Spatial relationship between climatologies and changes in global vegetation activity

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Abstract

Vegetation forms a main component of the terrestrial biosphere and plays a crucial role in land-cover and climate-related studies. Activity of vegetation systems is commonly quantified using remotely sensed vegetation indices (VI). Extensive reports on temporal trends over the past decades in time series of such indices can be found in literature. However, little remains known about the processes underlying these changes at large spatial scales. In this study, we aimed at quantifying the spatial relationship between changes in potential climatic growth constraints (i.e. temperature, precipitation and incident solar radiation) and changes in vegetation activity (1982–2008). We demonstrate an additive spatial model with $0.5\,^\circ$ resolution, consisting of a regression component representing climate-associated effects and a spatially correlated field representing the combined influence of other factors, including land-use change. Little over 50% of the spatial variance could be attributed to changes in climatologies; conspicuously, many greening trends and browning hotspots in Argentina and Australia. The nonassociated model component may contain large-scale human interventions, feedback mechanisms or natural effects, which were not captured by the climatologies. Browning hotspots in this component were especially found in subequatorial Africa. On the scale of land-cover types, strongest relationships between climatologies and vegetation activity were found in forests, including indications for browning under warming conditions (analogous to the divergence issue discussed in dendroclimatology).

Keywords: climate- and human-induced change, climatologies, Gaussian random field, growth constraints, regression, spatial additive model, vegetation-activity trends

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Introduction

Vegetation is the main component of the terrestrial biosphere, and remotely sensed VI are commonly used in climate-change studies as a proxy for vegetation cover and photosynthetic capacity (Myneni et al., 1995). Changes in vegetation activity – as we use to refer to changes in vegetation index, following Zhou et al. (2001) – form a complex system of biotic and abiotic interactions, which differ between land-cover classes and may evolve over time themselves (Nelson et al., 2006). Today, VI time series are available at large spatial extents and dense time intervals. As a consequence, studying the available satellite imagery at global scale involves the analysis of large quantities of data. This has commonly been targeted with per-pixel approaches. For example, temporal VI changes have been quantified using parametric linear models on data aggregated on a yearly basis (Bai et al., 2008), on a seasonal basis (Eklundh & Olsson, 2003), nonparametric models on the full time series (Pouliot et al., 2009) or seasonal-trend decomposition algorithms (De Jong et al., 2012). General patterns of detected changes coincide with increasing vegetation activity over time (greening) in many areas of the world, conspicuously in Europe (Stöckli & Vidale, 2004; Julien et al., 2006), the Sahel (Eklundh & Olsson, 2003; Anyamba & Tucker, 2005; Herrmann et al., 2005; Hickler et al., 2005; Olsson et al., 2005), India (Jeyaseelan et al., 2007) and the Northern Hemisphere in general (Tucker et al., 2001; Zhou et al., 2001; Slayback et al., 2003). Decreases (browning), on the other hand, have been identified in parts of the Southern Hemisphere (e.g. South America), but also in boreal forests (De Jong et al., 2012). These results illustrate the temporal change in vegetation activity over the past decades, but leave relationships with underlying processes open. Relationships with climate, including oceanic oscillations (Woodward et al., 2008), can be anticipated and have been substantiated by various modelling (Nemani et al.,...
and can fraction of absorbed photosynthetically active radiation (Tucker satellite imagery at global scale since the early 1980s variations in vegetation activity have been inferred from previous century (Mitchell & Jones, 2005). At the same time, among others) are available globally as gridded data types and other land-use/land-cover types (Alcantara et al., 2012; Van Asselen & Verburg, 2012). Climate observations (temperature, precipitation, cloudiness, among others) are available globally as gridded data sets with monthly intervals since the beginning of the previous century (Mitchell & Jones, 2005). At the same time, variations in vegetation activity have been inferred from satellite imagery at global scale since the early 1980s (Tucker et al., 2005) using the normalized difference vegetation index (NDVI). This index directly correlates with the fraction of absorbed photosynthetically active radiation (fPAR) and can – in combination with an efficiency conversion factor and the amount of incident PAR – be used to quantify gross primary productivity (Running et al., 2004). Using these data sources, associations between climate change and changes in vegetation activity can be made for the last decades (Fensholt et al., 2012). Such associations are likely to vary with land cover, as each class may respond differently to climate change and to land-use change (Chapin et al., 2000; Verburg et al., 2011).

