analysis is mainly based on a multifactor approach allowing approximately 54% of interannual NDVI variations to be accounted for. Results show that spatio-temporal NDVI variability in the River Basin is highly dependent on land use, be it forest, wooded savanna, farmland or areas undergoing conversion.

Keywords

Oueme Basin (Benin); Land Cover; NDVI from SPOT-VGT; Principal Component Analysis; Seasonal and Interannual Variability

Introduction

In the late 1960s West Africa experienced persistent drought characterized by both duration and irregularity (Lebel *et al.*, 2010). The rainfall deficit in the 1970s (Lebel and Ali, 2009), when the whole water cycle was greatly affected, seriously impacted agriculture, food security (Redelsperger *et al.*, 2006) and vegetation (Philippon *et al.*, 2007). For natural reasons such as climate change, or through anthropogenic change such as agricultural activity, the seasonal dynamics of vegetation cover have been considerably affected in recent decades in West Africa. However, the lack of long-term data has hitherto prevented detailed investigation of climate–vegetation and spatio-temporal relationships at regional scales (Chamaille-Jammes *et al.*, 2006), although such knowledge could help understand climate variability and lead to improved seasonal forecasting ability and predictions of ecosystem responses to climate change (Philippon *et al.*, 2007; Mberego *et al.*, 2013). In this context, the AMMA (African Monsoon Multidisciplinary Analysis) Program was tasked with long-term observation of the West African monsoon and its features with the aim of assessing hydrological impacts of climatic or anthropogenic changes (Redelsperger *et al.*, 2006; Lebel *et al.*, 2010). AMMA has monitored a wide range of factors, carrying out ocean, land and atmospheric measurements over time scales ranging from daily variability up to changes in seasonal activity over several years, in areas covering the scale of West Africa, the meso-scale of Mali, Niger and Benin to that of super-sites such as Agoufou, Nalohou or Wankama (Zin *et al.*, 2009).

In this tropical African region, satellite observation is a reliable, efficient tool for multi-temporal monitoring of land surface, and for obtaining information about long-term changes in land characteristics and processes (Reed *et al.*, 1994; Chamaille-Jammes *et al.*, 2006; Redelsperger *et al.*, 2006). Remote sensing data is also efficient for monitoring seasonal and interannual vegetation response at a regional scale (Fensholt *et al.*, 2011), while seasonal characteristics of vegetation activity, such as emergence and senescence, are closely related to annual temperature, precipitation and humidity cycles (Reed *et al.*, 1994). Changes in phenological events can be identified and classified year-to-year for different land-cover types (Roehrig *et al.*, 2005). The most common and reliable index for studying vegetation activity is NDVI (Normalized Difference Vegetation Index), which has been shown to be associated with biomass and photosynthetic activity (Gurgel *et al.*, 2003; Rigina and Rasmussen, 2003; Lasaponara , 2006; Fensholt *et al.*, 2011; Miranda-Aragón *et al.*, 2012; Mberego *et al.*, 2013).

The present study in the Upper Oueme Basin (Benin) will allow us to determine specific phenological variations in wooded savanna typical of Sudano-Guinean formations, in a region covered by a very dense observational network. These environmental regional diagnostics will facilitate the different requirements in hydrological and climate modeling using regional model calibration. So incorporating vegetation dynamics into a regional climate model used for future prediction is potentially critical to realistic simulation of future climate changes in West Africa. The problem is to be able to extract seasonal and interannual phenological signals from remote sensing (especially at low spatial resolution, e.g. 1 km) in the Upper Oueme Basin according to the main vegetation formations, to discriminate natural forest areas and agro-forest mosaics. However, assessing land-cover maps is known to be difficult, and assessing land-cover-change maps is even more challenging, mainly due to the difficulty in obtaining accurate land-cover-change reference datasets (*Grinand et al.*, 2013). The main research question thus is to estimate if the spatio-temporal vegetation dynamics are relatively similar on interannual scale, with maybe notable differences in intraseasonal variations.

The principal goal of this study was to better understand seasonal and interannual variations of vegetation activity from NDVI analysis for the main land cover classes in the Upper Oueme Basin from 2002 to 2012. This first step was to establish the major regional differences according to land cover, while the long-term objective is to understand variability according to climatic constraints.

Data and Methods

Study Area and Recent Land Cover Changes (1973-2012)

The Upper Oueme Basin is located in central Benin (8.5°-10.5°N/1.5°-3.0°W) and covers an area of 14,366 km² (Figure 1). The study area has a small altitude range going from an average of 200 to 600 meters asl, with the Atacora Mountains in the western part being the highest (between 500 and 800 m). The terrain gradually slopes down to the south in the river's confluence zone (Figure 1). The whole area has a Sudanese climate with a unimodal rainy season. Annual average rainfall is 900-1200 mm; the rainy season normally starts in April and ends in October (Figure 2; Roehrig *et al.*, 2005; Zin *et al.*, 2009). The natural vegetation consists of forest, wooded savanna, and a patchwork of woodlands and grassy savannah (Hahn-Hadjali *et al.*, 2010). Due to small scale farming with fallow and fire, natural forest is now observed only as relic or protected areas like the *Forêt classée de l'Ouémé Supérieure* (Upper Oueme Forest Reserve; Speth *et al.*, 2004; Klein and Roehrig, 2006). Agriculture is small-scale with periodic fallow and fire, the main crops being yams, manioc, maize, millet and peanuts (Klein and Roehrig, 2006; Judex *et al.*, 2006). Seasonal temperature variations range between a maximum of about 30°C in March and a minimum of about 24°C in August, with a significant upward trend since the 1980's (Do *et al.*, 2013). Recent climate change in the study area has caused variations in regional water resources, coupled with vegetation change in land use and land cover (Zannou, 2011; Igué *et al.*, 2012).

TABLE 1 DESCRIPTION OF THE THREE MAIN LAND COVER CLASSES IN THE UPPER OUEME BASIN AND THEIR EVOLUTION 1973-2012 (ADAPTED FROM LEROUX, 2012).

