

Determinants of the interannual relationships between remote sensed photosynthetic activity and rainfall in tropical Africa

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Abstract

The response of photosynthetic activity to interannual rainfall variations in Africa South of the Sahara is examined using 20 years (1981–2000) of Normalised Difference Vegetation Index (NDVI) AVHRR data. Linear correlations and regressions were computed between annual NDVI and annual rainfall at a 0.5° latitude/longitude resolution, based on two gridded precipitation datasets (Climate Prediction Center Merged Analysis of Precipitation [CMAP] and Climatic Research Unit [CRU]). The spatial patterns were then examined to detect how they relate to the mean annual rainfall amounts, land-cover types as from the Global Land Cover 2000 data set, soil properties and soil types. Yearly means were computed starting from the beginning of the vegetative year (first month after the minimum of the NDVI mean regime), with a one-month lead for rainfall.

One third of tropical Africa displays significant (95% c.l.) correlations between interannual NDVI variations and those of rainfall. At continental scale, soil types and soil properties are only minor factors in the overall distribution of the correlations. Mean annual rainfall amounts and land-cover types are much more discriminating. The largest correlations, mostly over 0.60, are distinctly found in semi-arid (200–600 mm annual rainfall) open grassland and cropland areas. The presence of one of these two determinants (semi-aridity, and favourable land-cover type, i.e. open grassland and cropland) in the absence of the other does not systematically result in a significant correlation between rainfall and NDVI. By contrast, NDVI variations are independent from those of rainfall in markedly arid environments and in most forest and woodland areas. This results from a low signal-to-noise ratio in the former, and the fact that precipitation is generally not a limiting factor in the latter.

The marginal response of NDVI to a given increase/decrease in rainfall, as described by the slope of the regression, displays a similar pattern to that of the correlation, with maximum slopes in semi-arid regions, except that a weaker response is noted in more densely populated areas, suggesting an incidence of particular land-use and agricultural practises.

One-year lag relationships between annual rainfall and NDVI in the next year were also considered. Ten percent of the grid-points show significant correlations, but the spatial patterns remain difficult to interpret.

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1. Introduction

In the tropics in general, and in tropical Africa in particular, water availability is regarded by far as the most important determinant to vegetation growth. In the absence of water storage systems, agricultural activities are heavily dependent upon precipitation. The high evaporative demand also makes natural vegetation very sensitive to rainfall variations. In principle, the effects of such variations could be recorded in the photosynthetic activity of the vegetation cover, as deduced from satellite mea-

surements. In tropical Africa, different monitoring programs actually resort to the Normalised Difference Vegetation Index (NDVI) to provide assessments of the rainy season, and to warn for possible food crises in case of much lower than average NDVI values (e.g., USAID Famine Early Warning Systems, FAO-ARTEMIS, MARS crop yield monitoring and forecasting system of the European Commission Joint Research Centre).

Several regional or comparative studies have demonstrated a significant response of NDVI to interannual rainfall variations in African regions such as the Sahel (Herrmann et al., 2005; Malo & Nicholson, 1990; Tucker et al., 1985), East Africa (Davenport & Nicholson, 1993; Justice et al., 1986), the Kalahari area (Farrar et al., 1994; Nicholson & Farrar, 1994; Scanlon

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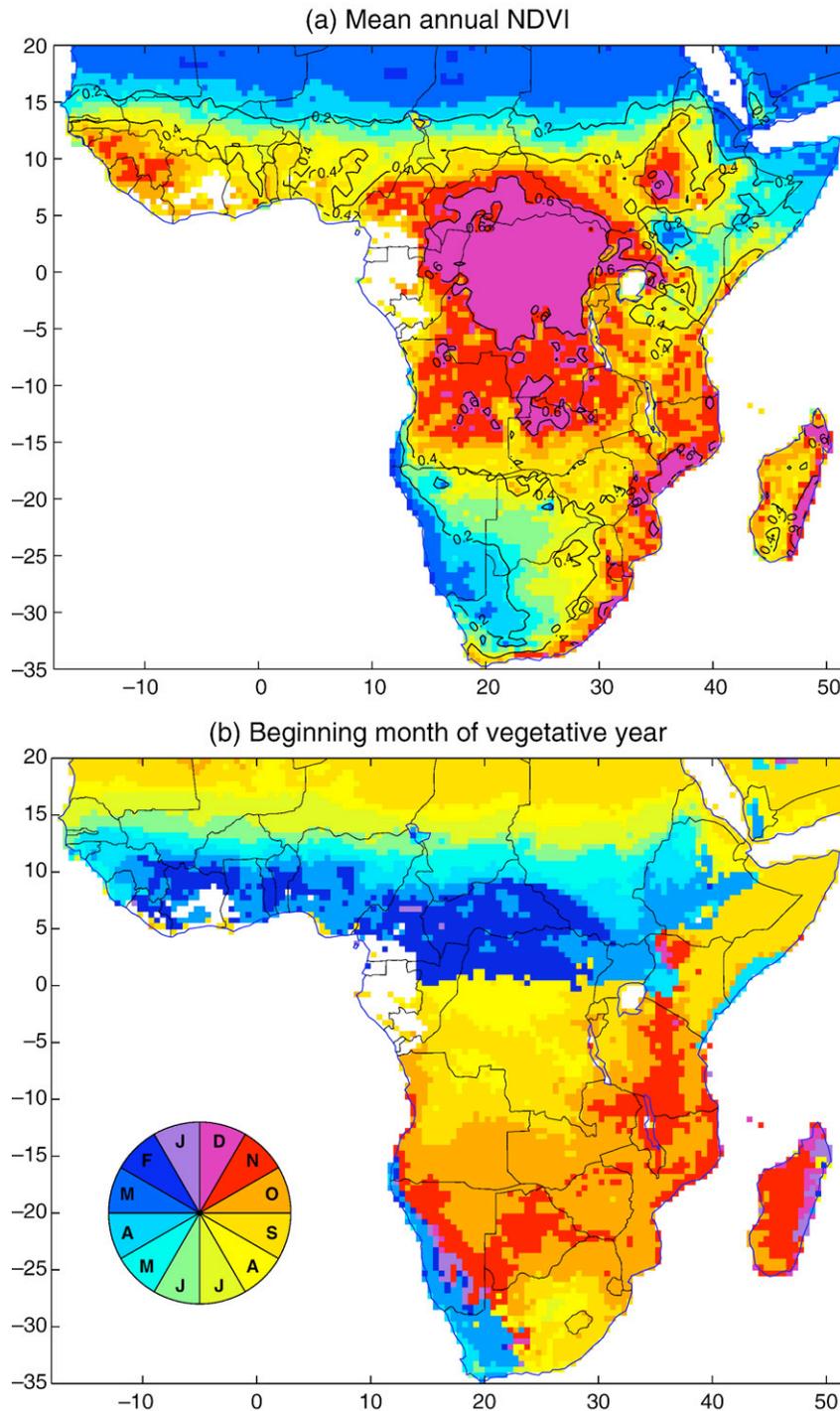


Fig. 1. Mean NDVI patterns over tropical Africa: (a) mean annual values; (b) beginning month of the vegetative season (BVS, see text).

et al., 2002) or southern Africa as a whole (Gondwe & Jury, 1997; Richard & Poccoard, 1998). Spatially more limited studies are available for countries like Ethiopia (Hellden & Eklundh, 1988), Sudan (Hielkema et al., 1986), Senegal (Diouf & Lambin, 2001; Li et al., 2004), or parts of South Africa (e.g., Archer, 2004), among others. In some regions, it has been found a high spatial variability in the sensitivity of NDVI to interannual rainfall variations (Richard & Poccoard, 1998). Though Lambin and Ehrlich (1997) suggested that year-to-year land-cover changes in tropical Africa as a whole are mostly due

to interannual climatic variability, there is a lack of a detailed mapping to show areas where the NDVI response to interannual rainfall variations is strong/weak. The present study aims at filling the gap, by examining the spatial patterns of this response (discontinuities, regional differences) and seeking explanations to them.

An important question is first to assess to what extent the NDVI-rainfall relationship is dependent upon the mean amount of precipitation. Is there any continental threshold of mean annual rainfall after which the dependence would be reduced?

What is the part played by the type of vegetation cover? For instance, forest ecosystems are considered to be less dependent on interannual precipitation variability than grasslands, but are there sharp spatial discontinuities in this dependence across the continent, or is there a gradual transition from grasslands to forests? Second, if they are local and inter-regional differences in the relationship, how can they be explained? For instance, do they reflect uneven soil properties, exogenous water resources, or human intervention? Or are they only a reflection of the imperfect nature of the global precipitation data sets available, unable to fully document the complex spatial variability of rainfall? On the contrary, may weak rainfall-NDVI relationships be ascribed to the intrinsic characteristics of NDVI products in wet regions (where a persistent cloud cover biases NDVI) and/or forested regions (where NDVI saturates and reflects the “greenness” of the canopy only, irrespective of that of undergrowth vegetation)?

Interannual relationships between NDVI and rainfall are usually studied by computing correlation coefficients between the two variables, possibly with a lag to take into account the delayed adjustment of soil moisture content. In addition to the correlation, the slope and intercept of the linear regression between interannual values of NDVI and rainfall deserve an analysis of their spatial patterns and dependence on mean annual rainfall. The slope can be considered as the response of vegetation activity per unit increase in rainfall (i.e., a marginal response; Verón et al., 2005), which may be different from the rain-use efficiency *per se*. The intercept is a descriptor of interannual variation in rain-use efficiency, and partly reflects ecological attributes. How do they vary across the African continent, especially in areas where the NDVI-rainfall relationship is significant, and what aspects of the ecosystems behaviour do they materialise?

To answer these questions, it is necessary to work on relatively long interannual time-series, and use is made here of a recently released version of bias-corrected NDVI data. These data (Section 2) serve as a basis to study interannual variations, after a determination of the “vegetative year”. Correlations and regressions between NDVI and annual rainfall totals for the period 1981–2000 are then computed using two different rainfall data sets. One-year lag-relationships are also considered. At local scales, Oesterheld et al. (2001) found that the net primary production (NPP) of Colorado grasslands was significantly explained by previous-year (in addition to current-year) rainfall. For three regions of Africa, Martiny et al. (2005) demonstrated a weak but distinct influence of a given year rainfall on NDVI of the following year, though the relationship is not fully linear. The spatial patterns of the zero-lag and one-year lag relationships between rainfall and NDVI are thus presented (Section 3). Finally, the way the NDVI-rainfall relationship is modulated by mean annual rainfall, vegetation types, as well as soil properties, is examined using a range of gridded data sets (Section 4).