In this study, we modelled the observed changes in vegetation activity as the additive combination of fixed (climate-associated) effects, spatially dependent random effects and independent residuals. We developed a land-cover–specific deterministic model and a globally applicable regression-tree approach to associate variation in vegetation activity with climate changes. Covariates for these models were selected under the assumption that maximum plant growth is affected by either one or any combination of three climatological constraints: water availability, temperature and incident radiation (Field et al., 1995). This assumption was found to hold for most parts of the terrestrial surface (Churkina & Running, 1998). Other environmental control factors are not accounted for in this model. These may include changes in hydrology (e.g. permafrost thaw), atmospheric characteristics (e.g. wind, humidity, biological and chemical constituents), species composition, degradation of soil (nutrient) resources or land use and management. The effects of these factors on vegetation activity were expected to be spatially autocorrelated (Zhou et al., 2001). Therefore, we tested the application of a spatially autocorrelated Gaussian random field (GRF) model for representing the combined effect of all other drivers not accounted for in the cli- atology-driven model.

Accordingly, in this work, we hypothesized that a part of the spatial variation in vegetation-activity trends can be associated with trends in potential growth-limiting climatologies. This research investigated this hypothesis by quantifying the role of trends in climatologies on vegetation activity as well as the associated geographical distribution. Furthermore, realizing that the system of causation is complex, we aimed at quantifying the combined response of nonmodelled drivers (including land-use change), in terms of length scale and strength, as a spatial field. We demonstrate that the maps associated with this decomposition reveal spatial patterns that help the interpretation of relationships between vegetation activity, climate change and human-induced changes.

Materials and methods

Data

**NDVI record.** The National Oceanographic and Atmospheric Administration (NOAA) acquired the longest series of data using advanced very high-resolution radiometer (AVHRR) sensors. We used the latest release of the global inventory modelling and mapping studies (GIMMS) NDVIs data set, which is an extension of earlier versions (Tucker et al., 2005). The data set consists of 28 years (from 1981 through 2008) of fortnightly acquisitions at ~8 km (0.072°) spatial resolution. The fortnightly scenes are maximum value composites of daily 4 km global area coverage data. This procedure largely removes atmospheric noise (Holben, 1986), although some inaccuracy remains, especially in hazy and cloudy conditions (Nagol et al., 2009). We applied the harmonic analysis of NDVI time series (HANTS) interpolation algorithm (Roerink et al., 2000; De Jong et al., 2011) to remove remaining noise in areas with persistent cloud cover. Areas with very sparse or no vegetation cover (yearly median NDVI < 0.1) were masked out, as well as regions at higher than 72° northern latitude. As such, we excluded the northernmost regions of Russia and Canada where NDVI signals have been found impacted by high solar zenith angles and by snow and ice (Brown et al., 2006). Orbital decay and changes in NOAA satellites are known to affect AVHRR data, but processed NDVI data have been found free of trends introduced from these effects (Kaufmann et al., 2000). Alcaraz-Segura et al. (2010), Baldi et al. (2008) and Zhou et al. (2001), among others, provided discussions on the quality of GIMMS and derived trends.

**Climate data.** The Climatic Research Unit (CRU: University of East Anglia Climatic Research Unit, 2008) provides high-resolution gridded data sets with global coverage. The latest TS 3.1 data sets (Mitchell & Jones, 2005) were released in April 2011 and updated in July 2012 because of a systematic error in the precipitation data. The data sets provide time series for a range of climate parameters (Table 1). In the CRU processing
Table 1 Climate parameters from the CRU TS 3.1 data set (Mitchell & Jones, 2005). Each parameter is represented in a high-resolution monthly grid with a spatial resolution of 0.5°, for the time span 1901–2009. PET (monthly mean mm day−1) was multiplied by the number of days in each month to obtain mm month−1. PRE was taken from the recent CRU TS 3.10.1 data set.