Land cover classes	Characterization	Area (2012)	Evolution from 1973 to 2012	
Clear forest / riparian forest	Deciduous clear forests (more than 75% tree canopy cover) and dense forests along rivers	3080 km²	-87%	*+48% for savannas*
				+39% for crops, bare soil
Savannas	Grasses forming a continuous layer, 30-60% tree or shrub canopy cover	6876 km²	+71%	*+2% for forest, riparian*
				+69% for crops, bare soil
Crops / bare soil	Including cropland (e.g. cotton, corn), fallow and villages	4231 km²	+77%	*+27% for forest, riparian*
				+50% for savannas

Following the work of Leroux (2012) covering the Upper Oueme area and thanks to Landsat and MODIS data, land cover can be classified in three major classes of vegetation types (Figure 1 and Table 1): clear forest and riparian forest (21.7% of the study area), savannas

(48.5%), and crops and bare soil (29.8%). Cartographic simplification into three classes enables the Upper Oueme Forest Reserve to be distinguished, as it is almost entirely surrounded by farmland except to the north. The diachronic analyses from automatic classifications show significant modification of land-use patterns between the two study dates, 1973 and 2012 (Table 1). Over the forty-year study period, regional forested zones lost 87% of their area, mainly to savanna (48%), cropland or bare ground (39%). Farmland stretches all the way along the Djougou-Ouberou-Parakou road and sometimes encroaches on supposedly protected forest reserves (Judex and Thamm, 2008). Savannas are also spreading considerably (71%), mainly through being converted into cropland. Land areas already classified as cultivated in 1973 had evolved significantly (77%) by 2012, into either forest (27%) or farmland (50%). Leroux (2012) notes here the complexity and possible confusion between the evolution of former fallow and wooded savanna, with very similar spectral and phenological signatures. Each type is affected by anthropogenic constraints obviously influencing the corresponding NDVI values (whether by seasonal bush-clearing fires, deforestation, crop sowing, fallow land at different stages of grow-back, etc.). Associating the appearance of forest cover with that of dense riparian crop-growing is clearly a simplistic shortcut which interpretations should take into account. In the same way, it is areas classified as agricultural which a priori should show the greatest radiometric variations, due to contrasts in land use (cultivated fields or fallow) and vegetation activity during different stages of cultivation, at both seasonal and interannual scales.

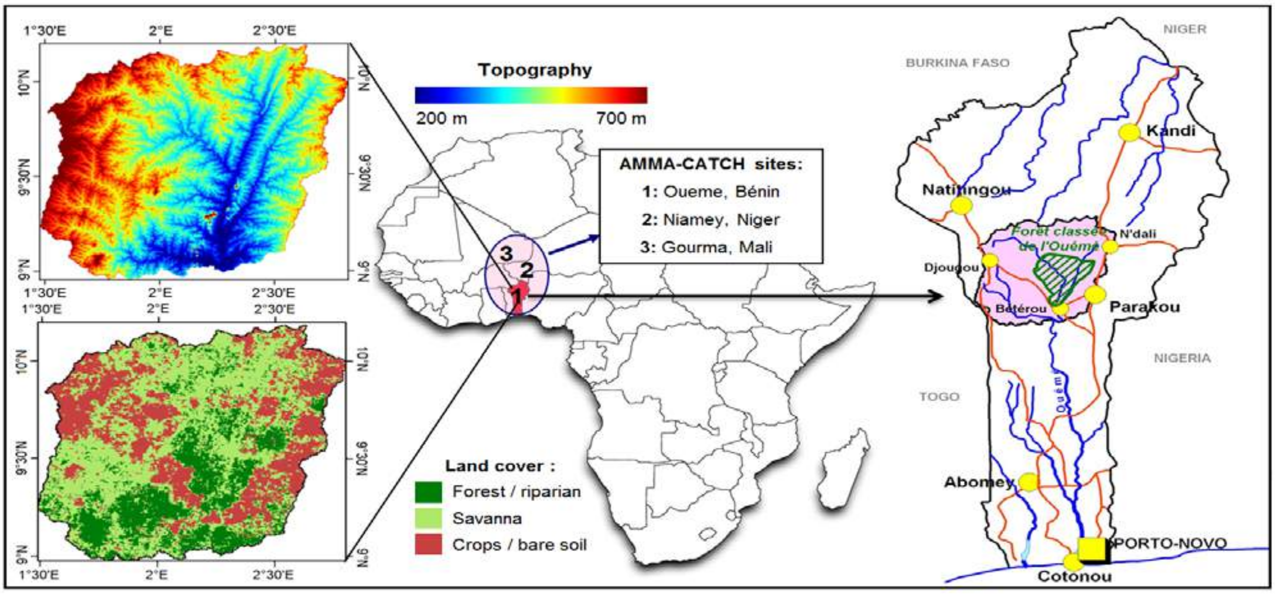

FIG. 1 LOCATION OF THREE MAIN AMMA-CATCH SITES, INSTRUMENTED TO STUDY THE SURFACE-CLIMATE PROCESSES IN WEST AFRICA, ONE LOCATED IN THE UPPER OUEME BASIN (BENIN): TOPOGRAPHY (TOP LEFT; FROM ASTER GDEM AT 30M SPATIAL RESOLUTION), THE THREE MAIN LAND COVER CLASSES (BOTTOM LEFT; ADAPTED FROM LEROUX, 2012) AND LOCATION OF THE BASIN IN BENIN (WITH LOCATIONS OF THE MAIN CITIES, ROADS AND RIVERS).

The NDVI Data Set

The choice of SPOT-4 VEGETATION data (rather than MODIS data for example) depends greatly on the huge experience from these long-term satellite NDVI data within the AMMA program. This experience can thus facilitate comparisons which can so allow to validate results obtained in this study. SPOT-4 VEGETATION data have been available since 1998 from the Vlaamse Instelling voor Technologisch Onderzoek (VITO) based in Belgium, freely distributed at http://free.vgt.vito.be/ (Lasaponara, 2006; Jarlan *et al.*, 2008). The VEGETATION (VGT) sensor has four spectral bands: blue (0.43-0.47 μm), red (0.61-0.68 μm), Near InfraRed (NIR, 0.78-0.89 μm) and Short Wave InfraRed (SWIR, 1.58-1.74 μm). The spatial resolution is approximately 1 km with a daily repeat cycle at an altitude of about 820 km (Baret *et al.*, 2006; Jarlan *et al.*, 2008). Products were pre-processed using a consistent algorithm including radiometric calibration, precise geo-location and correction of atmospheric effects. The VEGETATION instrument covers almost all the Earth's land every day. Changes in vegetation cover are inferred using the NDVI index. In this study, we used S10 VEGETATION products, a 10-day synthesis elaborated with the Maximum Value Composite (MVC) of NDVI. The descriptive analyses presented in the beginning of the study are based on the 10-day

NDVI composite data, while multivariate analyses are calculated from monthly average NDVI. Cloud-cover influences are therefore favorably reduced in each image (Roehrig *et al.*, 2005; Baret *et al.*, 2006; Jarlan *et al.*, 2008). The 2002-2012 time-series was finally chosen to show recent variations, and used to calculate the NDVI average regimes.

