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The impact of land-use change on the sensitivity of terrestrial productivity to precipitation variability: a modelling approach

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Abstract

Larger climate variability and more frequent extreme events (e.g. droughts) are expected to occur. Hence, assessing the sensitivity (response) of terrestrial net primary productivity (NPP) to climate variability is crucial for future estimations of terrestrial carbon sequestration. We hypothesize that land-use change (LUC) can modify this sensitivity, defined here as the anomaly correlation between annual NPP and precipitation in the growing season. To assess this changing sensitivity, we use the LPJmL model driven by observed climate variability and two different land-use sets.

We find that the effect of LUC is mostly extended in semi-arid grasslands: sensitivity increases with conversion into rainfed crops, but it does not change for managed pasture expansion. Reforestation in temperate regions generally decreases sensitivity: trees are able to respond later to water deficit due to their deep root system. The expansion of irrigation in northern India reduces sensitivity since water availability is not a limiting factor for crop growth. Although we are able to identify spatial patterns
of changes in NPP-precipitation sensitivity, the significance of our results focusing at isolation of the land-use effect is limited.

1 Introduction

Net Primary Productivity (NPP) is the process of accumulating atmospheric carbon in the form of plant biomass (photosynthesis minus autotrophic respiration), and it is
 a key element to evaluate terrestrial carbon sequestration. The interannual variability (IAV) of NPP is associated with climate variability (Wu et al., 2013): large anomalies in precipitation patterns can affect terrestrial productivity. For instance, the increasing vegetation growth in mid- and high-latitudes of Eurasia (due to CO₂ fertilization and warming) ceased between 1997 and 2006, which is attributed to a decline in the grow ing season (summer) precipitation (Piao et al., 2011). At the global scale, Zhao and Running (2010) reported a NPP decline during the warmest decade ever recorded



(2000–2009), which was related to large-scale droughts, especially in the Southern Hemisphere.

The sensitivity (or response) of NPP to IAV of precipitation varies spatially (Vicente-Serrano et al., 2013) and temporally. For example Wu et al. (2013) reported an increase
 of NPP sensitivity to water availability in the dry regions of Europe from 1975 to 2009. Their findings of changing climate sensitivity of NPP and climate variability enhance the concern of future potential carbon sequestration by European ecosystems.

NPP sensitivity to precipitation also depends on the timing of precipitation deficit in the annual cycle. Stronger sensitivity to changes in precipitation is generally found in warm and dry regions or during the growing season (in bareal and temperate season).

- ¹⁰ warm and dry regions or during the growing season (in boreal and temperate ecosystems) than in wet regions and cold conditions (Gerten et al., 2008). Also, the relationship between precipitation and NPP is not symmetric: low precipitation has a stronger effect on NPP than higher normal precipitation amounts (Gerten et al., 2008). However, this feature was not evident in the earlier study of Knapp and Smith (2001).
- NPP sensitivity also varies with land-cover. But no consensus exists on which ecosystems and regions are considered to be most vulnerable to precipitation variability and climate extremes. Liu et al. (2013) suggested that the Amazon and the semi-arid and semi-humid climate regimes in low- and mid-latitudes are the most vulnerable, while Vicente-Serrano et al. (2013) postulated that humid biomes are more vulnerable, as vegetation in arid and semiarid regions is considered to be better adapted to water
- as vegetation in and and semiarid regions is considered to be better adapted to wate deficits.

Here, the intriguing question is to which extent changes in land-use may modify NPP sensitivity to precipitation variability, particularly to droughts. For example, Schwalm et al. (2010) related the distribution of croplands to the sensitivity of ecosystem produc-

tivity to droughts, being these systems the most sensitive to water deficit. Changes in land-use can modify ecosystem productivity, its temporal variability and its sensitivity to precipitation. For instance, forest clearing for agriculture modifies water requirements, the rooting system and the timing of the growing season. Irrigation clearly reduces this sensitivity to precipitation and generally increases annual productivity, as shown for





instance in India (Nayak et al., 2013). Yields of rainfed crops have improved by CO_2 fertilization, technological development and regionally specific climate warming, but further warming and changes in precipitation variability and droughts may negatively impact on crop productivity (Lobell et al., 2011; Osborne and Wheeler, 2013).