<table>
<thead>
<tr>
<th>Label</th>
<th>Parameter</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLD</td>
<td>Cloud cover</td>
<td>%</td>
</tr>
<tr>
<td>DTR</td>
<td>Diurnal temperature range</td>
<td>°C</td>
</tr>
<tr>
<td>FRS</td>
<td>Frost day frequency</td>
<td>days</td>
</tr>
<tr>
<td>PRE</td>
<td>Precipitation</td>
<td>mm</td>
</tr>
<tr>
<td>TMP</td>
<td>Daily mean temperature</td>
<td>°C</td>
</tr>
<tr>
<td>TMN</td>
<td>Daily minimum temperature</td>
<td>°C</td>
</tr>
<tr>
<td>TMX</td>
<td>Daily maximum temperature</td>
<td>°C</td>
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<tr>
<td>VAP</td>
<td>Vapour pressure</td>
<td>hPa</td>
</tr>
<tr>
<td>WET</td>
<td>Wet day frequency</td>
<td>days</td>
</tr>
<tr>
<td>PET</td>
<td>Potential evapotranspiration</td>
<td>mm</td>
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</tbody>
</table>

scheme, several station-based data sources were harmonized to obtain most reliable estimates. For each parameter, reference climatologies (or: normals) were calculated for the 1961–1990 period and deviations from the normal (or: anomalies) were calculated for all measurements in the record. After spatial interpolation and superposition on the reference climatologies, these anomalies constitute the final 0.5° grids (720 × 360 cells). See Mitchell & Jones (2005) for details about the data sources and processing steps. The data sets cover 1901–2009 and subsets matching the time span of GIMMS were used here. Nonterrestrial pixels were masked, resulting in approximately 65 000 grid cells per corresponding GIMMS time step.

Climatologies were selected under the assumption that plant growth is limited by water availability, temperature and/or incident radiation (Field et al., 1995). Changes in either of these parameters might induce changes in vegetation productivity and in the proxy NDVI signal. For most regions, water availability is determined by the amount of precipitation, although snow melt should be taken into account in high northern latitudes and in mountainous regions. In this study, we confined this parameter to precipitation as productivity in the mentioned regions is temperature limited rather than water limited (Nemani et al., 2003). Time series of incident PAR are not globally available, but the amount of PAR is to a large extent determined by the intensity and duration of cloud overcast (Zhuravleva et al., 2006). Furthermore, the CRU cloud-cover data have been augmented with PAR-related sunshine records to complement sparse cloud observations in recent decades (Mitchell & Jones, 2005). For these reasons, trends in temperature (TMP), precipitation and cloud cover (CLD) were selected as covariates for the deterministic prediction of NDVI trends. Potential Evapotranspiration (PET) is a reflection of the energy available to evaporate water given that ample water is available. It may reflect growth limitation by radiation and was adopted as additional covariate. PET was calculated as reference value for grass according to the method used by the United Nations Food and Agricultural Organization (Ekström et al., 2007), which is a variant of the Penman-Monteith method (Allen et al., 1994). The gridded TMP, TMN, TMX, VAP and CLD (Table 1) were used as input for this calculation. PET units are mm day−1 and were multiplied by the number of days in each month to obtain mm month−1.

Land-cover data. In the International Geosphere and Biosphere Programme (IGBP), a 1 km land-cover product (DISCover) was developed. The data set consists of 17 general land-cover types (Loveland & Belward, 1997; Loveland et al., 2000), based on AVHRR data and a vegetation-classification logic that is climate independent (Running et al., 1994). The classification scheme was later adopted within the moderate-resolution imaging spectrometer (MODIS) land-cover products (Friedl et al., 2002). We used the 2009 MCD12C1.005 product, which provides aggregated land cover at 0.05° resolution, as well as the subpixel frequency of each class. The product is based on a full year of composited 8 days MODIS observations (reflectance and land-surface temperature) and can be considered representative for the state of the land surface around the end of our analysis period. This information was used to develop land-cover–specific regression models. Figure 1 provides a conceptual design of the various processing steps that are discussed in the following sections.