2. Data

2.1. NDVI

The NDVI data set was obtained from the Global Inventory Monitoring and Modeling Systems (GIMMS) group at NASA

(Tucker et al., 2005). The vegetation index is computed from NOAA Advanced Very High Resolution Radiometers (AVHRR) satellite data, and covers a 23-year (1981–2003) period on a bi-monthly time-scale. Data are from NOAA-7 (1981–1985), NOAA-9 (1985–1988 and August 1994 to January 1995), NOAA-11 (1989–1994), NOAA-14 (1995–2000), and NOAA-16 since 2000. The GIMMS data set includes improved corrections of problems related to calibration, illumination, volcanic aerosols, and other effects unconnected to actual vegetation activity. Here, the original data (twice a month at an 8-km resolution) were resampled to the monthly time-scale and a 0.5° latitude and longitude resolution, in order to match the rainfall data as described below. Despite the efforts undertaken in the making of the data set, there remain some biases originating from aerosols, water vapour and bare soil contamination in sub-arid regions, mainly the saharo-sahelian belt (Martiny et al., *in press*), cloud contamination in regions with a persistent cloud cover, or the presence of surface water. A standard compositing technique (maximum NDVI over 15 days) was used in the computation, but a close analysis of the data revealed unexpectedly low values in some areas around the Gulf of Guinea and around some water bodies. The data set was screened for values below 0.05, and any pixel with one such value in the 23 years was set to missing, since it was seen as potentially recurrently contaminated. For this reason, parts of Ivory Coast and Gabon have missing data (white areas on Fig. 1a). The possible incidence of residual cloud contamination will be discussed below.

To obtain the time-series of annual mean values used below, the NDVI data are pre-processed as follows. The year is defined as the vegetative season. In this study, the vegetative season is considered to end on the month of the lowest long-term mean NDVI, and to start a month later. The beginning of the year therefore coincides with the first rise in NDVI, most often in coincidence with (or slightly lagging) the mean rainy season onset. Annual NDVI values are computed as 12-month averages starting from this month. The beginning of the vegetative season (BVS) is in February–March over most of the Guinea coast regions of West Africa (Fig. 1b), gradually shifting to the north (e.g., June in southernmost Niger). In equatorial regions, they are often two rainy seasons and two dry seasons, and the BVS starts after the drier/longer of the two dry seasons (for instance, in September–October south of the equator and in much of eastern Africa). In the Congo Basin, the two drier seasons (6-month apart of each other) display almost identical NDVI values, hence the equivocal shift between February and August at about 0°N on Fig. 1b. Note that in some areas (esp. with all-year round rainfall and high mean annual NDVI, Fig. 1a), any delimitation of the vegetative year is arguable, but this actually affects very few grid-points. Across southern Africa, the BVS is quite uniform (around October), except for the Namib desert and much of South Africa. The early onset in central South Africa (July to August) is related to winter wheat growth, and further south (March–June) to winter rains. Note that in a few cases the selected month may not strictly be the BVS, since NDVI may be biased by non-vegetative factors, as mentioned above.

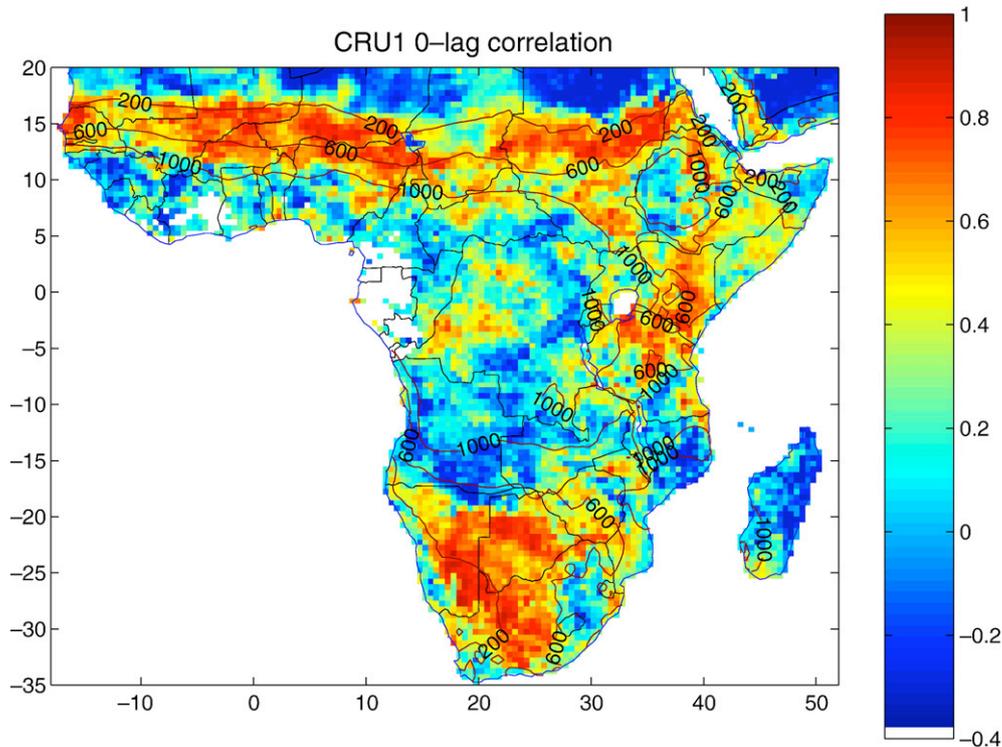


Fig. 2. Zero-year-lag correlation coefficients between interannual variations of annual NDVI and annual CRU rainfall (1981–2000). Contours show the 200, 600 and 1000 mm mean annual isohyets.

2.2. Rainfall

The primary rainfall data set is that from the Climatic Research Unit (CRU), which consists of land-only gridded (0.5° latitude \times longitude) monthly rainfall data (New et al., 2000). The period 1980–2000 was extracted. Annual rainfall amounts were computed, starting from 1 month before the beginning of the vegetative cycle, as determined above. This one-month lead was introduced in order to take into account the lag between photosynthetic activity variations and those of rainfall, which is on average of 1 month for the African continent (Poccard & Richard, 1996; Shinoda, 1995). However, the results obtained using zero-month or two-month leads were very similar, except that the correlations were sometimes slightly lower. Note that the CRU product is derived from station data only, and spatial gaps are interpolated using angular-weighted averaging (New et al., 2000). The station network was quite dense in the 1980s, but much less so in the 1990s. Being a global product, it is not necessarily reliable at small scales in all regions. For instance, little data was available in Angola and the Democratic Republic of Congo during the whole period. For these reasons, alternative rainfall data sets were also considered.

Combined rain gauge/satellite estimates from the CPC Merged Analysis of Precipitation (CMAP, Xie & Arkin, 1997) were extracted for the same period as the CRU data set. This product is available on a 2.5° latitude \times longitude grid, therefore it was interpolated to a 0.5° grid in order to match the resolution of the CRU and NDVI products. In principle, the lower initial resolution makes it inferior to the CRU data set, though it is probably more reliable than CRU in areas/years devoid from rain

gauge data, since the simple interpolation done in the latter may not be always adequate.

2.3. Land-cover

The land-cover map of Africa (Mayaux et al., 2004) prepared in the framework of the Global Land Cover 2000 project (GLC2000) enables to distinguish 27 major vegetation types and non-vegetated land surface formations. These mainly derive from VEGETATION sensor data from the SPOT-4 satellite, added to radar data, high resolution imagery and expert consultation. It is to be noted that, although this product also uses satellite (esp., NDVI) information, it can be considered as relatively independent from the one used in the present study to investigate interannual variability (GIMMS-AVHRR), since GLC2000 vegetation types were identified mainly based on mean annual values and seasonal variations (phenology). The initial resolution of the digital GLC2000 product is 1 km. It was downgraded to the same 0.5° grid as for the rainfall (CRU) data set. In each 0.5° grid-square, the dominant land cover type was determined. If for a given grid-square no single land cover type exceeded 50% of the 1 km pixels, the grid point was set to type 25 (mixed land cover types).

A few classes in the GLC2000 data set depict croplands, but the intensity of cultivation is not adequately portrayed. In order to assess the role of cultivation, data on population density were used as a rough indicator of the human pressure on the land-cover (it is the primary predictor of cultivation percentage in the models developed by Wint et al., 1999). These were obtained from the Gridded Population of the World Version 3 (GPWv3)

data set, produced by the Center for International Earth Science Information Network, Columbia University, and by Centro Internacional de Agricultura Tropical (CIESIN/CIAT, 2005). The raster data are at 0.25° resolution, and were aggregated to a 0.5° resolution. They contain population densities for 2000, adjusted to match United Nations totals.

2.4. Soil properties and soil types

Quantitative information on three soil properties was extracted from the World Inventory of Soil Emission Potentials Database (WISE) at the International Soil Reference and Information Centre (ISRIC), Wageningen, the Netherlands (Batjes, 2000). A first variable depicts soil pH (for topsoil up to 30 cm, and subsoil between 30–100 cm). Over Africa, the two soil layers show very similar distribution maps, therefore only subsoil pH is considered in the analyses below. A second variable quantifies soil moisture retention (0–1 m) expressed as the total available water capacity (AWC). Soil organic carbon density (SC) is the third variable. It is expressed as kg C per square-meter, to a 100-cm depth. All these variables are available on a global 0.5° latitude \times longitude grid. Caution must be exerted in the use of this data set, since being a global, low resolution product, it has a limited accuracy.

As a more qualitative approach, a digital, 0.5° grid square version of the Zobler global soil map was additionally used (Post & Zobler, 2000). It comprises 106 soil types classes, following the Food and Agriculture Organisation (FAO) soil classification. They have been regrouped into 26 basic groups (+ ice). Note that the precision of the set is relative since it is a degraded version of an original 1° square map.

3. Spatial patterns of the NDVI-rainfall relationship

3.1. Zero-year lag correlation

The relationships between interannual variations of NDVI and rainfall (1981–2000) are assessed by computing a correlation coefficient (r_0) and a linear regression equation for each 0.5° grid-point. CRU (interpolated rain gauge) precipitation is first considered. The correlation map (Fig. 2) shows contrasted values, with large areas having nil or insignificant correlations, while significant values (0.45 to 0.90) are found in three well-defined areas: the sudano-sahelian belt (from Senegal to Eritrea), west-central parts of southern Africa, including the Kalahari desert and its surroundings, and parts of East Africa, including north-eastern Ethiopia, eastern Kenya and central Tanzania. In all, 32.7% of the grid-points display significant (95% c.l.) correlations, with a slightly higher percentage during the 1980s than during the 1990s, a reflection of the lesser quality of the precipitation data in the latter decade. Correlations close to zero or even negative are found in the Sahara, in several regions around the Gulf of Guinea, in parts of the Congo Basin, from Angola to northern Mozambique, in Madagascar, as well as in smaller areas like western Ethiopia, north-eastern Somalia and eastern South Africa. In order to account for possible non-linear relationships between NDVI and rainfall (NDVI was found to

‘saturate’ above about 1000 mm rainfall in western and eastern Africa; Davenport & Nicholson, 1993; Malo & Nicholson, 1990), log transformations of the rainfall data were carried out, and the correlations recomputed. There was however very little change in the results (only 0.2% of additional grid-points reach 95% statistical significance). Only a few pixels did show a significant increase in their r -square, and some others showed a decrease. Therefore the linear approach was retained in the rest of the study.