- Previous studies analysing the relationship between NPP and precipitation used satellite observations to estimate NPP (e.g. Lotsch, 2003; Zhao and Running, 2010). These observational analyses do not allow disentangling the effect of different environmental factors on plant growth such as the effects of LUC. The separate contributions from climatic trends and land-cover change can be analysed using a modelling ap-
- ¹⁰ proach, which allows isolating and quantifying these individual effects. Process-based dynamic global vegetation models (DGVMs) are prevailing tools to evaluate the effect of climate and land-use changes on vegetation distribution/dynamics, and the associated carbon and water fluxes. They have been widely validated with observational data (e.g. Piao et al., 2013), and used for the Intergovernmental Panel on Climate Change 15 (IPCC) assessment activities. Being driven by observed climate and land-use maps,
- they allow an extension of the analysis period to the pre-satellite era.

In this study, spatio-temporal patterns of changes of the NPP sensitivity to precipitation are examined, and the role of land-use change (LUC) in determining these patterns is isolated. For this we use the DGVM LPJmL (Bondeau et al., 2007; Sitch et al., 2003).

We run the model throughout the 20th century with two different land-use sets representing 1901 and 2000 conditions respectively. We determine the spatial patterns of these sensitivities in both runs, and assess the impact of LUC on NPP sensitivity by comparing these runs. Specific hotspots of LUC are selected for further analysis.

The method is further explained in Sect. 2, and results are discussed in Sect. 3. ²⁵ A discussion of the approach and concluding remarks are provided in Sects. 4 and 5, respectively.



2 Methods

2.1 Overview of LPJmL

The Lund–Potsdam–Jena (LPJ, Sitch et al., 2003) managed Land model (LPJmL; Bondeau et al., 2007) is a biogeochemical process-based model that simulates the dynamics of terrestrial ecosystems, the associated carbon and water cycles, and agricultural productivity with a daily time step at 0.5° × 0.5° spatial resolution. LPJmL is a well known and a widely used DGVM at the global (Friend et al., 2014; Müller and Robertson, 2014) and regional (Jung et al., 2007; Lapola et al., 2009; Poulter et al., 2010) scales. Estimated carbon fluxes for natural and crop vegetation have been validated (Bondeau et al., 2007; Sitch et al., 2003) as well as water fluxes (Gerten et al., 2004), irrigation requirements (Rost et al., 2008) and river discharges (Biemans et al., 2009). It is a prevailing tool to analyse the impact of climate warming, climate extremes and anthropogenic LUC on vegetation distribution (Warszawski et al., 2013), terrestrial productivity (Rammig et al., 2014; Zscheischler et al., 2014), crop yields (Waha et al., 2013), irrigation (Elliott et al., 2014) and the global water cycle (Haddeland et al., 2014; Schewe et al., 2014).

Simulations are driven by a monthly climate forcing (temperature, precipitation, number of wet days and cloud cover) from the University of East Anglia's Climatic Research Unit (CRU) TS 3.10 climate data set that is disaggregated to daily values within

- the model (Gerten et al., 2004). Additional inputs are the annual value of atmospheric CO₂ concentration and soil properties. The fractional cover of natural vegetation (represented by nine plant functional types, PFTs; Sitch et al., 2003) is prescribed per grid cell, but their distribution within this fraction is dynamically modelled, based on climatic factors, competition for space and resources (water and light), and disturbances (e.g.
- fires or LUCs). Crops are represented by twelve different annual crops that cover most of the important annual crop types (CFTs; Table 1), and management options such as irrigation or removal of residues can be specified. Managed grasslands are modelled as native grassland and management factors are applied to simulate grass harvest.