Spatial aggregation of NDVI and land-cover data. The native spatial resolution of the CRU TS 3.1 climate data is 0.5°, whereas the land-cover data from the MCD12C1 product and the GIMMS NDVI data have spatial resolutions of 0.05° (~5.6 km) and 0.073° (~8 km) respectively. Therefore, both the land-cover data and the temporal NDVI trends needed to be resampled to 0.5° spatial resolution. In case of the discrete land-cover data, the spatial aggregation scheme affects the prevalence of the different classes and the spatial coherence of each land-cover class within the aggregated product (Dendoncker et al., 2008; Verburg et al., 2011). For this reason, careful selection of the aggregation scheme is crucial. A central pixel approach best preserves the relative area of the individual classes, especially the minor classes. A majority approach, on the other hand, provides the best result in terms of spatial structure of the major classes. In this study, we adopted the

Fig. 1 Conceptual design of the various data sources and processing steps.
majority scheme to assign the prevailing land-cover class (Fig. 2a) and we used the subpixel frequency (Fig. 2b) to select relatively homogeneous pixels for fitting the regression models. The original GIMMS data were used for determination of temporal trends in NDVI between 1982 and 2008 at 0.073° (~8 km) spatial resolution. The resulting map of vegetation-activity changes was aggregated to 0.5° using the areal mean. All analyses were carried out using R statistical software (R Development Core Team, 2012) and the geospatial data abstraction library (GDAL, 2012).

**Temporal changes in vegetation activity and climatologies**

The total amount of change was determined for both NDVI and climate time series using linear regression after seasonal adjustment (De Jong et al., 2011). The seasonality was modelled by using additive harmonic functions with periods of 12, 6 and 3 months respectively. The seasonal component was subtracted from the original data before fitting the linear model. The magnitude of change was obtained by multiplying the slope coefficient of the fitted model by the length of the time series. As mentioned before, trend analysis was applied before any spatial resampling was performed. The resulting change maps (Fig. 3) were used for the additive model, which is described in the next section. Significance of the slope coefficients was assessed using generalized least squares. In this way, possible short-lag temporal autocorrelation, which remains after subtracting the seasonal component, is accounted for in the calculation of the P-values. All trends at 0.05 confidence level were
retained; other slope coefficients were neglected (and appear as zero values in Fig. 3).

Based on the climatologies, two regression approaches – one land-cover specific [multiple linear regression (MLR)] and one globally applicable [regression tree (RT)] – were used.

**Land-cover–specific model for observed NDVI changes**

Different land-cover classes (or biomes) are likely to respond differently to changes in climatic conditions (Chapin *et al.*, 2000). To assess the relative influence of each of the four climatologies, we used land-cover–specific MLR models. Eqn 1 shows the common structure for each of the 12 models. In this equation, $b_n$ represents regression coefficients and the climatologies vector $\Delta_n$ contains changes in the CRU parameters (Table 1) as covariates. The latter were determined for the same time span as the NDVI data using seasonal decomposition and a linear trend model. For the seasonal decomposition, we estimated the seasonal signal using the HANTS algorithm (Roerink *et al.*, 2000; De Jong *et al.*, 2011). The model (i.e. $\beta$) was parameterized for each of the 12 land-cover classes separately.

$$\Delta \text{NDVI} = \beta_0 + \begin{bmatrix} \Delta \text{TMP} \\ \Delta \text{PRE} \\ \Delta \text{CLD} \\ \Delta \text{PET} \end{bmatrix}^T [\beta_1 \beta_4]^T + \varepsilon$$

