Responses to Anonymous Referee#1's comments

We would like to thank Reviewer 1 for his/her interest in our manuscript and helpful comments. We detail below a point-by-point response to all his/her comments/suggestions. Modifications to adapt the paper to Referee1's comments can be tracked in the marked MS submitted as supporting information for this response.

Point-by-point reply:

Comment 1: *"This is an interesting study aiming to model the contribution of shrubby and grassy patches to the yearly time course of MODIS-NDVI in drylands and then to use remotely sensed proxies to quantify the Aboveground Net Primary Productivity (ANPP) of each Plant Functional Type (PFTs) over the last 13 years and across a 18km2 area in the Chihuahuan "desert". The context of the study is that of a well-documented conversion from grasslands to shrublands over the last century triggered by a combination of overgrazing, summer drought and modification of the fire regime, and that of the impact of these vegetation changes to ecosystem functioning. This is clearly stated in the paper."*

Response to Comment 1:
We very appreciate the positive evaluation of the scope and contents of our study.

Comment 2: *"Overall, I find the analysis looks like a long and winding road. Essentially, authors have to solve an inverse problem. They assume that the MODIS-NDVI signature at a 230m resolution results from the growth response of a mosaic of two PFTs: shrubs and grasses. Given a growth response model for these two PFTs, the NDVI time series is decomposed in two parts and the contribution of each PFT is estimated. To solve this problem, I think a more straightforward approach could be used. First, I would have slightly refined the two differential equations (eq. 1 and 2) capturing the key ecohydrological processes of the system (see below). Second, I would have extracted the NDVI time series from a set of calibration sites where cover of each PFT is known (to be chosen among the 27 sites) and used these remotely-sensed data to optimize the few parameters governing the plant biomass dynamics (eq. 1). Third I would have assessed the performance of the model when applied to the entire area"*.

Response to Comment 2:
We studied the spatial organization and dynamics of herbaceous and shrub ANPP in a grassland-shrubland ecotone using detailed analysis of the relationships between time series of antecedent precipitation and MODIS NDVI. The final purpose of our work was to generate a new, parsimonious, semi-empirical approach for the analysis of grassland-shrubland ecotone dynamics that could be easily implemented using coarse-grained remote sensing data in dryland systems affected by shrub encroachment. The main assumption of our approach was that herbaceous and shrub vegetation respond differently to antecedent precipitation (i.e. herbaceous vegetation shows quick growth pulses in response to short-term rainfall while shrubs have a slow response to longer term antecedent precipitation) and therefore, grassland-shrubland ecotone dynamics may be reflected in the analysis of landscape-scale vegetation-rainfall relationships. We used a simple process-based model to briefly illustrate, from a conceptual point of view, the validity of the general assumption. This model was not further implemented for the rest of the study. Conversely, actual analysis of the relationships between antecedent precipitation and vegetation dynamics in the field was applied using a semi-empirical study approach, based on the biophysical principles illustrated with the

model. First, we determined empirically the length of the antecedent rainfall series that best described vegetation growth for herbaceous and shrub vegetation in control sites using NDVI values as a proxy of green biomass. We used these vegetation-type specific relationships as lumped (or black-box) spatiotemporal criteria to (i) classify landscape types and (ii) decompose NDVI time series into herbaceous and shrub components of landscape ANPP. Performance of both the semi-empirical landscape classification and NDVI decomposition methods was evaluated against ground-based data on spatial distribution of vegetation types (27 points, one year, 2013) and ANPP temporal series (2000-11 series for two approx. 1000 m^2 core sites), obtaining a very strong agreement with field data. Remote-sensed classification of landscape types and ANPP estimations were further applied to analyse the spatiotemporal dynamics of vegetation across the ecotone.