In order to enhance the NDVI analyses, the metadata provided by SPOT-VGT enable the mean seasonal signature of regional cloud cover to be determined from the start, as it is a factor potentially engendering considerable interpretation bias. Calculating the number of pixels which are disturbed by cloud throughout the study area by ten-day periods showed that it was mainly the 18th to the 26th periods which were affected, i.e. from late June to mid September (Figure 2). The maximum level of interference by cloud, affecting 65% of pixels, was reached in early August, corresponding to the middle of the rainy season when temperatures are coolest. Consequently, cloudy pixels flagged in the SPOT-VGT metadata should not be used to calculate the monthly average values analyzed hereafter.

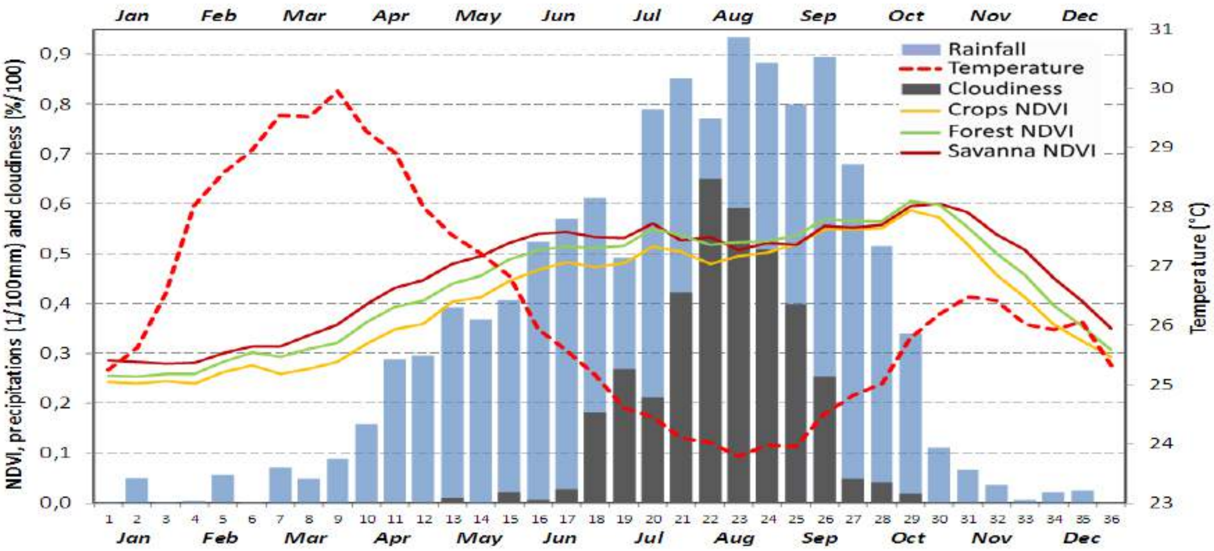

FIG. 2 THE SEASONAL CLIMATE REGIMES OF THE UPPER OUEME BASIN (BASED ON 10-DAY MEANS): PRECIPITATION AMOUNT (IN 1/100 OF MM; FROM A 2002-2009 FIELD-BASED RAIN-GAUGE INDEX), AIR TEMPERATURE AT 1.5 M ABOVE GROUND LEVEL (IN °C; DJOUGOU STATION, 2002-2012), CLOUDINESS (IN % / 100; FROM SPOT-VGT ESTIMATIONS) AND NDVI FOR THE THREE MAIN LAND COVER CLASSES (SPOT-VGT DECADAL COMPOSITES 2002-2012) REGIMES.

Based on the three main land-use classes, (forest, savanna and cropland; Figure 1), the three mean NDVI regimes were calculated by integrating all pixels corresponding to each category. It was apparent from this that from August until the end of the rainy season, the different NDVI signatures were hard to distinguish, firstly because the NDVI values became saturated on reaching their maximum (about 0.55-0.60) and secondly because of atmospheric bias. This bias due to cloudiness explains partially that the highest values (corresponding to the saturation of NDVI) are here lower than those usually observed in dense forest (0.7 to 0.8). The difference also results from the dense river system on the forest parts of the Oueme basin which participate in the reduction in the maximal values of NDVI detected on the scale of a 1 km pixel. If the pixels most contaminated by cloud are eliminated (as no longer representing vegetation cover in any way but merely the weather), it can be seen that they are located mainly in the south-east of the study area, with over 4% of pixels eliminated in the 2002-2012 time period (Figure 3). In the Upper Oueme, the most affected areas correspond mostly to the peripheries of the main water courses in the east and south-west.

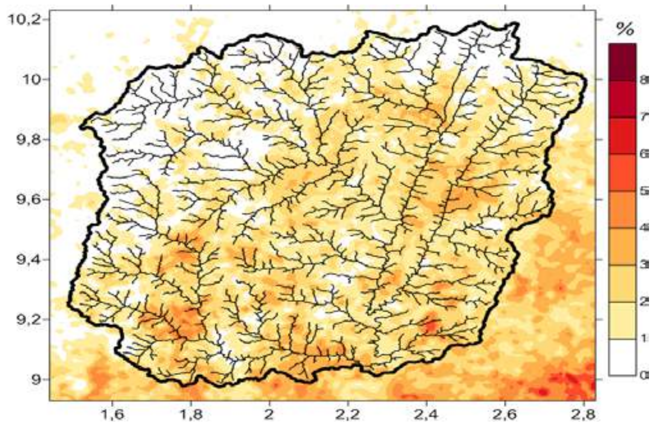

FIG. 3 MAP OF CLOUDY SPOT-VGT NDVI PIXELS (IN %) ELIMINATED FROM MONTHLY TIME SERIES (2002-2012).