At 0.5° spatial resolution, land cover is in most cases a composite of smaller patches, whereas homogeneous pixels are needed for model calibration. The subpixel frequency (Fig. 2b) of each class was used to exclude heterogeneous pixels for calibrating the regression models described in Eqn 1. The highest homogeneity threshold (i.e. the fraction of the 0.5° cell covered by a unique class) was selected such that the individual land-cover classes retained sufficient pixels for calibration. Above 80%, the number of grid cells in smaller land-cover classes (deciduous broadleaf forest and closed shrubland) appeared too limiting for model training and (bootstrapped) significance tests. At the 80% level, permanent wetlands – the major land-cover class in 514 grid cells (<1%) – was the only vegetated land-cover class that could not be incorporated into the model.

Clusters of pixels in large, homogeneous regions (e.g. Siberia, Amazon and the Great Plains) cause spatial dependency in the training data. While estimating model coefficients, a bootstrapping method was applied to avoid spatial-autocorrelation effects. This provides the possibility to calculate confidence intervals for the regression coefficients and to exclude covariates with an insignificant deviation from zero ($\alpha = 0.05$). The maximum number of bootstrap samples was set to 1000 for each land-cover class.

**Global model for observed NDVI changes**

An additive model was used for describing the observed temporal changes in NDVI (observations $y$). The model consists of a deterministic part where $y$ depends on a set of covariates $x$ with their coefficients $\beta$ (fixed effects), a spatial process $h$ and a residual white noise component $\varepsilon$ (Eqn 2).

$$y = x^T \beta + h + \varepsilon$$

The individual components were estimated using a backfitting approach, consisting of an iterative estimation of the fixed effects $\beta$ (regression step) and the spatial field $h$ (kriging step). The procedure is stepwise described as follows.

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Fig. 3 Temporal changes (1982–2008) in climatologies: (a) temperature, (b) cloudiness, (c) precipitation (PRE) and (d) potential evapotranspiration. Changes were derived at 0.5° spatial resolution using linear models, after seasonal decomposition, from monthly gridded data [Climatic Research Unit (CRU) time series (TS) 3.1/CRU TS 3.10.1 for PRE] (Mitchell & Jones, 2005).
model the reduction in covariance with increasing distance up to the maximum distance $\delta$, beyond which the spatial dependency was forced to zero. The optimal range was found to be around 900 km and was fixed before optimizing the sill parameter using maximum likelihood estimation. The estimated parameter set was used to model the spatial field $h$. The model is further described in Section S2.

**Residual component**

An almost pure-nugget variogram (not shown) indicated that the pixel values in the residual component are spatially uncorrelated. This implies that the combination of fixed and random effects captured virtually all spatial variance at 0.5° resolution. As mentioned before, the within-pixel variation due to smaller scale processes ($\leq 0.5°$) remains unexplained.

**Results and discussion**

**Model predictions**

**Land-cover-specific associations.** Bootstrap regression models provided insight in land-cover–specific associations between vegetation-activity and growth-limiting climate parameters. The performance, in terms of coefficient of determination ($R^2$), varied among land-cover classes (Table 2). There appeared to be a difference between forest and nonforest areas especially. The strongest relationships were found in forests, with the highest $R^2$ in deciduous classes and the lowest $R^2$ in the (tropical) evergreen broadleaf class. The latter was anticipated for several reasons: the use of NDVI is disputed in tropical regions (Huete et al., 1997), climatological observations are relatively sparse (Zhao & Running, 2011) and vegetation growth may not (only) be limited by the climatologies used (Churkina & Running, 1998). Outside of forests, the strongest relationship was found for closed shrubland (e.g. parts of the Sahel region) whereas the weakest relationship was found for open shrubland. The likely explanation of the latter is a heterogeneous distribution of this land-cover class over the globe (Fig. 2a). It includes, among other regions, the tundra, large parts of the African bush lands and thickets, central Australia and Argentina, each of which can be expected to react differently to climate changes (Chapin et al., 2000, chapter 2). For such reasons and as discussed before, the regression-tree approach was adopted for global prediction.