The referee suggests, as an alternative way of analysis, direct use of the model (or a refined version of the simple model presented in the paper) to extract the shrub and herbaceous components from the NDVI time series after calibration at control sites. We believe that the application of this alternative way would hardly be feasible for this study. The use of simple process-based models such as the one presented in equations 1 and 2 (Rietkerk's dynamic model, Rietkerk et al. 2002) is justified for hypothesis generation and steady evaluation of general assumptions (as we did in this study). Direct application of a fully physically based modelling approach for decomposing/estimating ground-based NPP for different types of vegetation in mixed systems probably would require completely explicit plant-competition equations (i.e. the model should be able to predict plant-plant interactions between herbaceous and shrub components) and details of soil-surface processes (e.g. runoff redistribution, soil erosion) that feedback on herbaceous-shrub interactions in grassland-shrubland desert ecotones. All these interactions and processes cannot be included in just two simple differential equations and would rather require the use of a variety of complex and spatially distributed coupled models for surface hydrology, soil moisture and plant production, for which we have little data to parameterise such a framework. Application of such very complex approach would add further difficulties, not least due to the inherent uncertainties in and availability of model parameters as discussed by Stewart et al. (2014). The referee suggests using discrete (one year) ground-measured abundances of shrubs and herbaceous vegetation for parameter optimization and model calibration in some of the 27 control sites we established in the field in 2013. However, model parameterization would require also other type of information (e.g. temporal trends of spatially distributed soil moisture and vegetation cover, detailed soil and surface hydrology data) that is not available for those sites. We are familiar with the use of complex ecohydrological models. Particularly, we are currently involved in the development of a complex, coupled-modelling approach for the analysis of grassland-shrubland transitions using a variety of models for surface hydrology (MAHLERAN, Wainwright et al. 2008), soil moisture (Soilwat, Parton 1978), and plant production (Daycent, Parton et al. 1998). However, the development of that framework constitutes a totally different and independent work, and the use of such very complex approach for this study is largely unfeasible. Developing this complex approach will require a significant programme of data collection, among others the large-scale decomposed ANPP trends for herbaceous and shrub vegetation obtained in this study across the Five Points SEV ecotone.

In the interim, we consider that we applied a very efficient study approach, which facilitates optimization of results with a low degree of complexity, limited data availability and robustness to parameter uncertainty. Our lumped semi-empirical approach is parsimonious (i.e. we used time series of rainfall and NDVI, together with limited ground-based NPP

datasets and vegetation-type abundances) and has a demonstrated ability to determine accurately the spatiotemporal dynamics of herbaceous and shrub vegetation for our site (i.e. agreement of our landscape classification and decomposed NDVI series with ground-based distribution of vegetation types and ANPP values is very strong, Figures 4 and 5). The simplicity of the approach will facilitate extension and exploration of the methodology broadly, and does not depend on having calibration data available for a specific field site. In order to facilitate application of the approach in other sites, we have thoroughly prepared detailed computing/modelling codes for all critical parts of the study that are available as supporting information of this paper. Overall the methods are simple and straightforward so any researcher interested in this work can easily apply our study approach (which would be less feasible with a complex modelling approach).

Comment 3: *"Model structure: The low-dimensional model coupling plant biomass and soil moisture (eq. 1 and 2) falls a bit short to capture the key ecohydrological processes that control ecosytem reponse in these drylands. First, the lag between the pulse of resource (rainfall event) and the production of biomass is an important parameter to contrast shrub and grass response as thoroughly discussed in the paper. So I do not understand why this parameter is estimated in a second step - i.e. by correlating simulated biomass dynamics and observed rainfall data - and not included in the model structure. I am not convinced that the growth rate and the mortality rate are per se sufficient to properly estimate this lag".*

Response to Comment 3:
We used Rietkerk's dynamic model as a theoretical tool to illustrate briefly and in a simple way the dependency of the relationships between vegetation growth patterns and antecedent precipitation on vegetation type, particularly for dryland herbaceous vegetation and shrubs. The model is consistent with general observations of herbaceous and shrub growth patterns in drylands, indicating that herbaceous vegetation shows quick growth responses to short-term precipitation (i.e. weeks) while biomass dynamics of shrubs show slow responses to longer-term cumulative precipitation (i.e. months). In other words, the antecedent rainfall period (or lag as described by the referee) that best describe plant biomass dynamics is sensitively longer for shrubs than for herbaceous vegetation. The lag emerges from the biophysical behaviour of the different vegetation types, and consequently cannot be pre-imposed into the model structure. In fact, a process-based model that requires a pre-imposed lag parameter to reproduce or approach correctly biomass dynamics is missing critical information on plant-growth patterns (particularly in the growth and mortality rates, and possibly other parameters that can also impact the time-scale of the plant responses to precipitation).