Principal Component Analysis

Principal component analysis (PCA) is now a normal multivariate statistical technique for revealing hidden structures in a data set, and for extracting spatio-temporal modes (or patterns). PCA (also known as empirical orthogonal functions – EOF) is appropriate for analyzing samples in environmental space and has become a widely used technique in remote sensing (e.g. Eklundh and Singh 1993; Gurgel *et al.*, 2003; Chamaille-Jammes *et al.*, 2006; Lasaponara, 2006; Miranda-Aragón *et al.*, 2012). The technique enables areas of localized change in multi-temporal data sets to be enhanced. With the PCA methodological approach, most of the total variance is contained in the first component, while only a little is found in the following components. In the present study, PCA was calculated from raw NDVI values (2002-2012), with no attempt to normalize series. It was a methodological approach that enabled the main coherent seasonal signatures to be shown and identified as a priority. Thus, in order for the results obtained from PCA (which could be interpreted as phenological processes) to be interpreted correctly, additional information was needed, such as biogeographical or environmental maps. All these validation data were collected during the AMMA Program and are now available from the AMMA database: http://database.amma-international.org/.

Results and Discussion

Seasonal Phenological Variations According to the Three Land Cover Categories

Differences in NDVI in accordance with land use are best distinguished from the dry season, beginning in November, until the middle of the rainy season in May-June (Figure 2). The lowest values correspond to cropland (around 0.25 in January), while forested areas have the highest NDVI. The distinction between the three radiometric signatures is visible mostly from the onset of the rainy season (March-April) or, on the other hand, when the rainy seasons ends (November). These periods correspond to the most distinctive phenophases in terms of plant productivity (growing and withering), while in the middle of the rainy season savannas often show short periods of NDVI values equal or even superior to those observed in areas of forest. NDVI mapping reveals all the important seasonal differences at the scale of the Upper Oueme (Figure 4). The most contrasted map is for April, with sharp differences between forest, savanna and farmland; the highest NDVI values (>0.5) are for forest areas in the south-west, while the central forest highland has lower values (0.35-0.45), about the same as those of the wooded savanna in the north of the Basin.

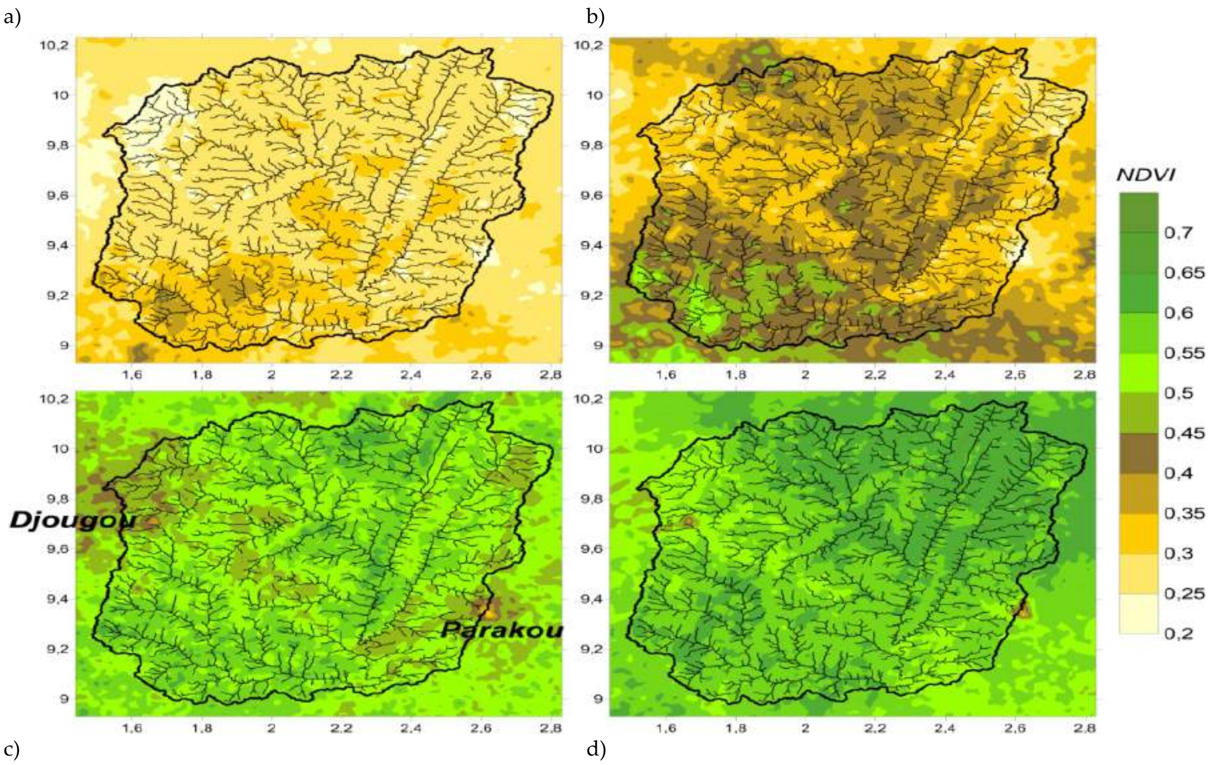

FIG. 4 SPOT-VGT MONTHLY NDVI MEANS (2002-2012) IN THE UPPER OUEME BASIN IN JANUARY (A), APRIL (B), JULY (C) AND OCTOBER (D).