Table 2 suggests that the relationship between cloudiness, which was used as proxy for incident radiation, and vegetation activity is more conspicuous for nonforest than for forest classes. A positive relationship between cloudiness and vegetation activity was found for all classes but savanna, which suggests that a reduction in incident radiation yields a positive impact on vegetation
activity in, among others, grasslands and croplands. A candidate explanation of this might be found in the higher influence of the diffuse component of incoming PAR, as compared with the direct component (Spitters et al., 1986). Clouds were adopted as a proxy for incident PAR, but they do not act as on/off switch for incident radiation. Rather, they determine the ratio between direct and diffuse radiation. For this reason, the efficiency of photosynthesis under overcast skies may be underestimated (Roderick et al., 2001; Gu et al., 2002). For some land-cover systems, the combination of higher temperatures and reduced cloudiness may increase the potential evapotranspiration, but limit vegetation activity, indications for which could be seen for savannas. These ecosystems are predominantly water limited, rather than temperature limited (Nemani et al., 2003), for which an increase in PET may not reflect in higher activity of canopies. The observed cloudiness associations may also be related to changes in global radiative forcing. A reduction, or global dimming, has been suggested for the 1960s until late 1980s, but it was suggested that the trend inverted towards global brightening afterwards (Wild et al., 2005). The latter was found to have raised the diffuse fraction of solar radiation, which, in turn, may have boosted photosynthetic efficiency.

Vegetation activity in the (boreal) needleleaf classes shows associations with temperature – as anticipated (Nemani et al., 2003) – although the deciduous needleleaf forests (Russia) show reduced vegetation activity despite the warming trend (Fig. 3; Table 2). This case of boreal browning has been referred to as the divergence problem and underlying processes remain largely unknown (D’Arrigo et al., 2008). Suggested causes include drought stress, pollution, global dimming, direct temperature stress and, likely, a combination of these (Goetz et al., 2011). Drought stress would be consistent with field observations in relatively dense forests (Goetz et al., 2011) and radiation-related causes may be expected in other cases, although in this study only found through association with potential evapotranspiration. Radiation–hydrology feedback mechanisms may further complicate this issue (Oliveira et al., 2011; Girardin et al., 2012). Finally, increased biomass burning (Soja et al., 2004) might have contributed to feedback mechanisms not fully covered within this approach.

Global associations with climatologies. Figure 4 shows the decomposition of the changes in vegetation activity into the fields described by the fixed effects (RT), the spatial process (GRF) and the uncorrelated residuals. The prediction based on the optimal regression-tree model fit (in terms of lowest cross-validation error) explained 54% of the spatial variation and is shown in the second panel of Fig. 4.

The general pattern of changes in vegetation activity is well captured by the fixed-effects model (i.e. by the changes in climatologies), although the greening patterns seem better represented than some of the browning patterns (e.g. in subequatorial Africa). A strong association between greening and precipitation was found in closed shrublands (Table 2), including parts of the Sahel. This region is known for its long anomalously dry period since the early 1970s (Nicholson, 2000), probably related to multidecadal oceanic

### Table 2 Results of the bootstrapped multiple regression model. For each of the nonmasked land-cover classes following Loveland et al. (2000), the table lists the coefficient of determination of the fitted model ($R^2$) and the Pearson correlation coefficient between the change in normalized difference vegetation index and the parameters used in the model. Homogeneous grid cells (subpixel frequency > 80%) were used for model training and climate parameters that did not significantly ($\alpha = 0.05$) contribute to the model were not included.