Each grid cell is composed by several spatial simulation units (stands). One stand is assigned to natural vegetation, represented by a mixture of PFTs (residing in a predefined fraction of the grid cell area), and each rainfed and irrigated CFT has its own stand, whose area depends on the chosen land-use scenario. All stands share the same climatological forcing, but a separate carbon and water budget is computed for each. This allows for competition for natural resources between different PFTs, but no such competition exists between the individual CFTs that are assumed to grow on separate patches. The land-use scenarios for 1901 and 2000 are based on Monfreda et al. (2008) and will be described in more detail in the results section.

2.2 NPP calculation in LPJmL

NPP (gC $m^{-2} d^{-1}$) is simulated at a daily time scale for each PFT and CFT as the net daily gross assimilation or photosynthesis (GPP) minus maintenance (mresp) and growth (gresp) respiration:

NPP = GPP - mresp - gresp.

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GPP (gC m⁻² d⁻¹) is based on the Farquhar-Collatz scheme (Collatz et al., 1992; Farquhar et al., 1980), and it depends on the response to the Rubisco enzyme activity (differing between C3 and C4 plants) and on the absorbed photosynthetically active radiation (APAR), which is related to the leaf area index (LAI). Daily LAI is controlled by
the daily phenology status and the annual biomass allocation, being water stress a key factor for this allocation. For crops LPJmL prescribes a CFT-specific optimal LAI growth curve as a function of phenological development (Bondeau et al., 2007); a maximum LAI value is prescribed per CFT and country (for more information see Fader et al., 2010). A more detailed explanation on the calculation of the carbon and water cycles by LPJmL can be found in Sitch et al. (2003), Bondeau et al. (2007) and Gerten et al. (2004).



(1)

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2.3 Experimental set up

To achieve an equilibrium state of all carbon pools, a spin up of 900 years driven by preindustrial CO₂ concentration and a repeated cycle of the first 30 years of the climate data set was carried out. This spin up was applied for each of two land-use scenarios, ⁵ where the land-use selected for 1901 is referred to as "no-LUC", while the land-use for 2000 is the "LUC" simulation. This set-up is different from the traditional application of LPJmL, where transient land-use scenarios are usually applied to account for historic LUCs in soil carbon pools at the beginning of each simulation. However, the focus here is not on soil carbon pools but on the land cover effect on the precipitation-sensitivity of NPP, for which a static land use description is more appropriate.

2.4 Land-use scenarios and definition of land-use transitions

Changes in land-cover and land-use between both scenarios are shown in Fig. 1. For each class of PFTs or CFTs the difference in the cover fraction is displayed. Deforestation occurs especially in temperate regions of South America and China, and in

the tropical Central America. Reforestation of agricultural lands takes place in eastern United States and Western Europe (Fig. 1a). Pastures show a large increase of covered area (Fig. 1e), and irrigation clearly expands in Asia, particularly northern India (Fig. 1d).

We have isolated land-use transition per grid cell as the change in land-use between

- the LUC and no-LUC runs that exceeds 20% of the cover (Fig. 1f). For that, we first calculate the difference of the fraction cover between the LUC and no-LUC runs per land-cover type, and select those differences that exceed 20% of the grid cell area. The land cover type that exhibits the greatest decrease is considered as the previous land-use, and the land-cover type with the highest increase is assigned as the new land-use.
- ²⁵ land-use. A two-letter transition label is assigned to every grid cell that reflects these dominant changes (Table 2). The first letter (sometimes supplemented by subscripts) defines the preceding land-use, while the second describes the new one. Hence, the





transition GC_{ni} , for example, denotes that grasslands are replaced by non-irrigated crops. Table 2 summarizes the main transitions that are considered in this study. This classification is used to identify regions with considerable LUC, such as India, southern Australia, United States, Inner Asia (Mongolia and Kazakhstan) and the Argentinian Pampas.