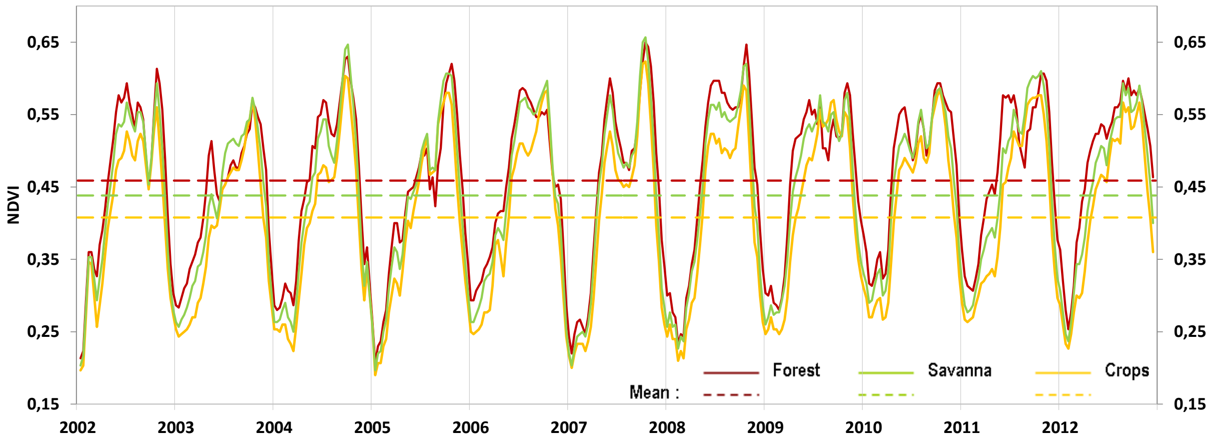

FIG. 5 INTERANNUAL SPOT-VGT NDVI (2002-2012) FOR THE THREE MAIN LAND COVER CLASSES IN THE UPPER OUEME BASIN (CALCULATED FROM 10-DAY COMPOSITE NDVI TIME-SERIES).

In the rainy season (e.g. July), when NDVI values are fairly similar everywhere (0.50 to 0.60), only the two urban areas of Djougou (in the north-west) and Parakou (in the south-east) are clearly different, with values below 0.40. Generally, the zones influenced by human activity (urban hinterlands and/or farmland, such as the areas located to the south of the forest reserve in the center of the Basin) stand out clearly, with NDVI values close to 0.35-0.40. The distinction can no longer be made in September and October when NDVI reaches saturation point independently of vegetation patterns. Klein and Roehrig (2006) observe that high rainfall leads to dense vegetation in Benin and hence to a saturation of NDVI values minimizing differences between land-cover types.

What Was the Interannual Variability over the 2002-2012 Period?

The first analysis of interannual NDVI variations was made on the basis of indices calculated from the three types of land use over the period from 2002 to 2012 (each index being obtained from the sample mean of all the pixels connected to a specific type of land use). The indices showed that there were several dry seasons (especially in January and February) where abnormally low NDVI values were recorded (<0.25), e.g. 2002, 2005, 2007, 2008 and 2012 (Figure 5). Peak values reached at the end of the rainy season (October) were observed in 2004, 2005, 2007 and 2008. Given the concordance of several of these dates, this simple observation confirms that the end of an extremely active vegetation period (NDVI > 0.60) can perfectly well be preceded by unusually low vegetation activity during the dry season.

Intra-seasonal NDVI variations during the rainy season, as well as the contrasts between the three mean signatures studied here, can vary greatly from one year to the next. For example, years during which the NDVI signature corresponding to cultivated land is very low have been observed (2002, 2006, 2008). It can also be seen that the bimodal nature of NDVI variations during the growing season is more or less marked (and can even disappear certain years, as in 2006 and 2012). Such interannual variations can originate, not only from bioclimatic conditions resulting in productivity and phenology varying from one year to another, but also from the varying effects of regional cloud cover disturbing the NDVI signature in the middle of the rainy season. Indeed, in spite of the elimination of cloudy pixels flagged in metadata, it remains certainly another persistent atmospheric biases and cloud contamination which the SPOT algorithm did not totally filter (Camberlin *et al.*, 2007). Based on coefficients of variation (CV being the ratio of standard deviation to the mean; in %) of mean monthly NDVI calculated for each pixel throughout the study period (N=132), the map of this statistical indicator shows a clear contrast between the south-west (CV<28%) and north-east (CV>35%) parts of the Basin (Figure 6). The areas with the highest coefficients, in the north-west and especially the north-east, correspond to the areas subject to the greatest human influence during the study period, with forest areas being converted to cropland or urbanized. Examining the relationship between interannual NVDI variability and the three main types of land use shows that it is cultivated land that on average records the highest coefficients of variation at over 31%, while those for savanna are lower, and those for forest areas do not exceed 28% (Figure 7). Greater interannual NDVI instability is characteristic of the evolution of farmland (which can evolve from bare earth, different stages of fallow, mixed crops, etc.), whereas NDVI of forests is subject to lower interannual amplitudes due their greater specific and phenological coherence. Apart from this, greater cloudiness over forests acts as an artifact and partly explains the lower local variability of NDVI (Figure 7).

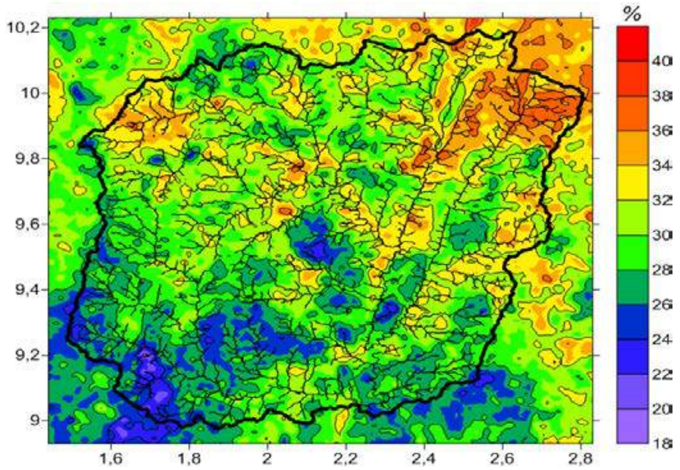

FIG. 6 INTERANNUAL RELATIVE COEFFICIENTS OF VARIATION (IN %) FROM SPOT-VGT MONTHLY VALUES (2002-2012).

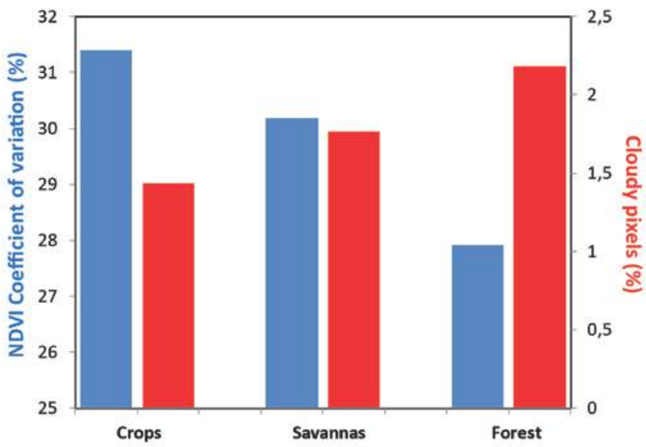

FIG. 7 AVERAGE VALUES FROM NDVI MONTHLY COEFFICIENT OF VARIATION (IN %; BLUE) AND CLOUDY PIXELS (IN %; RED), 2002-2012, ACCORDING TO THE THREE MAIN LAND-COVER CLASSES.