<table>
<thead>
<tr>
<th>Land-cover class</th>
<th>$R^2$</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TMP</td>
</tr>
<tr>
<td><strong>Forest</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Evergreen needleleaf</td>
<td>0.43</td>
<td>0.65</td>
</tr>
<tr>
<td>Evergreen broadleaf</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>Deciduous needleleaf</td>
<td>0.54</td>
<td>–0.57</td>
</tr>
<tr>
<td>Deciduous broadleaf</td>
<td>0.68</td>
<td>–0.23</td>
</tr>
<tr>
<td>Mixed</td>
<td>0.25</td>
<td>0.14</td>
</tr>
<tr>
<td><strong>Nonforest</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Closed shrubland</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>Open shrubland</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Woody savanna</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>Savanna</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>Grassland</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>Cropland</td>
<td>0.13</td>
<td>0.07</td>
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<tr>
<td>Cropland/natural mosaic</td>
<td>0.20</td>
<td></td>
</tr>
</tbody>
</table>

TMP, temperature; PRE, precipitation; CLD, cloud cover; PET, potential evapotranspiration.
oscillations (Zhang & Delworth, 2006). The record-low years were just before the satellite recordings and since then a positive trend in both precipitation and vegetation activity was found (Fensholt & Rasmussen, 2011), which likely underlies the detected association (Hickler et al., 2005). Nevertheless, associations were found to vary at regional scales (Bégué et al., 2011; Hein et al., 2011) and remaining greening and browning patches were therefore found in the GRF component.

Nonassociated spatial patterns. Large-scale browning patterns appeared in the spatially correlated field, which implies that they could not be directly associated with climate change. The underlying processes, however, are likely to act at large spatial scales. Here, we discuss some conspicuous regions including an effort to identify candidate drivers from literature.

In Africa, two regions stand out: south/east of Lake Victoria (mainly Tanzania) and Zimbabwe/southern Mozambique. In the former, the changes might be partly related to human activities, as the fixed-effect model indicated small increases in vegetation activity rather than decreases. In recent decades, population increased and agriculture intensified accordingly. Although small parts of the area are in protected national parks (e.g. Serengeti), the browning hotspots are concentrated in unprotected woodland and grassland, parts of which were previously marked as degraded (Pelkey et al., 2000). Wind erosion and overgrazing have been mentioned as causes for degradation in these regions (Dregne, 2002).

Severe degradation was also found in Zimbabwe and attributed to human land use, concentrated in communal areas (Prince et al., 2009). While relating potential productivity to actual productivity in this region, Prince et al. (2009) could establish no relationship between productivity declines and climatic factors, which is consistent with our results. In South Africa, similar conclusions were drawn based on NDVI analysis with correction for changes in precipitation (Wessels et al., 2007). Despite this, it remains contentious to assign browning patterns to land degradation, partly because its definition includes perception aspects and because the NDVI signal needs to vary substantially to capture the complex interaction of drivers (Wessels et al., 2012).

Browning in Indonesia and other places of south-east Asia might be related to the expansion of rubber and palm oil plantations at the cost of tropical forest, a conversion that has been documented to take place at scales large enough to be visible as browning in the analysis (Mann, 2009; Koh et al., 2011). Other conspicuous browning regions include large parts of the needle-leaf forests in Alaska, Canada and Russia. For these regions, the complicated relationship with climate and other abiotic factors was discussed in the previous section.

The random-effects component also revealed greening patterns that might be associated with land-use processes. Very obvious is the large-scale greening in Eastern Europe and the former Soviet Union. This greening is documented in the literature as being related to land abandonment in the postsocialist period, leading to large-scale regrowth of natural vegetation (Baumann et al., 2011; Alcantara et al., 2012; Prischepov et al., 2012).

The Sahel region showed patches of spatially correlated greening and browning. This indicates that – although the overall greening of the region can be reasonably associated with climate effects – large interregional deviations exist. This can be explained by the complex interactions between land use, grazing and climate that exist in this region (Seaquist et al., 2008; Bégué et al., 2011; Hein et al., 2011). These complex interactions cause spatial and temporal deviations in the greening impact of a wetter climate and therefore lead to the patchy pattern.

