ASSESSING VEGETATION RESPONSE TO CLIMATE VARIABILITY VIA TIME SERIES OF NDVI, PRECIPITATION AND SOIL MOISTURE CONTENT

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ABSTRACT

The forcing role of climate variability on vegetation was examined over East and Central Africa, using time series of satellite images and climate data. In search of a meteorological variable that best explains the temporal evolution of vegetation over multiple years, lagged correlations were tested between time series (1998-2011) of ten daily SPOT-VGT NDVI images and series of precipitation and soil moisture content from the ECMWF ERA-Interim re-analysis. First, it was found that NDVI displays an area-wide near-instantaneous response to soil moisture content as opposed to a regionally differing lagged response to precipitation. Second, interannual anomalies of NDVI correlate increasingly better with anomalies of soil moisture content in deeper soil layers, in a more spatially coherent pattern. This may be ascribed to the function of the soil as a buffering reservoir, reflected in relatively smooth series of soil moisture content with a gradual decline after the seasonal peak. Third, upon removal of seasonality from the series, the areas with the best NDVI-soil moisture response shift towards the semi-arid areas. Further investigation of dominant soil and vegetation patterns is needed to explain the observed spatial patterns. Furthermore, implementation of more detailed soil information is deemed necessary. Overall, the potential of soil moisture content as a climate descriptor for explaining vegetation dynamics was demonstrated in this study.

INTRODUCTION

A better understanding of the impact of climate variability on the dynamics of vegetative land cover is required for inventorying land use related carbon emissions. Partitioning the observed evolution of the vegetation in terms of natural and anthropogenic contributions is one of the remaining challenges in the present climate debate (1,2). The use of multi-temporal satellite imagery is an established technique for monitoring the evolution of vegetation on a global to regional scale (3,4). The Normalized Difference Vegetation Index (NDVI) is generally accepted as representing the photosynthetic activity of the canopy (5,6) and is a proxy for the overall green vegetation status. In view of evaluating human impacts on forests and other carbon-storing ecosystems, temporal NDVI patterns are to be explained in terms of their causal factors. Available image archives enable detailed investigation of the seasonal and interannual progression of vegetation status via pixel-specific time series analysis. In line with a signal decomposition approach (7,8), an NDVI signal is assumed to consist of distinct components relating to seasonal growing conditions, interannual varying conditions, land use changes and noise processes. Inferring the best descriptors of these components through signal correlation is a first step towards application of more advanced signal decomposition methods to partition the NDVI signal.

The role of climate variability on the progression of NDVI has been amply studied. In regional studies across tropical Africa, dealing with precipitation thresholds and modulating environmental conditions (e.g. soil types, dominant vegetation types) (5,9,10,11), the core premise is the lagged response of NDVI to aggregated precipitation. Overall, the strongest influencing factors to the NDVI response are found to be mean annual precipitation and vegetation type, while different weights are proposed for soil factors following the scale of study. Some authors (11) found different

NDVI sensitivity to precipitation across major soil types in Botswana, whereas others (5,9) rather found a minor effect of soil type and soil properties across Southern Africa and tropical Africa as a whole.

Obviously, precipitation can only drive plant growth as far as it is available as soil moisture in the root zone. A clear difference of rain-use efficiency (monthly NDVI / monthly precipitation) was marked among major soil types (11). Noticeably, higher rain-use efficiencies of soil types could not be ascribed to to corresponding higher rates of soil moisture generation per unit rainfall (12). Overall, the precise role of soil moisture in the fluctuating vigour of vegetation is not entirely unraveled. However, in view of identifying a meteorological variable that well represents climate variability and its effects on vegetation growth, the hypothesis of this research is that soil moisture is a superior climate descriptor.

The relative lack of measured precipitation data over Africa, the absence of frequent soil moisture data, and the sampling bias inherent in the locations of meteo-stations were noted as limitations in the above-mentioned studies. The continuous development and improvement of global meteorological data assimilation models offer scope to extract gridded meteo-data for pixel-specific signal correlation analysis with NDVI on a high temporal resolution.

The first objective of this study was to assess the capacity of modeled soil moisture data to explain the interannual variation in the NDVI signal, as compared to precipitation height. Second, the strengths and weaknesses of using modeled soil moisture data on this scale were conceptually evaluated, taking into account the role of the soil as a water reservoir. Finally, these answers must lead to a formulation of the data requirements to consolidate this approach in the follow-up of the study.