The distribution of high correlations well matches that of semi-arid areas (see isohyets of 200, 600 and 1000 mm on Fig. 2). This is confirmed by the plot of the correlation coefficients r_0 versus mean annual rainfall (Fig. 3): the temporal (interannual) relationships peak around 300–400 mm. The r_0 values quickly fall to nil or even negative values when rainfall is low. Above 400 mm, r_0 values also decrease but much more gradually. On median they become insignificant above 600 mm, but there is a large dispersion, for significant values may still be found above 1000 mm (the cluster of slightly higher values around 1700 mm is likely due to sampling). In particular, it is found that in western Africa and parts of eastern Africa significant values are found well above 600 mm (see smaller green/grey circles on Fig. 2, for western Africa). Reciprocally, in southern Africa, the correlations are higher for relatively dry areas, then drop sharply from 400 to 600 mm (see smaller blue/black circles on Fig. 2).

Fuller and Prince (1996), for southern Africa, using a few sample sites, found temporal correlations to reach a threshold at about 600 mm rainfall. Herrmann et al. (2005), for western Africa, obtained highest temporal correlations (at a monthly-time-scale, and mixing interannual and seasonal variations) in the Sahel semi-arid zone. For tropical Africa as a whole, Martiny et al. (in press) assessed the spatial relationship between the long-term averages of NDVI and rainfall. They found a linear relationship also in the 200–600 mm precipitation range, though with some dispersion. Together with the above findings, this indicates that in semi-arid areas both temporal and spatial variations of NDVI are unequivocally controlled by rainfall. However, the upper and lower bounds of high correlations depend on the region, with western Africa, in particular, contrasting with southern Africa. The interpretation of these results and the cases of the wetter and drier areas will be further discussed below.

Considering the small number of rain gauges incorporated in the CRU data set in recent years, especially in the 1990s and in some regions like Central Africa or war-torn countries like Somalia, the same analysis was carried out using the CMAP gridded data set. The basic r_0 correlation patterns between NDVI and CMAP rainfall are the same as for CRU rainfall (Fig. 4). On the whole, correlation are often marginally higher, though there is a substantial improvement over some countries (southern Somalia, Chad, central Nigeria) where the satellite data, included in CMAP, compensate the virtual absence of rain gauge data in the 1990s. Cases of degraded correlation are also found (central Tanzania, central Congo Basin), which are likely to be due to an incorrect satellite estimate of rainfall, and to the initial lower resolution of the data set (2.5°) compared to CRU. However, in general, the

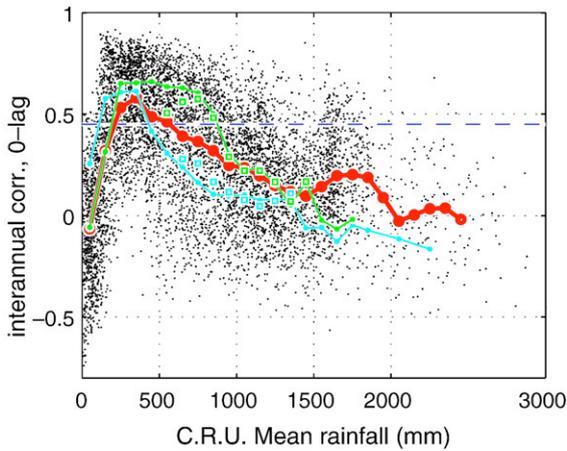


Fig. 3. Scatter-plot of zero-year lag correlation coefficients between NDVI and CRU rainfall (y-axis), versus mean annual rainfall (x-axis), for 7743 grid-points across tropical Africa. Dashed line: 95% significance level. Circles connected by a thick line indicate the median correlation for all successive 100 mm bins (i.e.: 0–100, 100–200, 200–300...). Thin lines: same but for western Africa (7.5°N–20°N, 15°W–15°E, grey) and southern Africa (south of 10°S, black). Squares: grid-points with a fire return period lower than 3 years.

smoothing resulting from this resolution is not found to alter the correlations (34.7% of the grid-points display significant correlations, as compared to 32.7% for CRU). In view of these results, only CMAP data were used in the rest of the study, but the above remarks should be kept in mind when analysing the detailed patterns of the correlations.

On the whole, and whatever the rainfall data set, a noticeable feature is the apparent poor response of NDVI to rainfall

variability in sub-humid to humid climates. Note that identical results were obtained using detrended time-series, ruling out the incidence of possibly different trends in rainfall and NDVI (which could be the result of human activities; Herrmann et al., 2005). Different factors may therefore explain these low correlations. One of them is related to the signal itself, which saturates above certain values (Mutanga & Skidmore, 2004; Nicholson et al., 1990). A second one relates to plant physiology: in very wet areas, photosynthetic activity (esp. that of trees) is relatively insensitive to rainfall variations, provided that a certain amount is guaranteed. However, we cannot rule out that cloud cover contamination does not remain in the remote sensed vegetative activity, despite the corrections carried out in the NDVI product used here. This problem is usually fixed by using a 10-day or 15-day composite, but contaminated NDVI values may remain (as discussed in the data section, around Gabon for instance). Though in given months and years this bias is likely to be still present, we hypothesize that it only weakly affects our results, which are based on yearly values. One of the clues to it is that the mean seasonal variations (as exemplified by the BVS map, Fig. 1b) are relatively conform to the observation, and replicate rainfall variations. Incidentally, this remark could be seen to contradict the hypothesis of an absence of vegetation response to rainfall in these regions. Similar observations were made in southern Africa by Fuller and Prince (1996) and Richard and Pocard (1998), whereby in wet areas the interannual correlations were found to be low, yet the NDVI mean seasonal variations closely follow those of rainfall. This points to the fact that phenology and interannual variations in photosynthetic activity denote different physiological and/or ecosystems responses to constraints in water availability.

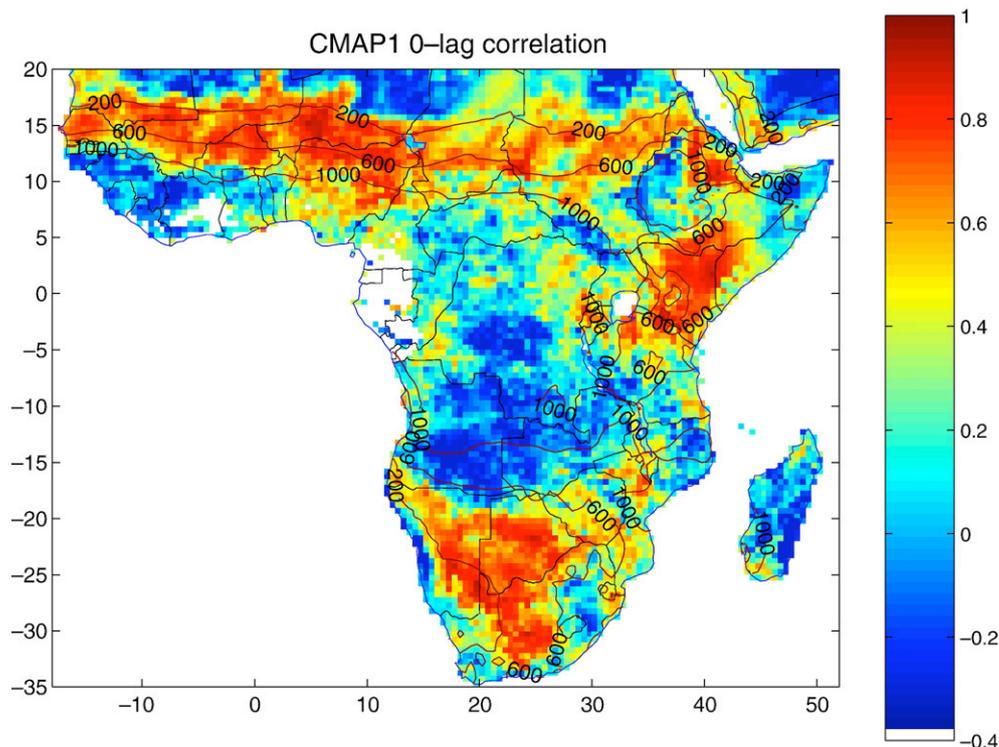


Fig. 4. Same as Fig. 2 but for CMAP rainfall.

The very low r_0 correlations found in arid areas (below 150 to 200 mm) are related to the fact that only a very small portion of the land surface is vegetated. Additionally, both rainfall and vegetation “green-up” occur over a very short period of time during the year. Hence, the annual signal is dominated by other surface properties (e.g., colour of bare soil), and maybe strongly biased by atmospheric effects. In the southern Sahara margins, the increase in atmospheric water vapour content in wet years, which results into lower NDVI values (Justice et al., 1991; Tanré et al., 1992), offsets that of increased rainfall, and explains the negative correlations sometimes found between NDVI and rainfall (Fig. 2).

The fact that maximum NDVI sensitivity to rainfall variations is found in drier environments in southern than in western Africa (Fig. 2) is related to the lower rainfall efficiency in the latter region, as noted in Prince and Tucker (1986), Farrar et al. (1994) and Martiny et al. (in press). Possible factors include, for western Africa, greater seasonal rainfall concentration resulting into higher runoff (though this aspect was discounted by Farrar et al., 1994), more agriculture, lower soil fertility, higher temperature, and biases such as those related to aerosol content.

Regression models between NDVI and rainfall were computed. The intercepts of the linear relationships were first plotted (not shown). They actually exhibit a simple pattern which is very similar to that of mean annual NDVI. However, when identical mean rainfall values are considered, some differences are found among the semi-arid regions. For instance, relatively higher than expected values are found in the Kalahari desert, and lower than expected in the Sahel. This reflects contrasts in rain-use efficiency (higher in southern Africa than in western Africa) as discussed above. The slopes of the regressions were next plotted (Fig. 5), together with the corresponding mean annual rainfall. As expected, the general pattern is similar to that of the correlations scatter plot (Fig. 3, which was obtained for CRU rainfall; the one for CMAP is essentially the same). The largest values are again found in the 200–600 mm range, peaking

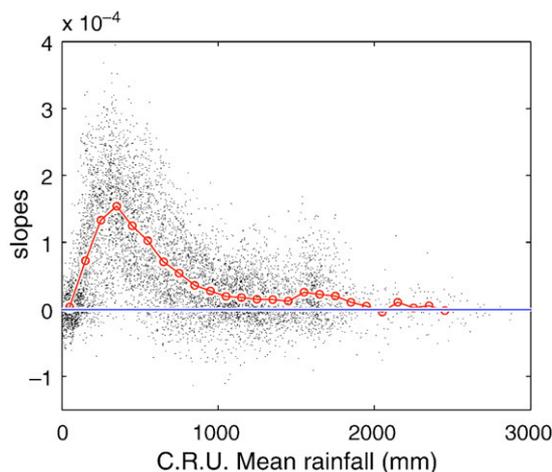


Fig. 5. Same as Fig. 3 but for the slopes of the regression between NDVI and CMAP rainfall. Note that the mean annual rainfall on the x-axis is taken from CRU, since whereas CMAP is adequate to depict interannual variability it does not have a sufficient resolution to depict small-scale (0.5°) variations in mean rainfall amounts.

around 400 mm. It is remarkable that slopes obtained for higher rainfall amounts fast drop to relatively low values. Paruelo et al. (1999), for temperate grasslands, studied the slopes in interannual models of NPP-precipitation relationships. They found the maximum slopes at annual rainfall of about 475 mm, which is close to what found in the present study, though for tropical regions. These authors suggested that in drier environments (i.e., well below 400 mm, showing low slopes), the dominance of species with low relative growth rates constrains the response to interannual rainfall variations. Drought resistance strategies have permanent implications on maximal photosynthesis and growth rates, even when precipitation is temporarily higher, hence the low slopes. By contrast, in wetter environments (i.e., well above 400 mm), the lower slope values are indicative of a predominance of growth constraints (e.g., biogeochemical, thermal,...) other than precipitation amounts (Huxman et al., 2004; Paruelo et al., 1999). This may also apply to most wet areas in Africa.