2.5 Standard Precipitation Index (SPI)

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Monthly precipitation from the CRU TS 3.10 data set for the period 1901–2009 is used to calculate the Standardized Precipitation Index (SPI), a drought index that quantifies precipitation anomalies in terms of duration and intensity. SPI is defined as the number of standard deviations that the cumulative precipitation in a given period of time deviates from the climatological mean for that period (Mckee et al., 1993). It requires a minimum of data and is flexible in its time scale definition. An alternative measure is the standardized precipitation and evaporation index (SPEI; Vicente-Serrano et al., 2013b), which adds the effect of temperature on droughts via evaporation. Since

- LPJmL computes evaporation it cannot be considered to be an external forcing of the (also model determined) NPP anomalies. To avoid contamination between internal and external information, we used the model-independent SPI index instead. For its calculation a gamma distribution is fitted to the monthly precipitation data, and its cumulative probability distribution is normalized (for a more detailed description of on SPI
- ²⁰ calculation see Lloyd-Hughes and Saunders, 2002). SPI values between -1 and -2 imply moderate to severe dryness, and SPI below -2 denotes an extremely dry period. A 3 month SPI is considered a short-term drought index, useful for agricultural drought analysis; values aggregated over 12 months SPI are intermediate term droughts, and longer scales are long-term droughts.



2.6 Standardized NPP anomalies

We calculate monthly and annual standardized NPP anomalies (NPP') similar to the SPI as the monthly/annual anomaly relative to the climatological mean (μ), normalized by the by the standard deviation (σ):

$${}^{5} \operatorname{NPP}_{i}' = \frac{\operatorname{NPP}_{i} - \mu_{i}}{\sigma_{i}}$$

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where the index *i* refers to the monthly/annual time scale. This standardization allows NPP anomalies comparable across space.

2.7 Calculation of monthly and annual sensitivities and the effect of land-use change

Monthly SPI was calculated from the precipitation data for 1 to 12 monthly time scales. Both SPI and NPP anomalies were calculated after removing the linear trend from the 109 year time series to avoid effects of gradual changes in other environmental factors (such as global temperature rise). For each calendar month and each grid point, Pearson correlations were calculated using the 109 annual values.

As an illustration, we show these monthly correlations for three different grid cells covering different climates and terrestrial ecosystems (Fig. 2, bottom row) together with their NPP and precipitation climatologies (top row). For the Amazonian cell (Fig. 2, first column), the strongest correlation occurs between June and August at SPI-2 (Fig. 1d).

- This 2 months time-scale can be also observed in Fig. 2a: a 2 month lag is seen between changes in precipitation (April–September) and NPP (June–November) in the dry season (months with a maximum precipitation average of 100 mm; Marengo et al., 2011). For the cell in Kazakhstan (Fig. 2, second column), significant correlations only occur in summer, independent on the SPI-time scale (Fig. 2e). The strongest correla-
- tion for 2 months SPI occurs in June. For the grid cell in Spain (Fig. 2, third column),
 two periods of high correlations can be distinguished (Fig. 2f): spring (the strongest



(2)



occurring in May for SPIs between 1 and 5 months time scale) and in autumn (the highest value in September for SPIs from 1 to 3 months). Precipitation peaks in these two seasons, but it is highly variable (Fig. 2c). NPP can be affected by precipitation anomalies of recent as well as previous months (up to 5–6 months).

- For most areas in the globe the strongest monthly correlation was found using the 2 month time-scale (SPI2). This index was selected as the drought index in our analysis. Assuming that precipitation variability during the growing season affects annual NPP, we correlate annual NPP anomalies and SPI2 of the growing season. Thus, we chose the SPI2 of the growing season defined here as the month with the maximum alimatelogical NPP within every grid cell. By this dependence on NPP, the reported
- ¹⁰ climatological NPP within every grid cell. By this dependence on NPP, the reported annual SPI2 may vary if LUC modifies the seasonality of NPP. Next, for both runs we compute correlations between annual SPI2 and annual NPP anomalies at the grid cell level ($\rho_{\text{NPP-SPI2}}$) and per land cover type (e.g. forest, grass). We refer to $\rho_{\text{NPP-SPI2}}$ as the NPP sensitivity to precipitation. Changes in this sensitivity due to LUC (δ_{LUC}) are calculated by the difference of sensitivities between both runs:

 $\delta_{\text{LUC}} = (\rho_{\text{NPP-SPI2}})_{\text{LUC}} - (\rho_{\text{NPP-SPI2}})_{\text{no-LUC}}.$

3 Results and discussion

3.1 NPP sensitivity to precipitation for natural vegetation

Figure 3 first depicts the timing of the growing and the dry seasons (first row), and next it shows the spatial distributions of NPP sensitivity to precipitation for trees (second row) and grasses (third row) during these two periods. In mid-latitudes the productivity (NPP) of trees is more sensitive to precipitation variability (high $\rho_{\text{NPP-SPI2}}$) during the growing season (Fig. 3c) than in the dry season (Fig. 3d). Droughts and heat waves in this period can strongly affect terrestrial productivity, as found for instance during the 2003 heat wave in Europe (Ciais et al., 2005). Likewise, evidence of enhanced NPP of forest during wet episodes in the growing season is found by Tang et al. (2010).



(3)



In high-latitude regions, temperature is the dominating factor determining the growing season, but water shortage in that period can limit tree growth. This is found here by a high $\rho_{\text{NPP-SPI2}}$ in the growing season (Fig. 3c).

In the tropical regions, especially in the Amazon, anomalies during the dry season ⁵ have the largest effect (Fig. 3d). Negative impacts on NPP have been found when droughts occur in the dry season, for example the 2005 and 2010 droughts in the Amazon (Lewis et al., 2011; Phillips et al., 2009). In the wet season, solar radiation and not precipitation is the main limiting factor for tropical forest growth (as shown by Holmgren et al., 2013; Nemani et al., 2003; Schuur, 2003) and thus we find a small $\rho_{\text{NPP-SPI2}}$ (Fig. 3c). 10

The annual productivity of grasslands is highly sensitive to changes in precipitation in the growing season, and thus a high $\rho_{\text{NPP-SPI2}}$ (Fig. 3e), especially for semi-arid grasslands (regions with a mean annual precipitation below 600 mm). In contrast, we find a low $\rho_{\text{NPP-SPI2}}$ in the dry season (Fig. 3f). Grasslands can adapt to water shortage during this period by suppressing their growth.

3.2 Regional changes in sensitivity due to land-use (δ_{LUC})

Figure 4a shows the spatial distribution of the NPP-precipitation sensitivity ($\rho_{NPP-SPI2}$) for the mixture of PFTs and CFTs in each grid cell, in which at least 20% of the area was subject to land-use transition. Areas with a high $\rho_{\text{NPP-SPI2}}$ coincide with semi-arid grassland regions. This is consistent with Zeng et al. (2013) who mapped strong posi-

20 tive correlations between NDVI-precipitation anomalies in regions covered by grass- as well as by croplands for the period 1982-2010.

Figure 4b shows the difference in $\rho_{\text{NPP-SPI2}}$ between the LUC and no-LUC run (δ_{LUC}), highlighting a number of regions where LUC and a difference in sensitivity coincide.

Positive (negative) δ_{LLC} implies an increase (decrease) in NPP sensitivity to precipita-25 tion variability after implantation of the LUC signal.



Below we analyse selected regions in more detail. For that, we identify the grid cells by their main land-use transition, and analyse spatial patterns of δ_{LUC} . Table 2 summarizes the main characteristics of these regions.

3.2.1 India

In India two types of LU transitions can broadly be discerned: the conversion of grass-5 lands to rainfed crops (GC_{ni}), and the expansion of irrigation in rainfed croplands (CniCi). In areas where the first LU transition predominates (central semi-arid region of the Deccan Plateau; Fig. 5a) δ_{LUC} is positive (Fig. 5c). Crops appear to be more sensitive than tropical grasses in these cells. This is not consistent with the findings of Nayak et al. (2013) who reported higher correlations for grasslands than for crops. 10 However, their definition of croplands is a mix of pastures, dry and irrigated crops, and this does not allow a straightforward comparison with our findings. In grid cells with the $C_{ni}C_i$ transition, found in northern humid subtropical region (known as the Indo-Gangetic plains, IGP: Fig. 5a), δ_{IUC} is generally negative. Irrigation promotes crop productivity in the dry season (highest productivity peak in March for the LUC run in 15 Fig. 6a), which implies a change of the timing of maximum growth between the LUC and no-LUC runs. The introduction of irrigation reduces the sensitivity in the dry season (November–May; Fig. 6b), but it has no effect in the rainy season (August).