METHODS

For this study, a regional block of countries in East and Central Africa (extending southwards from Ethiopia to Tanzania and eastwards from Rwanda to Somalia) was selected as the study area, which includes a gradient in climate zones and vegetation types. Mean annual rainfall as described in the IIASA database (13) increases generally from northeast to southwest and with altitude, i.e., from Somalia and eastern parts of Ethiopia and Kenya (below 400 mm yr-1), to the Ethiopian highlands and parts of Uganda, Rwanda and Burundi (above 1200 mm yr^{-1}). Along this gradient, the dominant vegetation type according to the GLC2000 classification (14) varies from herbaceous and shrub cover in the semi-arid areas, to broadleaved tree cover in areas that receive most annual rainfall. Prevailing dominant soil classes from the FAO/UNESCO Soil Map of the World (15) are regosols, yermosols and xerosols in Somalia and eastern Ethiopia, nitisols and cambisols in the Ethiopian highlands, vertisols in the White Nile flood plain, ferralsols in Uganda, Rwanda and Burundi and acrisols, luvisols and cambisols across Kenya and Tanzania.

Time series of NDVI images of this region were extracted from the SPOT-VGT ten daily synthesis archive (16). A time series of images at 1 km resolution was retrieved for the period April 1998 to November 2011. The NDVI dataset was spatially degraded for overlaying with the meteorological data at a 0.75° resolution. The median NDVI value of the 1 km VGT-pixels within a 0.75° grid cell was retained as the cell's attribute.

Corresponding time series of precipitation and soil moisture data over the same period and spatial extent were extracted from the ERA-Interim Re-analysis (1979 to present) by the European Center for Medium-range Weather Forecasts (ECMWF) (17) at a 0.75° grid. Twelve-hourly accumulations of precipitation ($m\ s^{-1}$) were extracted from the archive and summed over ten day periods. In the ECMWF model, the land surface is characterized by areal fractions of vegetation types covering a simplified 4 layered soil (0-7cm, 7-21 cm, 21-72 cm and 72-189 cm) with a homogeneous medium soil texture (18). The rate of change of volumetric soil moisture content ($m^3\ m^{-3}\ s^{-1}$) is calculated as the net effect of vertical water movement through and between layers and root extraction by the standing vegetation cover. At the upper interface, infiltration, surface run-off and evaporation processes take place. For every ten day period the mean daily soil moisture content was calculated.

The resulting data consisted of series of 491 ten daily values at 30 *x* 35 gridpoints at 0.75° spacing. Lagged correlation coefficients between the time series were iteratively calculated at every gridpoint. The amount of precipitation and soil moisture were accumulated over the current and the *n* preceding ten day periods, with *n* taking test values between 0 and 10. The highest correlation coefficient and its corresponding lag were identified at every gridpoint, and displayed on a map for interpretation.

A clear annual seasonality is expected in the signals of all three variables, enhancing overall correlations of the actual series. As the main interest goes out to additional interannual climate variability, it is desirable to remove the intra-annual pattern from the signal and to analyze the residual component. In addition, this approach copes with a part of the systematic inaccuracy in the forecast model, by removing linear bias and gain and only preserving the temporal variability. Anomaly series were calculated as the normalized departures from the mean historic annual cycle, in other words as z-scores per ten day period in the year. Lagged correlation analyses were performed between NDVI anomalies on the one hand and anomalies of precipitation and soil moisture on the other hand.

RESULTS

Before removal of the annual seasonality, there is a substantial lag in response between precipitation and NDVI in most of the study area (Figure 1). Its duration is regionally contrasting: 10 to 20 days in the dry areas, shorter in the wettest areas, and longer in the humid areas south of the equator. In contrast, NDVI follows soil moisture content in the top layer instantaneously or within less than ten days across most of the study area except in the most arid regions. Due to the seasonal covariance, correlations are relatively high everywhere, and highest in areas with moderately high annual rainfall (800-1000 mm yr^{-1}).