We did not use the model to estimate lags, but more accurately, we applied this simple process-based model to illustrate conceptually the impact of the different plant-growth patterns for herbaceous and shrub vegetation (i.e. differences in plant growth and mortality rates) on the relationship between plant biomass and antecedent precipitation. In other words, the model is used to explain why production of herbaceous and shrub vegetation might show different lags to precipitation. The model indicates that (as it is largely documented in empirical studies in drylands, for example Ogle and Reynolds, 2004, Pennington and Collins, 2007, Forzieri et al., 2011, Garcia et al., 2010) shrubs have a more delayed growth pattern that is sensitive to much longer periods of antecedent precipitation when compared to herbaceous growth patterns. Actual differences in the response of plant dynamics to antecedent precipitation for this study were empirically determined in control sites using the temporal trends of NDVI as a proxy of green biomass. Spatiotemporal analysis of those

empirical relationships was further applied for classifying landscape types and deconvoling time series of NDVI into herbaceous and shrub ANPP series across the ecotone.

Comment 4: *"Model structure: Second, rain use efficiency is very dependent on the timing of rainfalls as illustrated in the last part of the paper that distinguishes monsoonal and non-monsoonal rainfalls. The model structure neither accounts for this. Third, differences between shallow-rooted grasses and the complex rooting systems of shrubs lead to more or less flexibility in using different water sources. In this context, a one layer soil model with similar threshold values for grass and shrub biomass production looks like a strong simplification".*

Response to Comment 4:
The model is indeed simple. We deliberately selected the simplest model which could help to understand in an easy way the link between differences in growing patterns of dryland herbaceous and shrub vegetation and plant biomass responses to antecedent precipitation, so the readers can track without difficulty the conceptual underpinning of the study approach. Explanation of these differences is straightforward. Plant-production inputs for vegetation types with fast growing patterns (i.e. herbaceous vegetation with high growing and mortality rates) have a very short residence time in the system and therefore show a "short memory" on antecedent rainfall conditions (*sensu* Alonso-Sanz and Martin, 2004). Conversely, plant production for vegetation types with low growth and mortality rates (i.e. shrubs and woody vegetation in general) has a "long memory" of precedent rainfall. Although simple, the model provides a good starting point for addressing differences in plant responses to antecedent precipitation for herbaceous and shrub vegetation in drylands.

We do not deny that other factors can also influence the relationships between plant biomass and antecedent rainfall. In fact, a quick exploration of the sensitivity of the *Olr* (the optimal rainfall accumulation length that best explains plant biomass dynamics; described as RaL_{max} in the previous version of the paper) on other model parameters indicates that they can also influence to some extent the biomass-rainfall relationships (see the new Supplementary Figure 1). W_0, k_w, k_i, and c have negligible effects on simulated *Olr* values, while reductions on bare soil infiltration (i_0) and increases on water loss by direct evaporation and/or deep drainage (r_w) can impact Olr_{hv} and Olr_s values, ultimately amplifying the differences we obtained between vegetation types. In addition, as a simplistic approach with a one-layer soil structure, the model simplifies some properties of real systems. For example, differences in rooting systems are not explicit for the different vegetation types, although their influence on the use of water can be, at least in part, absorbed by differences in apparent plant growth and mortality rates (Gilad et al. 2007). We would like to stress that we have used this simple modelling framework just for introducing, from a theoretical point of view, the general assumption of the study: "Our modelling results illustrate conceptually the distinct dependence of the relationship between plant biomass and antecedent precipitation on vegetation type, particularly when comparing the dynamics of dryland herbaceous and shrub vegetation" (Page 7, lines 17-19). We applied the model neither for estimating lags nor for classifying landscape types or decomposing the NDVI series into herbaceous and shrub ANPP components. Contrarily, we determined empirically reference vegetation-rainfall metrics (i.e. site-characteristic *Olr* values and the associated *ARain* antecedent rainfall series for the two different vegetation types) and further applied these calculations to implement our landscape classification and NDVI decomposition methods. The referee already noticed that our herbaceous and shrub ANPP estimations are sensitive to both seasonality and differences in apparent rooting depths of the vegetation types (both points are extensively discussed in

section 5.3 of the paper). In fact, our semi-empirical approach consistently reproduces the observed distinct biophysical performance of the herbaceous and shrub components of vegetation in the grassland-shrubland ecotone studied with variable abundances of mainly *Bouteloua eriopoda* and *Larrea tridentata* plants.