There are some exceptions however, of wet areas displaying small slopes but significant positive correlations between NDVI and rainfall. Such cases (lower Zambezi valley, central Nigeria, Rwanda), and the reasons for this apparent contradiction, will be discussed in Section 4.1.

3.2. One-year lag correlation

One-year lag correlations (r_1) were also considered in order to detect possible persistence effects. Removing the effect of current-year rainfall is done by computing partial correlations between NDVI for year i and CMAP rainfall for year $i-1$ independently from rainfall in year i . On the whole, correlations are quite low (Fig. 6). However, positive and significant (95%) r_1 values are found over extensive parts of West Africa, as well as in the Republic of the Sudan and South Africa. In all, they add up to 9.9% of the grid-points.

There is no particular coincidence with a particular rainfall amount (Fig. 7). Similarly, significant one-year lag correlations can be found in regions of otherwise either non-significant or significant NDVI response to synchronous rainfall. Note that some degree of “memory” had been found in 3 different semi-arid regions of Africa (Martiny et al., 2005), though the lag-one correlation observed in eastern Africa (Kenya) is not reproduced in the present continental scale analysis (which uses coarser rainfall data). The spatial patterns obtained in Fig. 7 are somewhat noisy. This is suggested to be due to the coarse spatial and temporal scales, which mix different signals. In some of equatorial regions experiencing wet conditions almost throughout the year, cases of high r_1 values (e.g., eastern Congo Basin) may locally be interpreted as the influence of late year-1 rains onto the early year-2 vegetation activity, thus reflecting a possibly inadequate delimitation of the vegetative year.

The possible role of land surface discriminating factors (land-cover types, soil properties and soil types) on the correlation and slope patterns, for both r_1 and r_0 , is next explored. However, the results for r_1 failed to show systematic associations between high one-year lag correlations and any of these discriminating factors. This may be related to (i) the spatial scale under

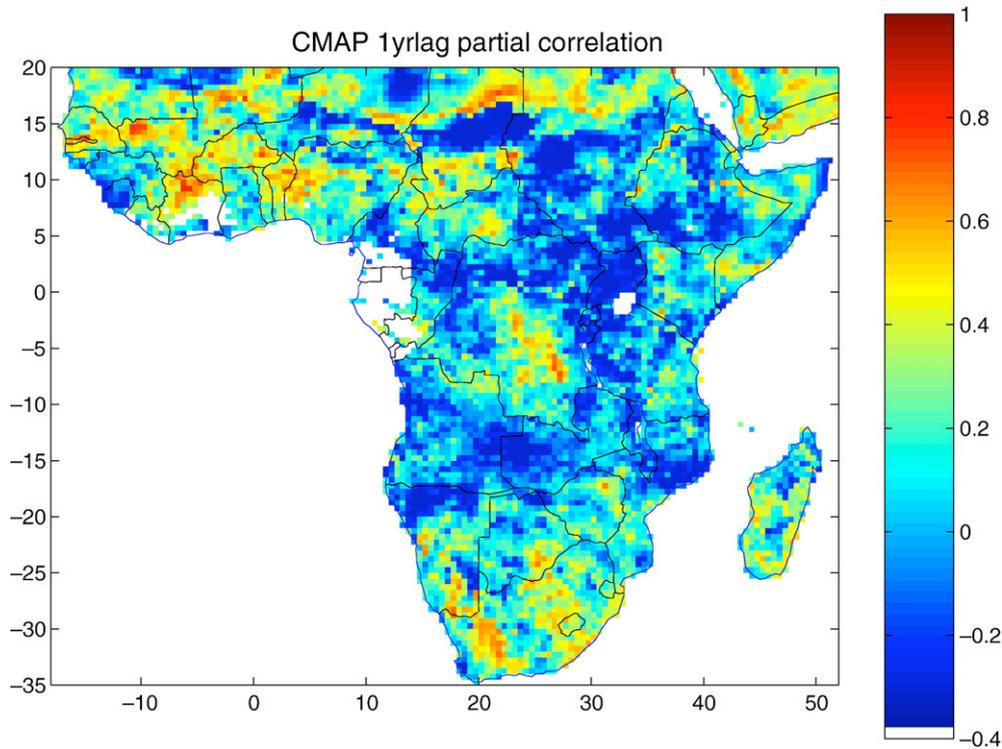


Fig. 6. One-year-lag partial correlations (1981–2000) between NDVI for year i and CMAP rainfall for year $i-1$ independently from rainfall in year i .

consideration, which is too coarse to accurately depict local factors; (ii) the weakness of the signal, compared to zero-year lag correlation. Therefore, only the results obtained for r_0 will be discussed in the following sections.

4. Role of land surface properties

4.1. Land-cover types

4.1.1. Zero-year lag correlation

The fact that the NDVI-rainfall relationship is stronger for a given range of annual rainfall amounts suggests that it is also related to vegetation types. For instance, forest and woodland environments are expected to coincide with lower correlations. This aspect is analysed by showing the distribution of the indicators of the NDVI-CMAP rainfall relationship (correlations and slopes, as discussed in Section 3) with respect to vegetation types and land-cover classes as from the GLC2000 data set.

Fig. 8 shows the box-plot of r_0 correlation coefficients for the GLC2000 classes which are represented by at least 25 grid-points. Five land-cover types are predominantly associated with significant (95% level) NDVI-rainfall correlations: open grasslands (classes 13 and 14), sparse grasslands (15), croplands (17), and croplands with open woody vegetation (18). The highest median correlation is for the open grasslands ($r_0=0.67$). It is noticeable that for this vegetation type 80% of the grid-points display significant correlations. Other land cover types (esp., tree-dominated ones) on average display non-significant correlations (Fig. 8). However, the range of values is quite large for some of them; for example, 30 and 27% of the montane forest

and open deciduous shrubland grid-points, respectively, show a significant correlation (see below).

On the whole, these results are not unexpected: the land-cover types which exhibit the largest NDVI-rainfall correlations are characteristic of generally semi-arid environments (open and sparse grasslands, croplands), in agreement with the largest correlation being found in the 200–600 mm belt (Section 3.1). However, is it possible to say whether the higher sensitivity is dominantly related to a certain amount of rainfall or to a certain vegetation type? Table 1 confirms that the highest sensitivity to rainfall (median $r_0=0.66$) is found at locations combining 200–600 mm rainfall and an open grassland or cropland land-cover

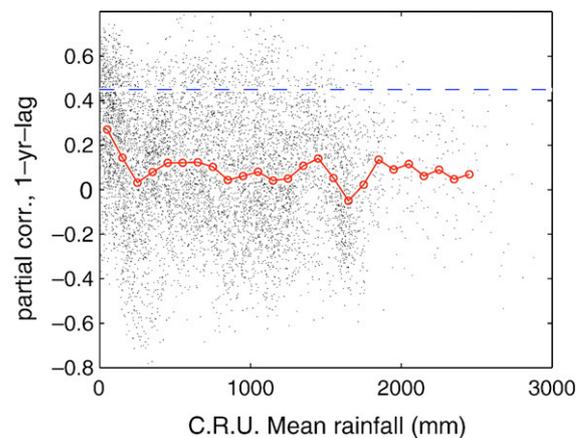


Fig. 7. Scatter-plot of one-year lag partial correlation coefficients between $NDVI_i$ and $rainfall_{i-1}$, independently from $rainfall_i$ (y-axis), versus mean annual rainfall (x-axis). Legend as in Fig. 3.

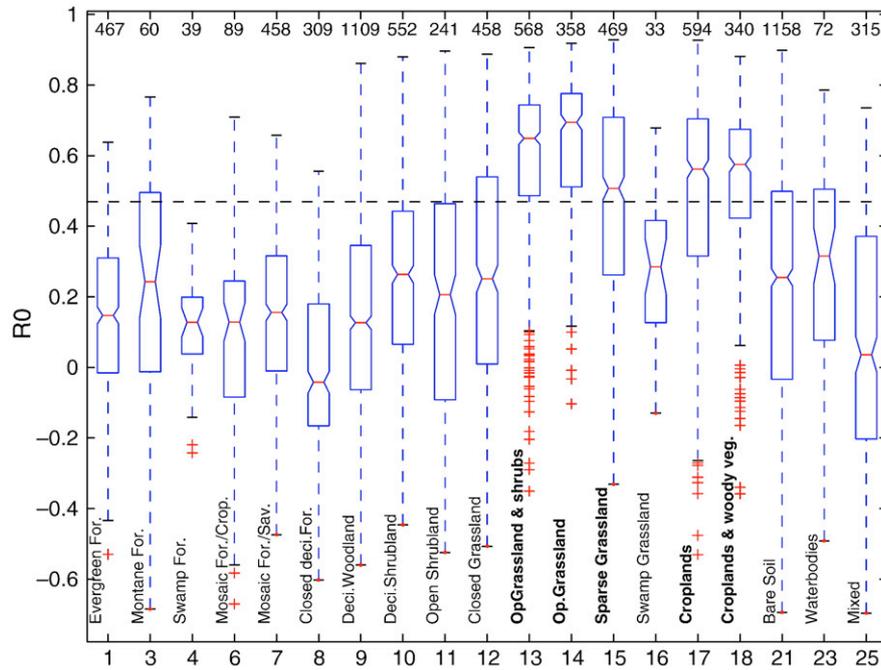


Fig. 8. Box-plot of zero-year-lag correlation coefficients between NDVI and CMAP rainfall, for different GLC land-cover classes (see full denominations under Table 1; type 23 stands for grid-points which include part of a waterbody; type 25 stands for grid-points with no dominant land-cover type). Only the land-cover classes which are represented by at least 25 grid-points are shown. Top numbers: number of grid-points. Horizontal dashed line: 95% confidence level. Box-plots are represented in the usual way (i.e., lower and upper limits of the box: lower and upper quartiles; central line: median; whiskers: lowest and highest values, with '+' showing outliers beyond 1.5 times the inter-quartile range).