Definition of the Main Spatio-temporal Patterns from PCA

In order to determine the main modes of NDVI spatio-temporal variability and their links to land use, a PCA was calculated from a series of monthly means over the period from 2002 to 2012. At the same time ten-day values were also analyzed, but did not make any significant change in the results. Factor analysis was calculated from raw values, without seeking to normalize the series (thus ensuring that each variable had the same weight in the process of obtaining the new components; Richman, 1986) and with no resort to statistical refinement such as rotating the axes, with the aim of extracting modes emanating directly from the initial NDVI data. According to the scree-test of the PCA, enabling component significance to be assessed graphically, only the first four components were pertinent (eigenvalues > 3) and accounted for 53.6% of total variance, while the following ones were deemed statistically degenerate. The remaining 46% of the information contained in the initial table of raw NDVI series will therefore not be described here, as it corresponds to extremely limited spatio-temporal variability modes or to statistical noise (which may in particular be linked to the contamination of pixels by cloudiness).

The first mode (PC1) accounts for 39.4% of total variance, and naturally displays a strong seasonal signature with excellent concordance with the major land-use classes (Figure 8). The first component mainly contrasts the variability of forest areas (in the south and east-center) with that of human-influenced areas, either cultivated or in the process of conversion (Figure 9). The two main urban areas stand out in particular, with the most negative factor scores. The corresponding temporal series shows the extent to which intra-seasonal phases are unstable from one year to the next, whether it be in the dry or the wet season. Two composite months calculated from extreme positive and negative values observed in the first factor were studied and enabled the spatial response during anomalies distinguished by the PCA to be compared, and the regional NDVI response to be clearly discerned. The composites were calculated respectively from the five months recording extreme factor scores, with the difference between them allowing the areas with the highest variation to be localized (Figure 10a). On the scale of the first component, sensitivity during extreme interannual NDVI phases mainly affects the northern part of the Basin (north of 9.7°N), all vegetation forms included (wooded savanna and farmland), but does not affect the most densely forested hills of the Forest Reserve. Such spatially coherent variability thus seems to be typically linked to a constraint of bioclimatic origin affecting savanna and degraded areas.

The second mode (PC2) explains 6.4% of total variance (Figure 8). It particularly contrasts the west and north-east of the study area, and basically corresponds to a variability signature of forest areas, detected by the negative scores of the factorial component (Figure 9). More specifically, it was in fact riparian forest forms in the north-east of the Basin which stood out. The timeline associated with PC2 is characteristic of dry-season variations (positive peaks; Figure 8) and allows the periods from 2002 to 2004 and from 2005 to 2012 to be contrasted (with 2011 being more closely related to the first period, however). Composite analysis showed high variability in the photosynthetic activity of forest areas in the western part of the Upper Oueme Basin, with NDVI amplitudes above 0.36 between activity-phase extremes (Figure 10b). The latter element thus suggests a high sensitivity of the densest forest areas along the major water courses, with distinct interannual phases over the study period.

The third mode (PC3) synthesizes 5% of interannual NDVI variance. As would be expected in the case of a factorial approach by principal components, PC3 is indicative of a more north-south organization, i.e. a spatial representation at right angles to the previous one (this being one of the intrinsic principles of a factorial approach). This mode thus contrasts NDVI variations associated with rapidly-changing forest areas in the north of the Basin (positive values also associated with some wooded savanna in the west) with areas under strong human influence located in the south-east (negative values – Figure 9). The component shows, firstly that 2002, 2009 and 2010 were quite different, and secondly that there has been a slight downward tendency since 2005, meaning that NDVI and thus the associated vegetation activity have fallen (Figure 8). Composite analysis suggests that change and extreme events mainly affect the northern part of the study area (Figure 10c).

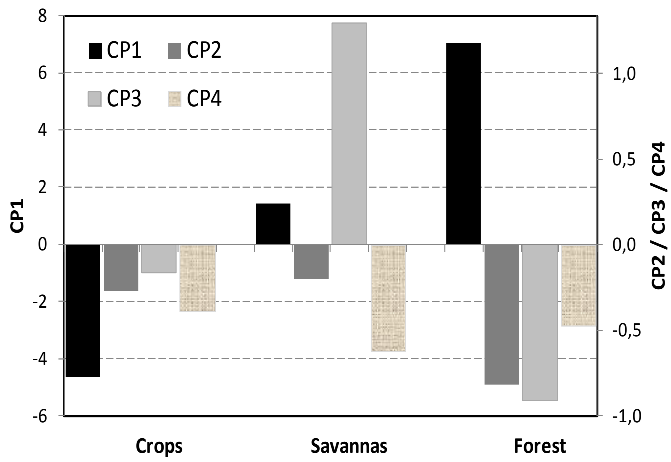

FIG. 9 AVERAGE VALUES CALCULATED FROM THE FOUR SPATIAL-FACTOR SCORES ACCORDING TO THE THREE MAIN LAND-COVER CLASSES.

PC4 is the last mode considered significant, despite accounting for a very low proportion of interannual variance (2.8%). It mainly corresponds to areas in the center of the Basin (Figure 8), and equally affects all three types of vegetation forms studied (Figure 9). It displays sharp interannual and intraseasonal variations, with the seasonal signal no longer being as explicit as for the three previous modes. With their plant activities not easy to analyze, extreme events mainly correspond to contrasts affecting the southern part of the Basin (Figure 10d). Although this mode could not be determined on the basis of this analysis alone, it is undoubtedly an artifact linked to cloud cover and partly expressed by NDVI.