In order to avoid incorrect interpretations of model application for this study, the general purpose for the use of Rietkerk's simplistic model in our study was clearly stated in the introduction of the paper: "This paper is organized in two parts. First, we present the conceptual underpinning and theoretical basis of our study, by using a simple, process-based ecohydrological model to illustrate the biophysical control of the relationship between plant biomass dynamics and antecedent rainfall for dryland herbaceous and shrub vegetation. Secondly, we empirically determine reference optimal lengths of rainfall accumulation (in days) for herbaceous and shrub vegetation (Olr_{hv} and Olr_s) in a 18 km^2 Chihuahuan ecotone, and use these vegetation-type specific NDVI-rainfall metrics to..." (Page 4, lines 25-31).

To clarify the scope and limitations of the model applied in the paper we have included/updated de following information (Page 7, lines 7-19):
"Sensitivity analysis of Olr to other model parameters (Supplementary Fig.1 in the online supporting information of this study) indicates that W_0, k_w, k_i, and c have negligible effects on simulated Olr values. Reductions on bare soil infiltration (i_0) and increases on water loss by direct evaporation and/or deep drainage (r_w) can impact Olr_{hv} and Olr_s values, ultimately amplifying the differences we obtained between vegetation types. Other factors not explicitly considered in our model, such as differences in root structure, may also reinforce herbaceous and shrub differences in time-scale plant responses to antecedent precipitation (Reynolds et al., 2004; Collins et al., 2014).
The simple model presented in this study provides a good starting point for addressing general differences in plant responses to antecedent precipitation for different vegetation types in drylands. Overall, our modelling results illustrate conceptually the distinct dependence of the relationship between plant biomass and antecedent precipitation on vegetation type, particularly when comparing the dynamics of dryland herbaceous and shrub vegetation".

Comment 5: *"Model structure: Finally, given the linear relationship between ANPP and integrated NDVI over the growing season (Fig. 5), equation 1 might be viewed as a prognostic model of NDVI. This should be clearly explained to connect this model with the rest of the paper".*

Response to Comment 5:
We think that, more appropriately, NDVI provides a proxy of aboveground green biomass. This point is specifically stated in the paper both in the introduction (Page 3 lines 25-29: "Satellite-derived chlorophyll-sensitive vegetation indices, such as the Normalized Vegetation Index (NDVI), provide important information on vegetation structure (e.g. surface cover, aboveground green biomass, vegetation type) and dynamics over broad spatial domains (Anderson et al., 1993…") and in the methods (Pages 8-9, lines 31-1: "We use temporal series of NDVI as a proxy of aboveground green biomass in our study area. NDVI is a remote-sensed chlorophyll-sensitive vegetation index that correlates with green biomass in semi-arid environments (Anderson et al., 1993; Huete et al., 2002…"). In addition, the very strong relationship obtained in this study between the time-integrated NDVI values and ground ANPP estimations (Figure 5) provides empirical evidence and validity of such links for our site.

In order to connect conceptual model simulations with the empirical results we have included the following text modification in the paper (Page 18, lines 26-28): "Our modelling results provide a biophysical explanation…" has been updated to "Given the strong relationship between time-integrated NDVI values and ground-based ANPP estimations in our site (Fig. 5b), our herbaceous and shrub exploratory modelling results provide a biophysical explanation…".

In addition, we have simplified concepts, so now they are concise and uniform throughout the paper, connecting the conceptual model simulations and the empirical results. For example, we have excised from the entire paper the term "NDVI-rainfall signature" that seemed to be confusing, and it has been replaced by the term "Olr" (for optimal length of rainfall accumulation). The "$ARain_{hv}$" and "$ARain_s$" terms have also defined in the modelling section (Page 7, lines 1-3), and now they are used consistently across the paper.