3.2.2 Australia

²⁰ Australia has diverse climatic regions covered with different natural ecosystems (varying from deserts to rainforest), being grasslands the greatest contributors to the national NPP (Haverd et al., 2013). In our simulations, natural tropical grasslands in northwest Australia are converted to pastures (GP), while temperate grasslands are mainly converted to rainfed croplands (GC_{ni}) in the southern part (Fig. 5d and f). Both land-²⁵ use transitions lead to a positive δ_{LUC} (Fig. 5e and f): crops are more sensitive than native grasslands, and the intensive mowing scheme applied for managed grasslands





in LPJmL increases $\rho_{\text{NPP-SPI2}}$ for pastures. Besides, the additional expansion of crops in the GP cells in the southern part may have also increased the sensitivity at the aggregated area.

3.2.3 United States

- ⁵ Grasslands that originally cover the semi-arid areas of the west and central US are converted to pastures (GP) and rainfed crops (GC_{ni}) (Fig. 5g). The spatial median of $\rho_{\text{NPP-SPI2}}$ for GC_{ni} cells increases with LUC (positive δ_{LUC}), but it does not change for GP grid cells (Fig. 5i). Nevertheless, there is a positive pattern of δ_{LUC} in central US (Fig. 5h) due to grazing and the additional expansion of crops, which enhances
- 10 $\rho_{\text{NPP-SPI2}}$.

For the period 1989–1997, Wang et al. (2003) evaluated the correlation between precipitation and NDVI for different land cover types (prairie, croplands, forests and grasses) in the state of Kansas in the central Great Plains. Within the growing season, grasslands showed higher correlations than prairies and forests. Croplands had the lowest values, but they did not distinguish between irrigated and rainfed crops. They

¹⁵ lowest values, but they did not distinguish between irrigated and rainfed crops. They pointed out that croplands are faster to respond to changes in precipitation, and forests respond slower due to their adaptive strategies, such as deep roots (crucial for drought events).

In the temperate northern central area, deforestation for crop expansion (TC_{ni}) is the main LU transition, while reforestation of croplands $(C_{ni}T)$ predominates in the eastern part. Because trees have more access to water in deeper soil layers in LPJmL, crops are more sensitive to precipitation. Grid cells with the TC_{ni} transition show positive δ_{LUC} , and conversely a negative value for grid cells with the $C_{ni}T$ transition.

3.2.4 Inner Asia

²⁵ The climate regime in Inner Asia varies between continental and arid, but a significant LUC in the semiarid areas in northern Kazakhstan, Mongolia and north of Inner



Mongolia make us focus on this region (Fig. 5j). NPP anomalies of these areas highly correlate to SPI2 (Fig. 3a), which agrees with the finding of Mohammat et al. (2013). For the period 1982–2009, they showed that 82 % of variance in the vegetation growth in Inner Asia is explained by water availability during the summer (growing) season, explaining more variance than temperature fluctuations.

In our model experiments, grid cells under GC_{ni} transition show positive δ_{LUC} (Fig. 5k and I). GP transition is widely spread in Inner Asia but no changes in spatial median values of $\rho_{NPP-SPI2}$ between runs are found (Fig. 5l).