(A on Table 1). If we now compare sites with the same land-cover but rainfall outside the 200–600 mm range (B), to semi-arid sites (200–600 mm) but neither under open grassland nor cropland (C), we find that they exhibit virtually the same median correlations. This tends to show that none of the two factors (land-cover and annual rainfall) is more important than the other in the sensitivity of NDVI to rainfall variability (as confirmed by a two-way analysis of variance, not shown).

The question is further explored by focusing on those areas where the NDVI response to rainfall is not what is expected. First, there are some grid-points located in semi-arid regions where non-significant correlations are found. On the contrary, there are non-semi-arid areas which nonetheless exhibit a significant correlation between rainfall and NDVI. Are both features associated with specific land surface conditions?

To illustrate the first point, the lower part of Table 1 displays the median correlation obtained for each land-cover type, for all semi-arid areas (left column). What is noticeable is that all the non-herbaceous land-cover types (shrubland, woodland) show weaker correlations between NDVI and rainfall, even if they fall within the 200–600 mm range. Such cases are found for example in parts of the Limpopo Basin. However, the presence of a significant tree-cover is not all since there are other semi-arid regions which similarly display a low NDVI sensitivity. They include parts of central Chad and Darfur, the Ogaden and central Somalia, and the Namibia–Angola border. These regions do not coincide with specific land-cover types. For instance, in Somalia they include sparse grasslands, but this formation both exhibit high ($r_0 > 0.7$) and low ($r_0 < 0.1$) correlations, from south to north. Apart from the possibility of

inaccurate rainfall data (few rain gauges are available in most of these areas), an hypothesis may be the influence of soil properties. This will be examined in Section 4.2.

If we now concentrate on those non semi-arid areas, where the NDVI sensitivity is nonetheless high, it is found that the amount of rainfall still has an important role. Most of the corresponding grid-points have a mean annual rainfall quite close to the above thresholds (100–200 mm, or 600–1000 mm). It is logical to think that water availability still impacts NDVI variations in such environments. However, it is also clear that a fraction of these non-semi arid lands, even with rainfall below 1000 mm, has a weak sensitivity. What makes the difference between the high and the low sensitivity areas in wet areas? An inspection of the GLC2000 map and data (Table 1, right column) shows that high sensitivity is clearly associated with three land-cover types: open grassland with sparse shrubs, open grassland, and croplands with open woody vegetation. These land-cover types are predominantly found in the sudanian belt from Senegal to Sudan, and in East Africa (northern Tanzania and Kenya). Non-significant correlations, on the contrary, tend to be associated with woodland or shrubland. This contrast in r_0 values, depending on the land-cover, matches the differences between southern Africa and western Africa, as displayed on Fig. 3. In order to better discriminate the effects of land-cover and mean rainfall, the case of western Africa is further analysed (Fig. 9). In this region, the change from high to low r_0 values is quite abrupt (less than 200 km) and strongly related to the transition from grasslands/croplands to woodland/forest. Though the separation between the rainfall factor and the land-cover factor is not easy, there are several instances (Mali, Burkina Faso...) where the high

Table 1
Median r_0 correlation coefficients between the interannual variations of annual NDVI and annual CMAP rainfall (1981–2000), for different land-cover types and annual rainfall amounts

GLC types (and numbers)	Mean annual rainfall	
	200–600 mm	Other amounts
All open grasslands (13–14) and croplands (17–18)	A 0.66 (1060)	B 0.53 (800)
All other land-cover types	C 0.52 (893)	0.15 (5012)
Evergreen lowland forest (1)	*	0.15
Montane evergreen forest (3)	*	0.21
Swamp forest (4)	*	0.13
Mosaic forest/cropland (6)	*	0.13
Mosaic forest/savanna (7)	0.44	0.15
Closed deciduous forest (8)	0.26	–0.05
Deciduous woodland (9)	0.44	0.11
Deciduous shrubland (10)	0.41	0.26
Open deciduous shrubland (11)	0.41	0.02
Closed grassland (12)	0.64	0.16
Open grassland with sparse shrubs (13)	0.65	0.56
Open grassland (14)	0.69	0.71
Sparse grassland (15)	0.60	0.38
		(>600 mm: 0.70)
Swamp grassland (16)	0.09	0.29
Croplands (17)	0.65	0.44
Croplands with open woody veget. (18)	0.65	0.56
Bare soil (21)	0.58	0.18
Mixed land-cover types	0.42	–0.11

Significant values (95% c.l.) are in bold. The number of grid-points used in the computation of the mean is in italics. Stars denote combinations represented by less than 5 grid-points.

correlation pattern more closely follows the latter than the former. The effect of tree cover in the reduction of NDVI sensitivity to rainfall is also apparent in southern Africa, at a lower mean annual rainfall threshold than in western Africa. Scanlon et al. (2002), along a Kalahari transect, show that the sharp drop in NDVI interannual sensitivity north of 20°S can be

interpreted as a marked increase (decrease) in fractional tree cover (grass cover).

In the northern part of West Africa (Fig. 9), towards the Sahara desert, there is also a clear coincidence between fast dropping correlations and a change from sparse grasslands to bare soil, though occasional high correlations overlap the GLC2000 ‘bare soil’ class in the south-western part of relatively high ground areas (Adrar des Iforas in Mali and Aïr massif in Niger). It is suggested that the latter exceptions are related to surface and sub-surface water inflow (the numerous wet season streams flowing down from the highlands induce local vegetation growth in wet years, which may be sufficient to enhance grid-point mean NDVI). Cases of significant r_0 for areas classified as predominantly ‘bare soil’ are also well shown in the box-plot for Africa as a whole (Fig. 8).

In the context of the high correlations found in grassland/cropland formations, there are however, for Africa as a whole, two grassland formations which display low sensitivities (Table 1): swamp grasslands (mostly represented by the Sudd swamps of southern Sudan) and closed grasslands. The former case is evidently associated with lateral inflow of water, which makes vegetation weakly dependent on local rainfall. Farrar et al. (1994) noted for Botswana, in a context of strong relationships between NDVI and rainfall, locally much lower correlations, which they attributed to ‘run-in’, i.e. lateral inflow of water, especially along the major valleys. The latter case of low sensitivity (closed grasslands) is related to the fact that much of this land-cover type consist of grasslands developed under relatively wet conditions, as in southern Congo–Brazzaville or in Madagascar. These grasslands, of edaphic or anthropogenic origin, are not at equilibrium with present-day climate (over 1000 mm/year in both regions). There is enough water in any year to enable herbaceous growth, hence the absence of significant correlation.

4.1.2. Zero-year lag slopes

Quite similar results are found when analysing the slopes of the regression between NDVI and rainfall (Fig. 10). Open grasslands, and secondarily croplands, clearly display the steepest

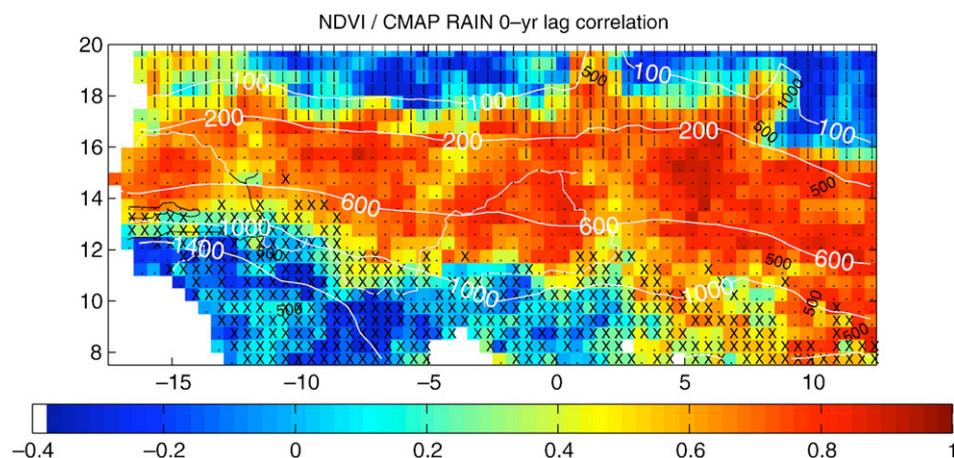


Fig. 9. Zero-year-lag correlation coefficients between NDVI and CMAP rainfall for West Africa. ‘X’: forest, woodland and shrubland (GLC2000 types 1–11). Vertical strips: bare soil (type 21). White contours: mean annual rainfall in mm (CRU). Dashed black contours: elevations of 500 and 1000 m.

slopes. Since the croplands categories listed above designate rainfed crops, it is clearly demonstrated that in tropical Africa the herbaceous and annual formations (either natural or not) exhibit the strongest response of NDVI to interannual rainfall variability. These formations are made up of relatively shallow-rooted plants which are very sensitive to any variation in annual rainfall. This is particularly so in regions which have a unique and rather short rainy season, whereby any rain failure is very unlikely to be compensated for by subsequent higher precipitation.

A noticeable feature is the fact that slopes in forest, woodland and shrubland environments are generally very small (Fig. 10). The trees' greenness is therefore little affected by year-to-year precipitation variations. As noticed above for wet regions, this is so even in those (few) regions where the correlation coefficients are relatively high, like parts of central Nigeria, lower Zambezi valley, among others. What statistically differentiates correlation and slopes is that the latter takes into account the absolute variability of NDVI per unit variation of precipitation. Thus, such an apparent contradiction (high correlations, small slopes) actually denotes a combination of a low NDVI variability and a high rainfall variability, but with an in-phase evolution of the two variables. Physiologically, this reflects a vegetation which is sensitive to any precipitation variations (high correlations), but in a damped way (small slopes). One possible interpretation would be a mixture of evergreen and herbaceous (or crop) signals. A closer examination was carried out of these regions, as well as other areas (this time within the semi-arid or 'grassland' belt) which also display relatively low slopes but high correlations. There is evidence that they often coincide with high rural densities (northern Nigeria around Kano, Rwanda, Sukumaland in northern Tanzania, Tigray in northern Ethiopia...). Reciprocally, in

semi-arid regions, the largest slopes (still with high correlation coefficients) are often found in less populated areas.