A multivariate statistical analysis of NDVI thus clearly shows distinct regional contrasts and responses specific to certain areas and vegetation forms in the Upper Oueme Basin. The contrast between areas of protected native forest (forest reserves) and areas undergoing transformation into farmland (crop-growing and fallow) is especially clear. An especially noticeable change in photosynthetic activity as expressed in SPOT-VGT data can be detected from 2005 onwards. In several cases, riparian forest forms established along the major water courses (the Oueme and its tributaries) also display specific interannual and intraseasonal signatures. In a context of significant regional hydroclimatic change being experienced by Sudanian and Guinean areas since the 1970s, with growing rainfall shortages and falling water tables, river flow has decreased by 40 to 60 % (Mahé and Paturel, 2009; Descroix *et al.*, 2009). Vegetation activity in outlying forest areas of the Oueme hydrographic network may thus be reliable short- and medium-term indicators of the repercussions of such climatic variations, as a number of studies have shown the close interactions between hydroclimatic change and land-surface state in West Africa (Philippon et al., 2007; Camberlin et al., 2007). On the other hand, it also seems clear that landscape change of agricultural and anthropogenic origin is impacting the signatures of regional photosynthetic activity, even if the regional study described here was carried out over a short lapse of time and with the low spatio-temporal resolution (at kilometric and ten-day scales) specific to SPOT-VGT imaging, and did not allow the change to be quantified.

Conclusions

The present study was a preliminary one, based solely on NDVI, with a descriptive statistical and factorial approach analyzing the variability of seasonal and interannual signatures. The results obtained in this study indicate that the first mode of interannual vegetation variability opposes the forest areas (here patches of natural protected forest) to highly anthropized landscapes (here agricultural mosaics, including fallows and woody areas). The hypothesis according to which the interannual trend (and consequently, the interannual sensibility) of these different landscapes would be globally identical is so not verified. In the same way, composite analyses on intraseasonal timescale reveal significant regional contrasts of NDVI variations, mainly due to land cover. This result explains it's important to take certain precautions to interpret environmental diagnostics or to elaborate models using the vegetation answers at very low spatial resolution (e.g. continental-scale) because dynamic patterns seems to vary strongly in space.

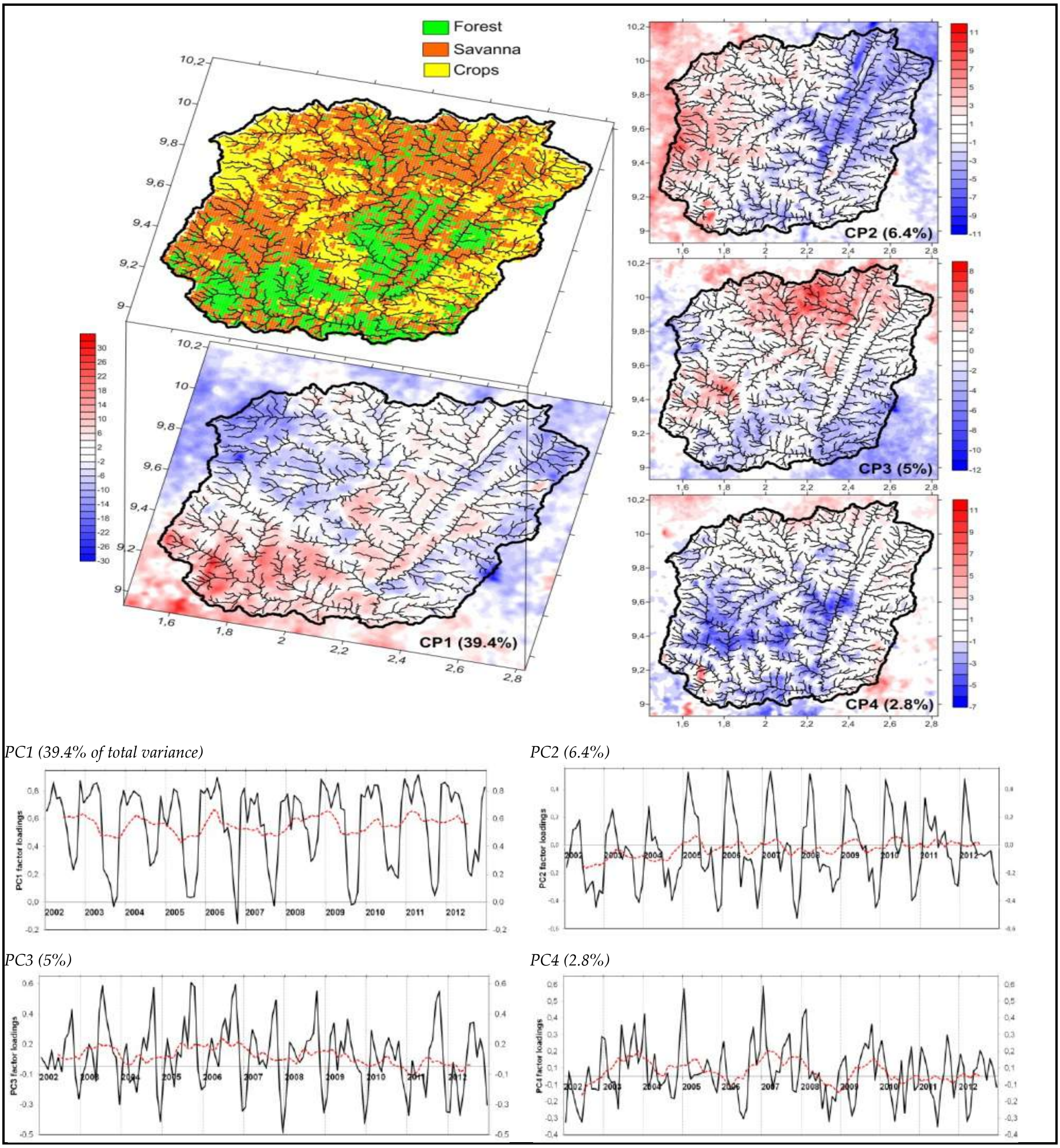

FIG. 8 SPATIO-TEMPORAL PATTERNS FROM A PRINCIPAL COMPONENTS ANALYSIS (PCA) PERFORMED ON NDVI MONTHLY TIME SERIES (2002-2012) OF THE UPPER OUEME BASIN (THE FOUR MAIN FACTORS EXPLAIN 53.6% OF THE TOTAL VARIANCE): A-TOP) MAPS OF THE SPATIAL FACTOR SCORES (THE MAP OF THE FIRST COMPONENT IS COMPARED WITH ONE OF THE THREE LAND-COVER CLASSES); B-BOTTOM) PLOTS OF THE TEMPORAL FACTOR LOADINGS.