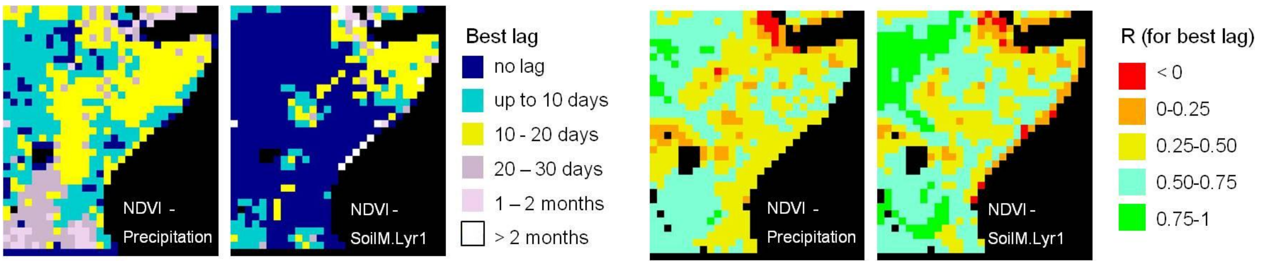

Figure 1. The optimal lag determined by the highest correlation of NDVI with accumulated precipitation and soil moisture over the 10 tested lag periods.

By removing the seasonality, the noise level increases and overall correlations drop. The NDVI anomalies show a spatially more coherent relation with soil moisture content anomalies (Figure 2), i.e. zero lag in areas with moderate rainfall (400-800 m yr^{-1}). Similarly, correlations at the optimal lag are very low or negative for precipitation everywhere, but tend to be higher for soil moisture content in the top layer in a clustered pattern where the lag is zero. For deeper soil layers, increasingly higher correlations are found as a growing cluster of pixels, while the lag pattern changes only slightly towards shorter lags.

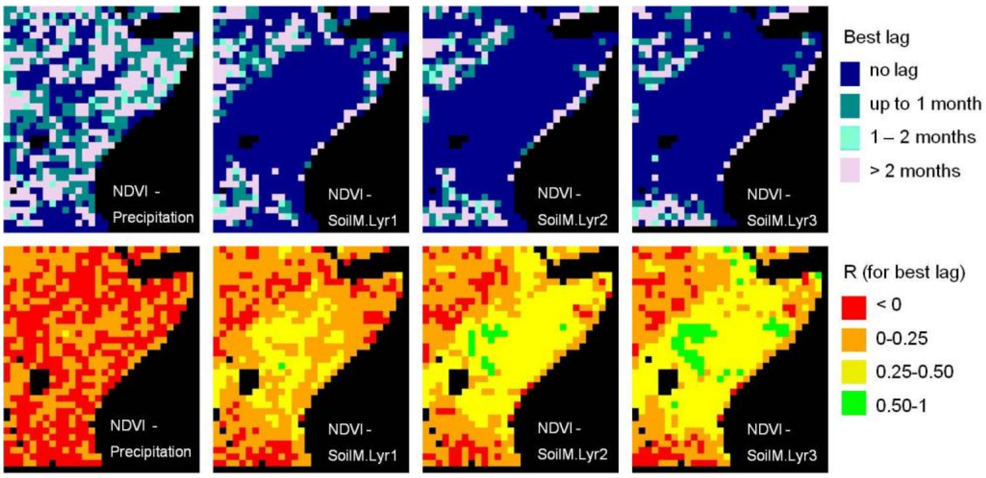

Figure 2. A scattered lag pattern for precipitation contrasts with an overall instantaneous response to soil moisture content. Correlations with NDVI increase systematically when considering deeper soil layers.

To visualize the role of the layered soil, the actual series at two locations are displayed (Figure 3). A first pixel is selected at a relatively humid location (precipitation of 775 mm yr^{-1}) in East Tanzania with sparse herbaceous and shrub vegetation where acrisols are dominant. A more arid location was selected in Southwest Somalia (precipitation of 225 mm yr^{-1}), covered with sparse herbaceous and shrub vegetation on dominantly weakly developed regosols. Besides being somewhat smoother than the precipitation signal, the multi-annual trend in the soil moisture series approximates better the NDVI signal for both pixels. Moving downwards into the soil, a more gradual decline after the seasonal peak is noted, as opposed to the more abrupt stop of the rainy season. Particularly for sparse rainfall events, the soil moisture series more continuous and hence more alike to the NDVI signal. However, the soil water model does not take into account the presence of a regosol with possibly no developed deeper layers. Still, the role of the soil as a buffering reservoir that fills up quickly and depletes more gradually is apparent from the data. If a re-modeling of the soil water balance with a model that incorporates more soil information would be carried out, the layered properties must be given due attention.