Remainder

The remainder component in Fig. 4d is spatially uncorrelated (variogram not shown). This component may contain small-scale human interventions, indirect climate effects – likely hidden in feedback mechanisms uncaptured at the given spatiotemporal scale – or measurement error (Zhou et al., 2001). It should, however, be noted that a substantial part of the local variation caused by small-scale processes was averaged out in the spatial aggregation procedure. Climatological observations at higher spatial resolution would be needed to further disentangle these processes.

Limitations and outlook

The results from the presented model showed plausible associations between limiting climate variables and vegetation activity. However, the approach also contains limitations that may guide future research. First of all, it is important to stress that correlation, on which this study relied, does not mean causation. The presented statistical methods form no physical process model and there are many processes that cannot be resolved while being of influence at the spatial scale the model was applied. For example, the large browning effect in Northern Argentina (mainly the Chaco region) was largely attributed to the climatologies (Fig. 4b). This area, however, is also known for large-scale land conversion into arable farming (Vigliizzo et al., 2011). As both could be responsible for the browning effect,
Fig. 4 Decomposition of (a) the observed changes in vegetation activity into (b) fixed climatology effects as represented by the regression-tree model, (c) other spatially correlated, or ‘structured’, effects as represented by the Gaussian random field and (d) residual term $\varepsilon$. The four insets illustrate the spatial structure of each model component at pixel level for the example of southern Africa. For few grid cells, fixed effects could not be estimated and, as a result, the spatial field was not predicted, due to masking of water bodies and permanent wetlands (e.g. Lake Malawi in the insets).
the causation and correct partitioning of the effects is difficult to establish (Zak et al., 2008). Sophisticated modelling of the deterministic component, including mentioned climate–vegetation feedback mechanisms, might be achieved with full spatial-temporal models, but comes with challenges. For example, estimation of many model parameters, given only NDVI as response variable, is likely to run into an ill-posed scenario. Furthermore, dynamic temporal lags between some climatic predictors and vegetation response need to be accounted for. The latter is neither simply nor straightforward at large spatial and temporal extents (Eklundh, 1998; Bégé et al., 2011).

The predictive power of the gridded climate data at hand is reduced by the spatial interpolation, that is the effective number of observations is lower than the number of 0.5° grid cells. This might inflate the weight of the current GRF component. A denser climate observation network would increase the predictive power, especially in remote areas, although great value of the CRU data set resides in its time span. As regards the cloudiness data, the observations have been augmented with sunshine records (Mitchell & Jones, 2005) and few observations are available outside of Europe, North America and Asia. Both may bias the prediction and render radiation the component where improvement is most needed.

Conclusions

In this study we hypothesized that a part of the spatial variation in vegetation-activity changes can be attributed to changes in potential growth-limiting climatologies (i.e. temperature, precipitation and radiation proxies) and that the remainder shows spatial patterns, which can be used to quantify the combined influence of other actors, including human effects. By modelling the deterministic climate effects and the nonassociated spatial process, we found the following:

1. At global scale, the deterministic relationship with climatologies explained about 54% of the spatial variation in vegetation-activity trends. In geographical sense, it especially accounted for large parts of the global greening trends and for the browning hotspots in Argentina and Australia.

2. The spatially correlated field, which combines actors other than climatologies, explained the majority of the remaining variation, leaving a minimal share in the residual component. For some sub-Saharan regions, including Tanzania and Zimbabwe, browning hotspots were detected within this component. In these regions, negative changes in vegetation activity may need to be explained by human activities. Other hotspots could be related to well-documented large-scale land conversions.

3. Land-cover–specific regression models demonstrated strongest relationships between climate change and vegetation-activity trends in forests, conspicuously in needleleaf forest. Here, negative relationships with temperature showed reduced vegetation activity under warming conditions: an effect, which is known as the divergence problem in boreal forests. Strong positive relationships between precipitation and vegetation activity were found in closed shrublands.

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References


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**Supporting Information**

Additional Supporting Information may be found in the online version of this article:

**Data S1.** Supporting online material (SOM).

**Figure S1.** Maximum likelihood estimation of spatial model parameters.