3.2.5 The Pampas of South America

¹⁰ The Pampas, located in northern Argentina and Uruguay, are characterized by a temperate climate, with rainfall distributed over the whole year. Agriculture greatly expanded in the Argentinian area, becoming one of the main global crop production regions. In our simulations, rainfed crops replaced trees and grasslands (Fig. 5m), and both LU transitions (TC_{ni}, GC_{ni}) showed higher $\rho_{\text{NPP-SPI2}}$ for the LUC run (Fig. 5o) and thus a positive δ_{LUC} , owing to a larger sensitivity of crops to precipitation variability. Trees were also converted to pastures (TP), mainly in Uruguay, causing a slight negative δ_{LUC} .

4 Discussion of our approach

Correlation analysis between observed NPP and precipitation has been previously
 applied with mean annual values or coefficients of variation (e.g. Fang et al., 2001; Peng et al., 2010; Wang et al., 2013; Zhu and Southworth, 2013), monthly anomalies (e.g. Zeng et al., 2013) or drought indexes (e.g. Chen et al., 2013; Pei et al., 2013; Zhao and Running, 2010). Here we expand on this by using the dynamic global vegetation model LPJmL to isolate the effect of the land-use forcing, and to evaluate and compare
 the effect of different land-use transitions on the sensitivity of terrestrial productivity



to precipitation variability in the growing season. These specific transition sensitivities are obviously inherently included in the LPJmL code, and not necessarily reflect the ecosystem behaviour in the real world. However, the main mechanisms could be well explained and justified.

- ⁵ The results of our study are partially dependent on the chosen time characteristics of our correlation analysis: we use a two-month SPI, and take the moment in the annual cycle where NPP is maximum, which is assumed to maximize the correspondence between SPI and annual NPP. Vicente-Serrano et al. (2013b) pointed at the importance to discern different time-scales to understand the response of biomes to droughts. While
- ¹⁰ most ecosystems responded at fairly short time-scales (between 2 and 4 months), they suggested that humid biomes respond to longer time-scales than arid ones. Such a distinction was not clearly found from our (modelling) results. Our selection of two-month SPI agreed with the findings of Zeng et al. (2013), who also found the two-month cumulative precipitation as the highest and most extended positive correlation between 15 precipitation and NDVI anomalies.

Various studies recently have addressed the issue of the timing of changes in precipitation (precipitation seasonality) and droughts. Examples are the negative impact on forest growth due to summer precipitation decrease (Poulter et al., 2013) and summer droughts (Mohammat et al., 2013) in Inner Asia, and the lower summer/autumn precipitation in Kazakhstan (Eisfelder et al., 2014). Here, we explored how precipitation variability in the growing season affects the annual terrestrial productivity. This is based on the assumption that droughts in the growing season affect annual NPP anomalies

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- most, since they affect the NPP during its maximum seasonal value, except for tropical regions, where water shortage becomes more significant in the dry season.
- ²⁵ Although the impact of LUC has low significance at the global scale, we can distinguish spatial δ_{LUC} patterns in regions that have undergone large LUC. Low levels of significance have been also found when investigating the biogeophysical impact of LUC on climate. For instance, the role of LUC on changes in precipitation is uncertain





and of low statistically significance (Pitman et al., 2012), and divergence exists among models (de Noblet-Ducoudré et al., 2012; Pitman et al., 2009).

5 Summary and concluding remarks

In this study, we carried out a model experiment to evaluate the effect of land-use change (LUC) in the sensitivity of terrestrial net primary productivity (NPP) to precipitation variability. We used 20th century simulations with the LPJmL model, run with two different LU scenarios (named as LUC and no-LUC runs), and calculate their sensitivities (anomaly correlations between NPP and precipitation). Differences in sensitivities between these two runs were assessed and attributed to LUC. We focused on the growing season to pick the fraction of the seasonal cycle that contributes most to the annual mean NPP production. We selected areas where LUC exceeded 20 % of the grid cell, and we characterized the main land-use transition.