Using the CIESIN/CIAT gridded population data set, an attempt was made to assess whether a statistical influence of population densities could be detected. Densities have been split into four arbitrary classes (below 10, 10–40, 40–100 and over 100 h/km²). Analyses of variance have been computed, for each land-cover type, to determine whether there was a significant difference in slopes depending on density classes. For open grasslands and croplands, slopes tend to be significantly smaller over higher population density areas. By contrast, no incidence of population densities on the distribution of correlation coefficients can be detected. A scatter-plot of correlations versus slopes confirms that the latter are, all things equal, significantly smaller in densely populated areas (Fig. 11a). For a given correlation coefficient, slopes are on average 50% greater in areas of below 40 persons/km² than in more densely populated regions. For West Africa, Fig. 11b confirms, though edaphic factors also play some part in the distribution, that the slopes are relatively smaller (larger) in higher (lower) density areas such as western Senegal (north-east Senegal), the Niger valley around Niamey (Burkina/Niger borders), north-central Nigeria from Kano to Sokoto (north-eastern Nigeria). We hypothesize that these low slope, high human density areas, correspond to densely cultivated areas. During crop growth and maturation, interannual variations in precipitation amounts are well reflected by those of NDVI, but after harvest, the NDVI catches a bare soil signal. When averaged over a year, the NDVI is a mixture of the pre- and post-harvest reflectances, thus the remaining signal is still linked with seasonal rainfall but is damped. A fairly similar mechanism may occur in heavily grazed areas.

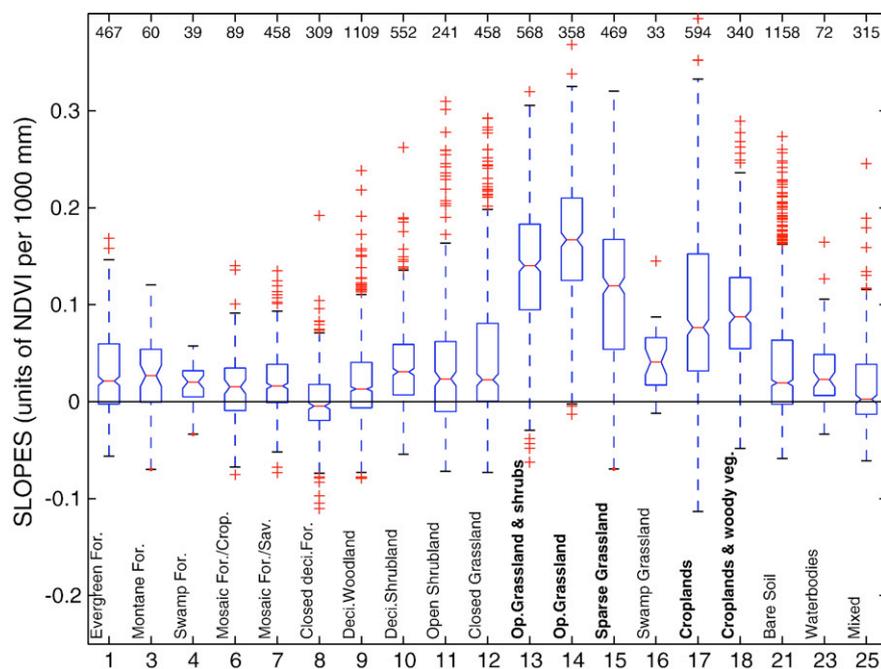


Fig. 10. Same as Fig. 8 but for the slopes of the regression between NDVI and CMAP rainfall.

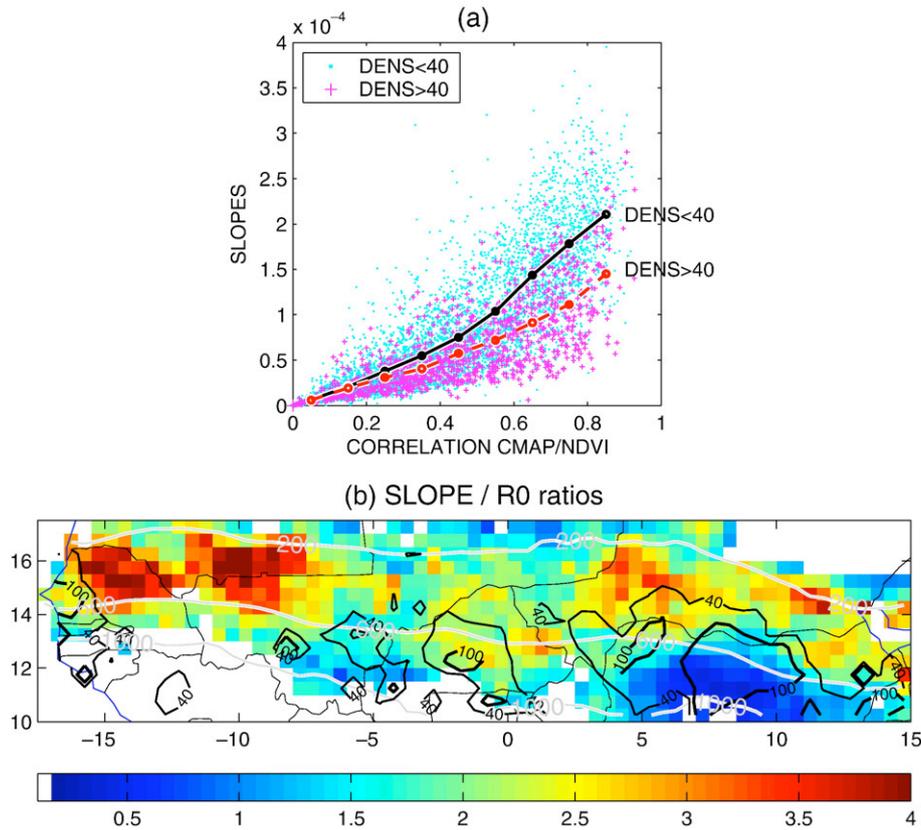


Fig. 11. Slopes and correlation coefficients of the linear relationship between interannual variations of NDVI and rainfall. (a) Scatter-plot for tropical Africa as a whole: grid-points with population densities below (above) 40 inhabitants per km^2 are shown as dots (pluses), with mean slopes for each 0.10 correlation bins joined by a solid (dashed) line. (b) Ratio between slopes and r_0 , for all grid-points with a r_0 above 0.40 in West Africa. Black contours: population densities. Light grey contours: mean annual rainfall amounts.

4.2. Soil properties

Three types of soil properties are examined: available water capacity (AWC), organic carbon content (SC) and pH. Soil properties have little relationship with NDVI sensitivity to current-year rainfall (r_0). Considering tropical Africa as a whole, all SC classes and AWC classes actually display quite similar median values of r_0 (Fig. 12a–b). Only pH shows a more robust incidence on the NDVI sensitivity to rainfall. The latter peaks for pH ranging from 5.5 to 7.3, while more acid soils ($\text{pH} < 5.5$) much more rarely display high sensitivity r_0 values (Fig. 12c). Acidity may therefore be viewed as a biogeochemical constraint which outweighs the influence of rainfall variability on vegetative activity. Acid soils are found mainly in equatorial regions in either forested or high rainfall areas. Reciprocally neutral to moderately acid soils display a significant sensitivity of NDVI to rainfall.

Since the impact of soil properties is expected to be secondary compared to that of climate, the variations in r_0 for different rainfall and GLC classes were examined independently. It is confirmed that the water capacity has very little incidence whatever the mean rainfall amount, as well as for most land-cover types (not shown). However, for open grasslands and croplands, which were shown to exhibit very large r_0 values, it is found that they are significant for low to moderate water capacities (Table 2, top), whereas when AWC is above

150 mm, the response of NDVI to rainfall variability becomes insignificant. In other words, a high soil moisture retention slightly dampens the impact of precipitation variability, but under selective land-cover types.

The incidence of soil organic carbon density (SC) was also tested. There is no difference between SC classes within semi-arid or wet areas, but in more arid environments, r_0 increases with the density of organic carbon in the soil, reaching 95% significance when it is above 8 kg/m^2 (Table 2, bottom). In such harsh environments, this may be interpreted as the requirement for the vegetation, in order to develop and react to rainfall variability, to benefit from soils with sufficient amounts of organic matter. Finally, the analysis of pH values for the different rainfall and GLC classes (not shown) confirms the above results, of an overall lower r_0 for highly acidic soils, while maximum values are obtained for pH ranging from 5.5 to 7.3.

4.3. Soil types

The distribution of zero-year lag correlation with respect to Zoller soil groups exhibits relatively small differences, compared to those found for land-cover types. Only 4 soil groups display median r_0 values above the 95% significance level (in green/light grey on Fig. 13): arenosols, vertisols, solonetz and solonchaks. The latter two, which cover less than 1% of tropical Africa, are saline and sodic soils mostly found in endoreic basins (e.g. Etosha

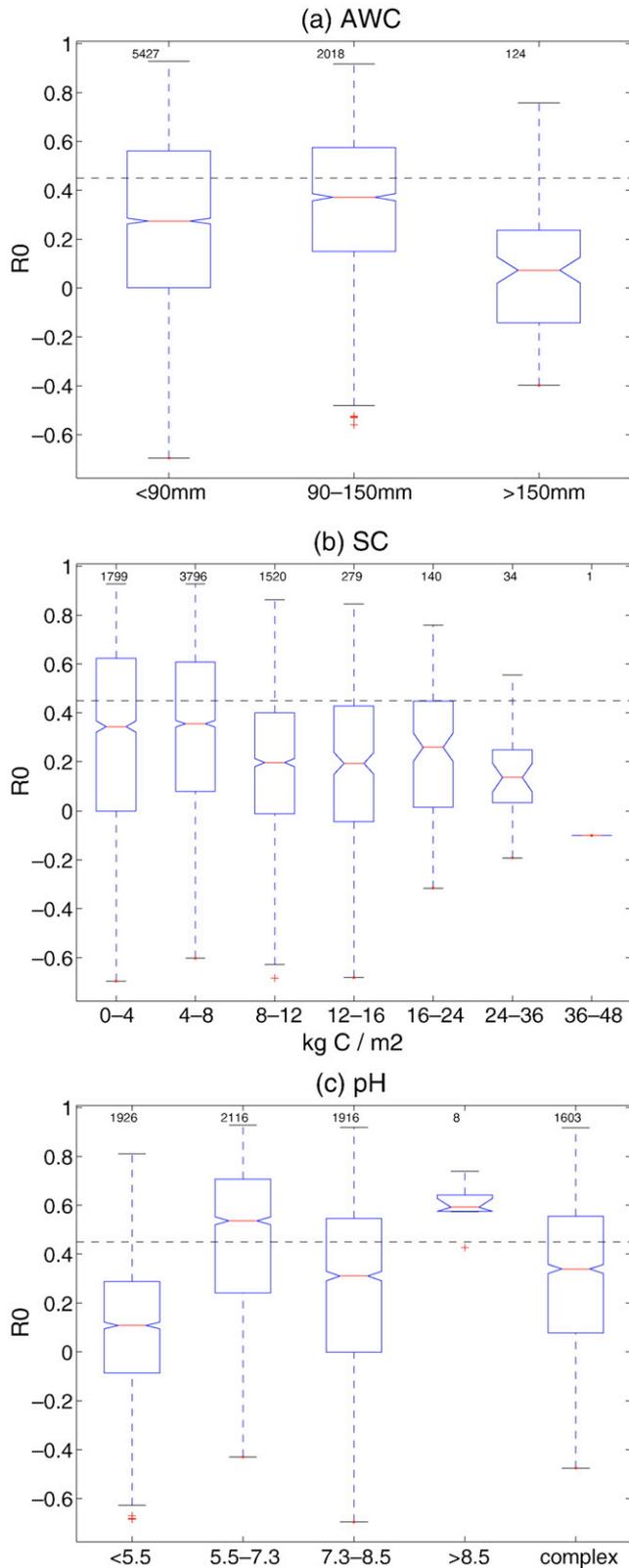


Fig. 12. Box-plots of zero-year lag correlation between NDVI and CMAP rainfall, for different soil properties. (a) Available water capacity (AWC, 0–1 m); (b) organic carbon content (SC, 0–1 m); (c) subsoil (30–100 cm) pH. Top values: number of grid-points.