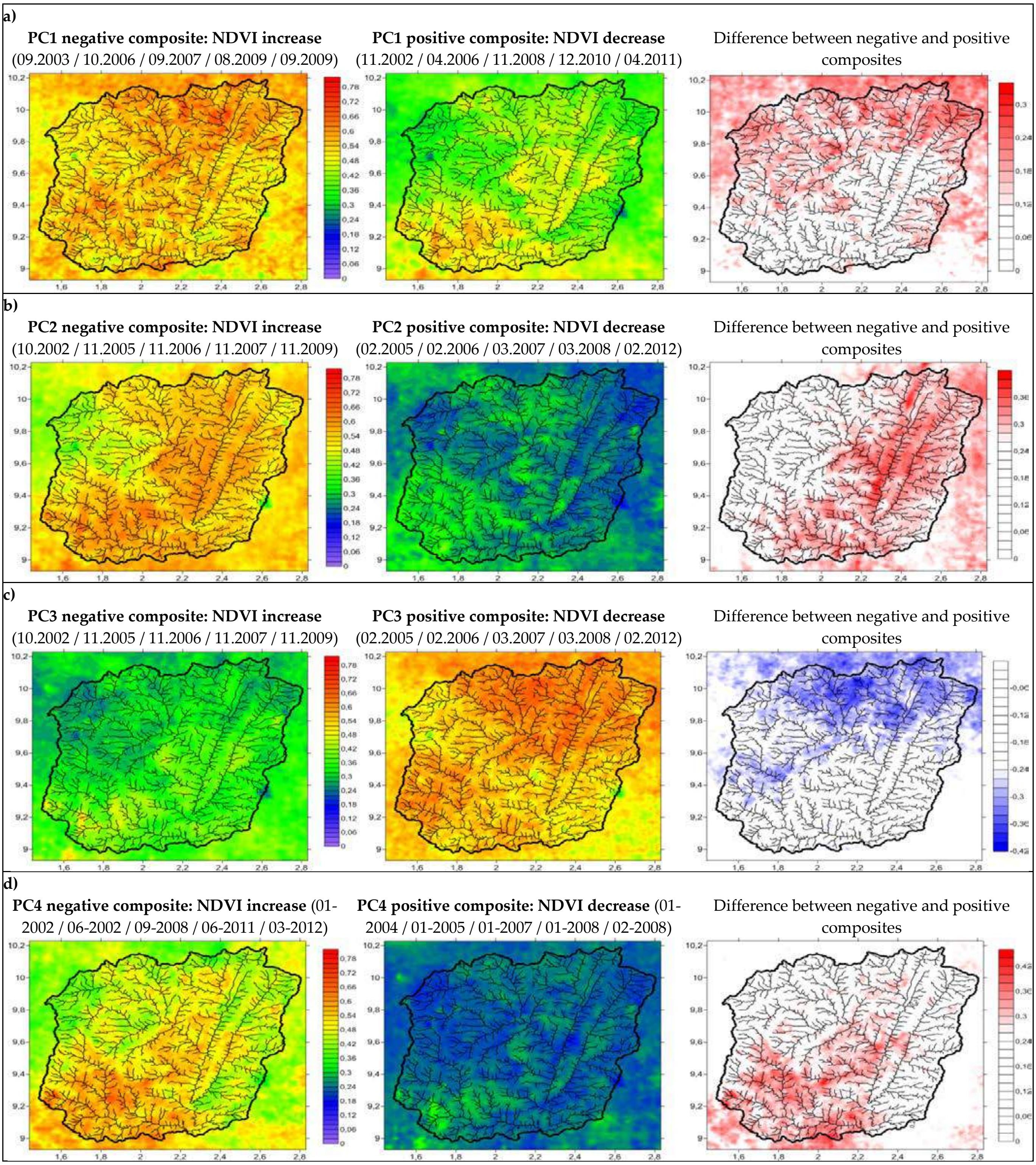

FIG. 10 NDVI SPATIAL COMPOSITES (NEGATIVE, POSITIVE, AND DIFFERENCE BETWEEN THEM) CALCULATED FROM EXTREME MONTHLY VALUES OF THE FOUR FACTORS FROM PCA (EACH COMPOSITE IS CALCULATED FROM 5 EXTREME MONTHLY VALUES).

One of the main implications of this work on the NDVI variability is that it is necessary to be able to now absolutely confront it with hydroclimate analyses. Results need to be completed by a further study involving the cross-impact analysis of regional climate (especially rainfall) series available through the network of measurements compiled over the course of the last twenty years by the AMMA Program. In particular, both dry- and wet-season extreme climate events need to be detailed on a daily scale, as do the discrepancies associated with vegetation dynamics of natural formations and forest/savanna/farmland patchworks. More precise analysis of the links between vegetation and rainfall should also enable the influence of cloudiness on radiometric signatures of vegetation indices to be better distinguished and thus eliminated. By relying on other eco-climatic data, whether from satellites or from on-site validation series, the work carried out over the Upper Oueme River Basin should enable researchers to apprehend and model the environmental trajectories favored by climatic vagaries together with anthropogenic influences. A forthcoming major objective is therefore to perform a Dynamic Factor Analysis (DFA). This is a powerful multivariate times-series dimension-reduction technique enabling the spatio-temporal dynamics of vegetation coverage to be analyzed, as well as the main physical and bioclimatic drivers of vegetation cover in the region (Campo- Bescós *et al.*, 2013) and regional anthropogenic land-use evolution to be identified.

But before these eco-hydro-climate studies, the main recommendation for the next stages is to merge various satellite data (e.g. fusion techniques adapted for different spatial resolutions) to improve spatiotemporal diagnostics of the vegetation dynamics according to land cover but also land uses. These analyses correspond moreover to the expectations of the ALMIP2 Project (second phase of the AMMA Land Surface models Intercomparison Project) which compares model, satellite and ground-based estimates of evapotranspiration and processes. For example, it would be necessary at first to be able to estimate the advantage of satellite products such as ECOCLIMAP-II (developed in the framework of AMMA Program) compared with those such as SPOT-VGT or MODIS.

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