We found low significance of changes in sensitivity due to LUC, but regional patterns could be identified. The most extended effect of LUC was located in semi-arid grasslands: their conversion to croplands enhanced sensitivity, but limited response was modelled when pastures expanded. These results highlight the role of LUC on sensitivity to water deficit in semi-arid regions, where the climate can become drier (e.g. in Australia; Zhao and Running, 2010), and where changes in precipitation and more frequent drought events are expected in the future (IPCC, 2007, 2012). For the two selected temperate areas (the Pampas and eastern United States), sensitivity increased with trees/grass conversion to crops, and it decreased with the reforestation of croplands.

No tropical regions were selected for two main reasons: (1) our definition of NPPprecipitation sensitivity was related to precipitation anomalies in the growing season, ²⁵ a period in which tropical productivity is poorly correlated to precipitation variability, and (2) the low LUC in these regions in the data set we used. Nevertheless, more





focus needs to be given to these regions since future deforestation in these areas will likely have large effects on NPP variability and sensitivity.

In order to increase the robustness of our results, we suggest to expand this analysis with a larger ensemble of ecosystem models, such as currently explored in the LUCID

⁵ (Pitman et al., 2009) and TRENDY (Sitch et al., 2013) programs. An analysis of effects of LUC in recently performed global climate projections (Brovkin et al., 2013) is subject of ongoing work.

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LU transition	Definition
TC _{ni}	From trees to rainfed crops
TC _i	From trees to irrigated crops
TP	From trees to pastures
GC _{ni}	From grass to rainfed crops
GCi	From grass to irrigated crops
GP	From grass to pastures
C _{ni} T	From rainfed crops to trees
C _{ni} G	From rainfed crops to grass
C _{ni} C _i	From rainfed crops to irrigated crops



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Table 2. Main I	and-use	transitions	for the	5 selected	regions.
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	Regions	Coordinates	Land-use transitions					
			TC _{ni}	ΤP	GC _{ni}	GP	C _{ni} T	C _{ni} C _i
India	Indo-Gangetic Plains	24–34° N 75–88° E						\checkmark
	Deccan Plateau	13–20° N 75–79° E			\checkmark			
Australia	North	14–22° S 133–150° E				\checkmark		
	South	10–40° S 100–160° E			\checkmark			
US		30–49° N 70–130° W	\checkmark		\checkmark	\checkmark	\checkmark	
Inner Asia		40–55° N 50–120° E	V		V	V	•	
The Pampas		29–38° S 50–67° W	\checkmark	\checkmark	\checkmark	-		



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Figure 1. Differences in the extent cover of trees (a), natural grasslands (b), rainfed and irrigated croplands (c and d) and pastures (e) between the two land-use scenarios. (f) Map of land-use transitions (see Table 1 for acronyms).







Figure 2. Climatology of net primary productivity (NPP – green line) and precipitation (blue line) (top row panels) and contour plots of Pearson correlation coefficients between detrended monthly NPP anomalies and the 1- to 12-detrended SPI (bottom row panels) for three grid cells located in the Amazon (left panels; 8.75° S– 58.25° W), in Kazakhstan (middle panels; 50.25° N– 82.25° E) and in Spain (right panels; 40.75° N– 0.75° W).







Figure 3. (a) Timing of the growing (month with the maximum NPP) and **(b)** the dry (month with the lowest precipitation) seasons. Spatial distribution of Pearson correlation coefficient between annual NPP anomalies and the SPI2 of the growing season and the SPI2 of the dry season for trees (\mathbf{c} and \mathbf{d}) and for grasses (\mathbf{e} and \mathbf{f}).



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Figure 4. Spatial distribution of (a) $\rho_{\text{NPP-SPI2}}$ at the grid level for the LUC run; and (b) the difference of $\rho_{\text{NPP-SPI2}}$ between LUC and no-LUC runs (δ_{LUC}) over the time period of 1901–2009. For both maps just grid cells that follow our definition of LU transition (see Sect. 2.4) are shown.







Figure 5. Maps of land-use transitions (first column); Spatial distributions of δ_{LUC} (second column); and the frequency of LU transition types and the spatial medians of $\rho_{\rm NPP-SPI2}$ per land-use transition for the LUC and no-LUC runs over time period of 1901–2009 (third column).