Comment 6: *"Model structure. If I understood well, this model was not calibrated with biomass data and so mortality and growth parameters were retrieved from published data. I wonder why authors did not use published values for the other parameters they do not include in the model (i.e. the delay effect)".*

Response to Comment 6:
Referee 1 is right. The model was not calibrated with field biomass/soil moisture data and parameter specifications were motivated by published modelling studies on dryland shrub-herbaceous systems. Particularly, parameter values were retrieved from studies that have applied theoretical modelling frameworks with a similar structure (i.e. simple one-layer models). The model was used as a conceptual tool to introduce our semi-empirical approach, so we did not try to calibrate the model with field data. Model simulations (Fig. 1a) approach consistently the general behaviour of the vegetation types analysed in this study (Fig. 3a). Growth peaks are smaller for the shrubs than for herbaceous vegetation, and shrubs also show in general a smaller reduction of plant biomass in dry periods after rainfall. In addition, the response of the shrubs is delayed when compared with the dynamics of herbaceous biomass. Indeed, the model provides a good starting point to explain, from a conceptual point of view, differences in plant responses to antecedent rainfall by herbaceous vegetation and shrubs.

The purpose of the application of this simple model is to offer a conceptual biophysical explanation of the time-scale dependencies of plant biomass-rainfall responses on vegetation type. The delayed responses emerge from the process representation, so the inclusion of any (additional) pre-imposed "delay-effect" parameters in the model is completely unnecessary (see also our response to Comment 3).

Comment 7: *"NDVI decomposition approach. There is some disconnect between the ecohydrological model (eq. 1 and 2) and the model of NDVI decomposition (eq. 3). Although the ecohydrological model highlights the key role of soil moisture dynamics the rest of the paper only focuses on rainfall data and on NDVI-rainfall relationship. Why? Soil moisture dynamics is like a low-pass filtering of rainfall data and is more informative to model biomass response compared to rainfalls. For example, winter-spring recharge is probably essential to explain the spring growth of shrubs".*

Response to Comment 7:

Eqs. 3 and 4 describe the general assumptions of our NDVI decomposition approach. First, the time series of NDVI at any locations reflect the additive contributions of background soil, and the herbaceous and shrub components of vegetation for that particular site (eq. 3). Secondly, the primary determinant of the dynamics of both NDVI and green biomass in drylands is the rainfall pattern, and therefore the partial contributions of herbaceous vegetation and shrubs can be estimated as a function of their characteristic use or dependency on antecedent rainfall (eq. 4). In addition, our model (eqs. 1 and 2) describes the different dependency of herbaceous and shrub vegetation on antecedent rainfall and therefore is fully connected with our NDVI decomposition approach. We have re-worded a sentence in the methods to clarify this point (Page 12, lines 29-31): "and therefore the partial contributions of herbaceous vegetation and shrubs to NDVI can be estimated as a function of their vegetation-type characteristic use of rainfall" has been changed to "as a function of their characteristic dependency on antecedent rainfall".

We agree with the referee that soil-moisture dynamics are more informative than rainfall patterns for modelling dryland vegetation. Soil-moisture changes in time and space (both vertically and horizontally) vary quickly and rule vegetation dynamics in drylands, where the availability of water is the most limiting factor for plant production. However, the use of detailed records of broad-scale soil-moisture data for this study is not an option, since this type of data is not available in our site. Furthermore, such data are exceptionally rare, especially in dryland environments. This unavailability of data explains further the relevance of our study, which analyzes the coupling between remote-sensed vegetation greenness and rainfall patterns to explore broad-scale dynamics of herbaceous and shrub vegetation in a dryland ecotone. We explicitly detail in the introduction of the study the general links between remote-sensed dryland vegetation, soil-moisture dynamics and rainfall pattern/antecedent precipitation that justify our approach (Pages 3-4, lines 31-7): "In drylands, where vegetation dynamics are particularly well coupled with rainfall patterns, the relationship between time series of NDVI and precipitation provides specific information on the use of water for the production and maintenance of plant biomass (Pennington and Collins, 2007; Notaro et al., 2010; Veron and Paruelo, 2010). Investigations of the relationships between NDVI and rainfall suggest that arid and semi-arid vegetation responds to antecedent (or preceding cumulative) precipitation rather than to immediate rainfall, since plant growth is affected by the history of available soil moisture (Al-Bakri and Suleiman, 2004; Schwinning and Sala, 2004; Evans and Geerken, 2004; Moreno-de las Heras et al., 2012)".