and Makgadigadi pans in southern Africa, and localised areas in the Horn of Africa and in Chad). They are collocated with dry environments. Vertisols are mostly found in alluvial clay plains. Again, the coincidence with high correlations is mostly indirect. For instance, in Sudan along the Ethiopian border, r_0 correlations over the vertisols strongly decrease southward as rainfall increases. Arenosols have a loamy sand (or coarser) texture and are mainly found in arid to semi-arid areas, especially in Niger, Chad, western Sudan, and in the Kalahari Desert. In the Sahel however, high correlations are found over both arenosols and other soil types, suggesting that the high correlations are a result of semi-aridity, not soils. Similarly, some presently wetter areas also have arenosols (southern Mozambique, Central African Republic, and from southern Angola to Congo–Brazzaville), which do not generally support high sensitivity values. Low median r_0 correlations are found over 5 soil groups (in red/dark grey on Fig. 13): lithosols, yermosols, acrisols, ferralsols and gleysols. The first two correspond to very shallow and little evolved soils, on which vegetation growth is in any case severely limited by very low fertility. The latter three correspond to soils where water availability is generally good, either due to high rainfall (esp., ferralsols) or to drainage (gleysols). In such cases local inter-annual rainfall variations are expected to have a limited impact on photosynthetic activity. However, there is again quite a strong dispersion of r_0 within each soil group. Inspection of climatic maps reveals that much of the differences found across soil groups, at this scale, are an indirect consequence of the dependency of soil distribution to present-day precipitation conditions.

Given this dependency, the analysis was refined by selectively considering a given range of rainfall amounts, or a certain land-cover type (Table 3). Associations between soil groups and NDVI sensitivity are similar as above, but the contrasts between soil groups are weak, showing that the

Table 2

Median r_0 correlation coefficients between the interannual variations of NDVI and CMAP rainfall (1981–2000), for different combinations of soil properties, GLC land-cover types and annual rainfall amounts

		Land-cover types		
		Open grasslands (13–14)	Croplands (17–18)	
Available water capacity (AWC), 0–1 m depth	<90 mm	0.62	0.53	
	90–150 mm	0.59	0.45	
	>150 mm	0.35	0.37	
		Mean annual rainfall		
		<200 mm	200–600 mm	>600 mm
Organic carbon density (SC), 0–1 m depth	0–4 kgC/m ²	0.14	0.57	0.41
	4–8 kgC/m ²	0.40	0.56	0.22
	8–12 kgC/m ²	0.56	0.55	0.16
	12–16 kgC/m ²	*	0.31	0.18
	>16 kgC/m ²	*	*	0.20

Significant values (95% c.l.) are in bold. Stars denote combinations represented by less than 5 grid-points.

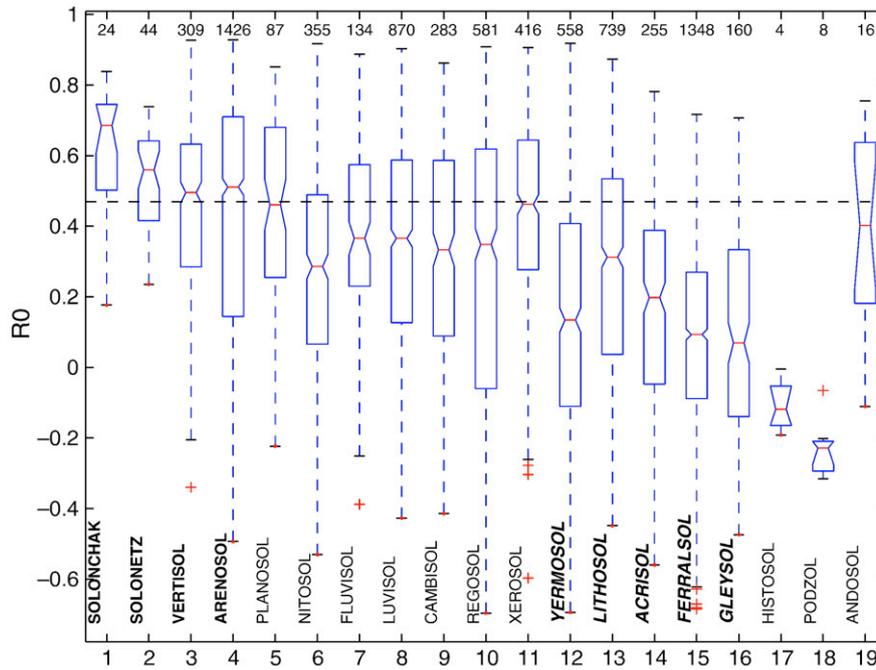


Fig. 13. Box-plot of zero-year lag correlation between NDVI and CMAP rainfall, for different soil types. Top values: number of grid-points. Horizontal dashed line: 95% confidence level.

climatic conditions have a much larger impact than the soil types. Analyses of variance (not shown) indicate that r_0 is nevertheless significantly discriminated by the soil types. Three soil groups recurrently emerge, whatever the rainfall amount and vegetation type, as resulting into lower correlation values: these are gleysols, acrisols and ferralsols. Even under land-cover types which usually exhibit significant r_0 values (croplands, open grasslands), these three soil types generally show non-

significant relationships between NDVI and rainfall. The use of soil moisture by the plants, over these soil types, is less dependent on precipitation than on drainage and plants' ability to efficiently tap these resources.

Nevertheless, it is emphasized that all cases of low NDVI sensitivity, in semi-arid and/or grassland areas, cannot be ascribed to specific soil types: there remains quite a large dispersion of correlation values within a given soil type. This

Table 3
Median r_0 correlation coefficients between the interannual variations of annual NDVI and annual CMAP rainfall (1981–2000), for different combinations of soil groups, GLC2000 land-cover types and annual rainfall amounts

Zobler soil groups	Mean annual rainfall (mm)			GLC land-cover types (selection)					
	Above 1000 mm: non significant for any soil group			Forest, forest mosaics and woodland : non-significant for any soil group					
	<200	200–600	600–1000	Deciduous shrubland (10+11)	Closed grassland (12)	Open grassland (13+14)	Sparse grassland (15)	Croplands (17+18)	Bare soil (21)
Solonchaks	*	0.70	*	*	*	0.70	*	*	*
Solonetz	*	0.56	*	*	*	0.52	0.40	0.66	*
Vertisols	0.59	0.60	0.42	0.37	0.28	0.67	0.60	0.54	0.52
Arenosols	0.62	0.67	0.18	0.24	0.41	0.69	0.71	0.62	0.57
Planosols	*	0.69	0.26	0.35	0.21	0.66	*	0.57	*
Nitosols	*	0.62	0.57	0.42	0.01	0.62	*	0.52	*
Fluvisols	*	0.68	0.40	0.44	0.70	0.69	*	0.58	*
Luvvisols	*	0.58	0.37	0.30	0.29	0.63	*	0.61	*
Cambisols	*	0.57	0.51	0.29	0.18	0.65	0.62	0.46	*
Regosols	-0.06	0.65	0.53	0.38	0.76	0.69	0.47	0.67	0.09
Xerosols	0.40	0.58	0.45	0.55	0.26	0.63	0.43	0.59	0.40
Yermosols	0.04	0.52	0.48	0.36	*	0.73	0.19	*	0.10
Lithosols	0.18	0.55	0.32	0.09	0.43	0.54	0.38	0.65	0.23
Acrisols	*	0.44	0.28	0.13	0.50	0.51	*	0.32	*
Ferralsols	*	*	0.11	0.10	0.11	*	*	0.29	*
Gleysols	*	0.38	-0.10	-0.19	-0.10	0.40	0.49	0.44	*

Significant values (95% c.l.) are in bold. Stars denote combinations represented by less than 5 grid-points.

may suggest that the very low correlations found in some regions (e.g., northern Somalia) are likely to be rather a reflection of inadequate rainfall estimates. Actually, some soil types shown above to be associated with quite low r^2 values (i.e., lithosols and regosols) for Africa as a whole nevertheless display significant correlations under open grasslands and croplands. These shallow soils, which are often found in arid environments, are still able to support an herbaceous cover (and sometimes marginal crops) which may thrive well provided that an adequate moisture supply exists (hence the NDVI signal).

Also noticeable is the fact that some soil types systematically display higher r^2 values than the average for any land-cover type (if forests are excluded). This is the case for fluvisols, with a r^2 of 0.69 for open grasslands, one of the largest values for any land-cover/soil type combination, and a significant r^2 even for closed grasslands (0.70), a land-cover type whose NDVI is generally not very sensitive to rainfall variations. Arenosols also display high r^2 values, particularly in sparse and open grasslands formations (Table 3). These patterns suggest that these soil types “magnify” interannual rainfall variability, inducing high NDVI in wet years and very low NDVI in dry years.

On the whole, these results suggest a weak to moderate impact of soil types (as well as soil properties, Section 4.2) on NDVI sensitivity to rainfall. Stratification based on rainfall amounts and land-cover types improves the results, but shows that soil patterns are a secondary factor compared to climate and/or land-cover. However, it should be recalled that soil properties actually vary on generally fine scales, which are not resolved in the present study; their impact is thus likely to be underestimated.

5. Discussion and conclusions

The interannual variations in annual NDVI across Tropical Africa during the period 1981–2000 were analysed with the aim to map, and explain, the patterns of their relationship with annual rainfall variations. Large spatial differences in the response of photosynthetic activity to rainfall are found across the continent. The highest correlations (r^2 mostly over 0.60) are found in the sudano–sahelian belt, and in parts of eastern Africa and south-western Africa. The general patterns are relatively robust, as demonstrated by the use of different rainfall data sets (rain gauge only and mixed rain gauge-satellite estimates).

Associations between the distribution of these interannual NDVI-rainfall correlations and different factors (mean rainfall amounts, land-cover types, soil types, soil properties) were explored. Mean annual rainfall amounts and land-cover types are by far the leading determinants in the spatial patterns of the correlations. A high sensitivity of NDVI to rainfall variations mostly coincide with semi-arid areas (200–600 mm), and two types of land-cover: open grassland and croplands. These two determinants are actually strongly related with each other, but relatively high correlations were also sometimes found when only a single determinant out of the two is present.