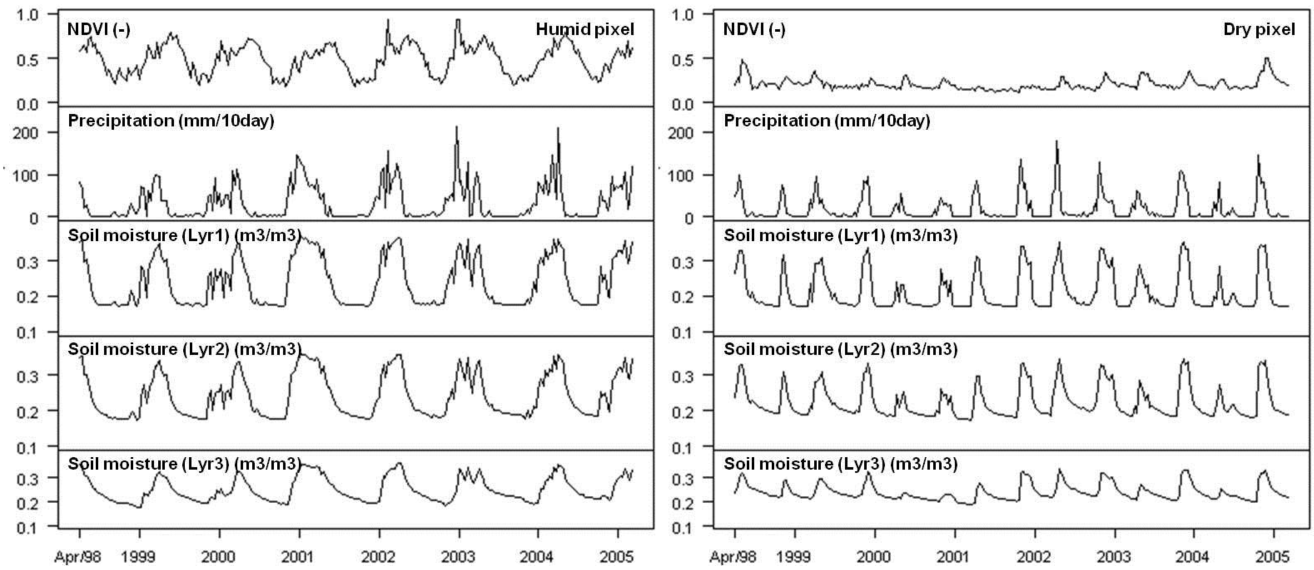

Figure 3. Actual series (1998-2005) of NDVI, precipitation and soil moisture in the upper 3 layers demonstrate the reservoir function of the soil matrix in dry conditions.

CONCLUSIONS

On this scale, modeled soil moisture anomalies tend to correlate systematically better with NDVI anomalies than anomalies of rainfall forecasts from the same model. The validity of the model assumptions of a universal deep multi-layer soil are questionable though. The soil moisture signal will indeed be highly inaccurate where no deep soils exist, or where the soil water reservoir is always saturated or frequently replenished by exogenous water resources (12). However, as noted in other studies (5,9), it is not possible to resolve soil variability on the studied scale (0.75°) and soil types proved to have far less impact on the NDVI-precipitation relationship than land cover types. Here, the vegetation characterization in the soil water balance model may be suspected to contaminate the soil moisture signal. But since the biome classification is a static layer in the model, no circular logic is at stake when attempting to explain the NDVI patterns.

Another question related to the soil water model, is whether it can be looked at as an advanced physically-based smoothing operator, and if so, whether it does perform better than known artificial smoothing techniques of precipitation series. Therefore, the influence of the evapotranspiration term in the soil water balance must be evaluated through regression of the soil moisture series on the precipitation series. If indeed evapotranspiration does affect the balance substantially, then the model can be regarded as different from a linear smoother. As argued above, re-modeling soil moisture content at the scale of study with more detailed soil information may be required to consolidate the soil moisture approach. In any case, both precipitation and soil moisture datasets require validation for the study area with ground data from stations or with regional satellite-derived datasets. In particular the reliability of the modeled temporal evolution must be verified.

The detected spatial patterns confirm the earlier findings that highest NDVI sensitivity to rainfall is associated with semi-arid areas with grassland vegetation (5,9). This was explained by these authors as NDVI saturation and guaranteed water availability in wet areas and as signal mixing in areas with low vegetation cover. Though from the results it is noted that highest correlations shift from more humid areas (800-1000 mm yr-1) to drier areas (400-800 mm yr-1) when the annual seasonal components are removed. It corresponds to assumed different physiological responses to water availability (9): phenonological response on the one hand and interannual variation in photosynthetic activity on the other hand. A further quantitative characterization of this climate-dependent sensitivity will be the subject of future research, as the aim is to conduct an area-wide climate-normalization of the temporal evolution of the vegetation status.

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