The fact that annual NDVI is most sensitive to rainfall variability at intermediate precipitation levels (200–600 mm) may be compared to evidence collated by Huxman et al. (2004) who

analysed net primary production at 14 observation sites representative of major world biomes. They found that annual precipitation variations remained the best correlate of NPP at the least productive sites. This is in line with the present results if we consider that the low correlations found at very dry locations result from the very weak (and partly biased) vegetation signal in NDVI data. Paruelo et al. (1999) found a more distinct peak (at around 475 mm) in the distribution of slopes (temporal regression models of NPP with annual rainfall for temperate grasslands) with respect to mean rainfall. This is in full accordance with our results, even if they are obtained using remote sensing proxies rather than in situ measurements. In drier environments, poor responses are explained by low relative growth rates of the vegetation, even when rainfall is temporarily higher (Paruelo et al., 1999). In wetter environments, water availability is no more a constraint, and the water stress may only be temporary, occurring mostly as a seasonal constraint to which the plants are well adapted. Nicholson et al. (1990), based on observations from the Sahel and East Africa, suggested that there is a rainfall threshold at 1000–1100 mm, above which NDVI is insensitive to rainfall fluctuations. The present results indicate that on average the relationship between NDVI and precipitation becomes insignificant at a lower threshold, though there are many instances on which significant correlations still occur in the 600–1000 mm range. These are mainly found in West Africa and parts of eastern Africa, which does not contradict Nicholson et al.’s findings.

The present study also suggests that vegetation formations are almost as important as the mean annual rainfall, as a factor accounting for the sensitivity to rainfall. It is of course difficult to separate both effects since vegetation is to a reasonable extent at equilibrium with climate, and smaller-scale studies should help to understand the respective roles of climate and plant physiology. However, the role of land-cover is suggested by the strong gradients in r^2 found over some regions, which coincide with a change from grasslands/croplands to tree-dominated vegetation formations. Forest ecosystems actually almost always display non-significant relationships, which is not an unexpected result for the evergreen forest, but is also apparent in the deciduous forest (e.g., miombo of southern Africa). This absence of NDVI response to interannual rainfall variability may not be ascribed to NDVI biases, such as cloud contamination, since seasonal variations are still found to match those of rainfall. The hypothesis is that such vegetation formations are generally supported by wet climatic conditions, whereby even lower than average rainfall amounts are sufficient to induce leafing. Additionally, trees are able to tap deep soil water resources, therefore damping the effects of a moisture deficit. This is true where the mean annual rainfall is above 1000 mm, but it is noticeable that non herbaceous land-cover types (shrubland, woodland) still show mostly non-significant correlations between NDVI and rainfall, in both the 600–1000 and 200–600 mm ranges. In addition to the role of deep soil moisture storage, there are two explanations to this: (i) NDVI only portrays vegetative activity of the canopy, and may not be representative of the true leaf area, hence there is little apparent change in NDVI between wet and dry years; (ii) contrary to open

grasslands (and croplands), where higher rainfall may result in a more extensive grass (and crop) cover, the area covered by active vegetation does not change much in tree-dominated ecosystems.

Exceptions to the association between high NDVI sensitivity and semi-arid grasslands take two main forms. First, there exist several regions in Africa where the presence of one of the above two determinants (semi-aridity and grassland/cropland land-cover) is not sufficient to induce a strong NDVI correlation with rainfall variability. These cases are often associated with particular soil patterns. Gleysols, acrisols and ferralsols all display low correlations of NDVI with rainfall, even under otherwise favourable climatic conditions or vegetation cover. This is related to the properties of these soils (especially in terms of water storage and ability of the vegetation to tap the water resource), which disturb the rainfall-photosynthetic activity relationship. Most acid soils are also found to exhibit a lower response of NDVI to rainfall, as compared to neutral to slightly acid ones ($5.5 < \text{pH} < 7.3$) for which the response is distinctly stronger. Finally, fluvisols and arenosols, outside forest environments, tend to exhibit slightly higher correlations than most other soils types. However, it is demonstrated that soil types and soil properties are only minor factors in the overall distribution of NDVI-rainfall correlations and regression slopes. This is in agreement with results obtained for northern Senegal, where [Diouf and Lambin \(2001\)](#) did not find much evidence of soil type incidence on local discrepancies in the response of vegetation to rainfall. In southern Africa, [Richard and Pocard \(1998\)](#), using gridded 1° square data for the period 1983–1988, found that the spatial variations of NDVI sensitivity to rainfall anomalies were much better explained by the mean precipitation amount and vegetation type than by the soil types. [Nicholson and Farrar \(1994\)](#) and [Farrar et al. \(1994\)](#) in their study on Botswana found significant differences among soil types. This discrepancy could be due to the fact that they were considering semi-arid environments only, in one region only, whereas the present study deals with a large array of ecological conditions.

Second, evidence was provided of some cases of high correlations between rainfall and NDVI outside the areas featuring the above two determinants (200–600 mm mean annual rainfall, and open grasslands/croplands land-cover). The corresponding areas are neither found to display specific soil properties, nor specific vegetation formations, though the tree cover is generally limited. A puzzling observation is that such locations exhibit small slopes in the linear regression between NDVI and rainfall. It is suggested that this denotes in part human influence on vegetative activity. A clear correspondence is found between these low slopes (while correlations are high) and high rural population densities. This is interpreted as the effect of cultivation (and possibly grazing pressure), in areas not necessarily detected as croplands in the GLC2000 classification. In Senegal, [Li et al. \(2004\)](#) found equally high correlations between NDVI and rainfall for agriculture, steppes and savanna land-cover types, but cases of very low correlations, at a local scale, were demonstrated to be the result of land degradation due to strong human pressure. However, the impact of agriculture on the NDVI is complex: in arid areas of Syria, [Evans and Geerken \(2004\)](#)

noted that introduced rain-fed agriculture was resulting in a strong increase in NDVI seasonal and interannual variability. The nature of crops and farming practises are both likely to affect the interannual NDVI signal.

Another important, man-related factor in vegetation dynamics of semi-arid to subhumid tropical climates, hitherto not discussed in this study, is fire (e.g., [van Langevelde et al., 2003](#)). In the spatial distribution of woody cover in African savannas, fire return is found to be second, after mean annual precipitation and before soil characteristics (sand content) ([Sankaran et al., 2005](#)). Frequent fires tend to reduce woody cover below an upper bound controlled by precipitation. Fire frequency and fire impact are constrained by the availability of dry fuel, and they are maximum in the grasslands and open savannah woodlands at intermediate rainfall amounts (about 550–750 mm per year), though modified by agro-pastoral practises ([Roy et al., 2005](#)). An attempt was made to evaluate the impact of fire frequency on the relationship between NDVI and rainfall, by using statistics on burnt areas in Africa for 1981–1991 ([Barbosa et al., 1999](#)), derived from AVHRR data. Fire return periods were estimated based on the number of years during which at least one fire occurrence was detected in 5 km grid-squares, and then resampled to a 0.5° grid. At this scale, there is very little evidence that fire frequency impacts on interannual variations of mean annual NDVI. In southern Africa, areas with short fire return periods (blue/black squares on [Fig. 3](#), to be compared with the blue dots) only display a modest increase in their correlations between NDVI and rainfall, in the 600–800 mm precipitation range. This may reflect the lower tree cover associated with frequent fires ([Sankaran et al., 2005](#)), combined to the fact that trees are less sensitive than grass to rainfall variations. However, the reverse pattern is found in western Africa (green/grey squares on [Fig. 3](#)), where in the 500–800 mm precipitation range, frequent fires result in a slightly lower correlation. A possible explanation could be a direct incidence of burnt surfaces on the NDVI signal, though the initial compositing technique should eliminate much of it. These contrasted results point to an overall limited influence of fire on the patterns of vegetation sensitivity to rainfall, though further research is required before reaching definitive conclusions.

Besides correlations, the present study also clearly showed the association between semi-arid conditions and large slopes in temporal regression models between NDVI and rainfall. Slopes (and correlation) maps actually display spatial patterns which are very different from those of rain-use efficiency (RUE), computed as the ratio between net primary production (or scaled NDVI) and rainfall ([Le Houerou, 1984](#); [Nicholson et al., 1990](#); [Prince et al., 1998](#)). For instance, equally large slopes and correlations are found in the semi-arid regions of East Africa, central Sahel, and Kalahari. But for similar mean rainfall amounts, RUE is distinctly higher in Kalahari (and to some extent East Africa) than in the Sahel ([Farrar et al., 1994](#); [Martiny et al., in press](#)). [Veron et al. \(2005\)](#) recently insisted on the different interpretation of slopes and RUE. The slope, in temporal models, can be viewed as the (marginal) response of vegetation activity per unit increase in rainfall. RUE, rather, implicitly includes runoff, evaporation and drainage components which are not used by plants. Hence, RUE

values are generally much larger than slopes (for semi-arid Africa, typically 2 to 5 times larger, using NDVI data). Following Veron et al. (2005), it is suggested that considering slopes and intercepts (or slopes and RUE), rather than RUE alone, may facilitate ecological interpretation of NDVI-rainfall relationships. The significance of intercepts, when using NDVI rather than primary production, and at large scales (e.g., the African continent), is actually not obvious, since they almost replicate the mean annual rainfall distribution. However, if ratios of the intercepts to mean annual rainfall are computed, we come to a meaningful map which displays similarities with that of RUE, and shows the background vegetative activity signal.

A last aim of the study was to detect possible lagged relationships between annual rainfall and annual NDVI. As a confirmation to other studies based on net primary production or NDVI in semi-arid regions, but for local sites or limited areas (Martiny et al., 2005; Oesterheld et al., 2001), a significant one-year lag-impact of rainfall on photosynthetic activity was also found in a number of regions of Africa, representing about 10% of the grid-points. The spatial patterns, however, are quite noisy, and it was not possible to find a distinct association of high lag-1 correlations with either land-cover types (e.g., woody versus herbaceous cover), soil properties or soil types. Martiny et al. (2005) noted, although the signal could be detected through lag-1 partial correlations, that the effect of previous year rainfall was not fully linear. This area therefore deserves further investigation.

The latter remark recalls general limitations of this study, first related to some shortcomings (and biases) of the NDVI data, over very cloudy areas and over deserts, as well as in the rainfall data sets in some regions with insufficient rain gauge information. Another limitation is in the way the relationship between rainfall and vegetative activity is considered: since the above results are based on linear correlations, possible asymmetric responses to drought and wet years are not treated. Beyond the general patterns which appear at continental scale, a complete assessment requires in-depth analyses at regional scales, or comparative studies focusing on similar ecological domains, and taking into account other possible determinants, especially fire frequency, herbivory, and farming practices. Finally, there are some limitations inherent to the use of annual data: the length of the wet and dry seasons (and in some extreme instances the virtual absence of any wet or dry season), the distribution of the rain events within the rainy season, both have some impacts on the NDVI signal, not only its regimes but to some extent its mean annual intensity as well. A full understanding of interannual variability therefore requires the seasonal cycle to be resolved. However, the present study has the merit to establish an overall hierarchy in some basic determinants of the vegetation response to interannual rainfall variations.

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