We also agree with the referee that winter recharge of soil moisture is essential to explain, at least in part, biomass production for shrubs in the area. The results of our study fully support that assertion. In fact, analysis of the impact of seasonal rainfall on our remote-sensed estimations of shrub ANPP indicate that shrub production is highly sensitive to non-monsoonal winter precipitation, which contrasts with the close synchronization of herbaceous (forbs plus grasses) production with summer monsoonal rainfall for the area (please see Fig. 7 and Table 2). Please, note that our remote-sensed ANPP estimations for herbaceous and shrub vegetation in the ecotone were derived from the application of our NDVI decomposition method, revealing the very good performance of our study approach. The impact of winter rainfall on shrub ANPP is explicitly discussed in the paper and constitutes one of the main conclusions of our study:
Page 21, lines 17-25 (Discussion): "Our results suggest that primary production is differently controlled by seasonal precipitation for herbaceous and shrub vegetation across the 18-km^2 Chihuahuan Desert ecotone (Fig 7, Table 1). Monsoonal summer precipitation (June-

September) controls ANPP for herbaceous vegetation (Fig. 7a), while ANPP for shrubs is better explained by the preceding year's non-monsoonal (October-May) plus the summer monsoonal precipitation in the present year (Fig 7b). Accordingly, field observations of ANPP for Chihuahuan landscapes found that grassland primary production is particularly coupled with monsoonal rainfall, while desert shrublands appear to be less dependent on summer precipitation (Fisher et al., 1988; Reynolds et al., 1999; Huenneke et al., 2002; Muldavin et al., 2008; Throop et al., 2012)".

Page 22, lines 9-15 (Discussion): "Non-monsoonal precipitation (about 40% annual precipitation, primarily from November to February) typically falls in the form of long-duration low-intensity frontal rainfall that often percolates to deep soil layers (Snyder and Tartowsky, 2006). *Larrea tridentata*, the dominant C_3 shrub in the studied ecotone, has a bimodal rooting behavior that facilitates the use of both shallow and deep soil moisture for plant production (Fisher et al., 1988; Reynolds et al., 1999; Ogle and Reynolds, 2004). Deep creosotebush roots (70-150 cm depth) may acquire winter-derived soil-water resources that are unavailable to grass species…".

Page 24, lines 12-15 (Conclusions): "Analysis of remote-sensed NPP dynamics at the grassland-shrubland ecotone reflects a variable performance of dominant vegetation types. Herbaceous production is synchronized with monsoonal summer rainfall, while shrub NPP shows a flexible response to both summer and winter precipitation".

Comment 8: *"NDVI decomposition approach. The key point here is that I am not convinced that the so called "Arain" function captures adequately the growth response of individual PFT and its coupling with soil mositure dynamics. For example, in the creosotebush core sites, the adjusted NDVI-rainfall relationship is somewhat biphasic and seems to capture both grassland and shrub responses (Fig. 3B). I also wonder if the persistence of high NDVI in shrublands during the dry period is adequately captured by the model (it seems this is more pronounced in observed data (fig. 3A) compared to the simulated data fig. 1A). In short, I do not have the feeling that the NDVI decomposition based on these Arain empirical curves is the best option for the coherence of the paper".*

Response to Comment 8:
It is true that the NDVI-rainfall correlogram (Fig. 3b) captures also the response of herbaceous vegetation in the Creosotebush Core Site, although this effect is only evident for three years with very strong summer precipitation (cycles 2006-07, 2007-08 and 2008-09). Nevertheless, this does not constitute a weak point of our analysis, but just represents the normal response of this shrubland (and other shrubland sites) to its mixed nature with a herbaceous seed pool that germinates during particularly wet summers and can grow to partially cover the shrub interspaces. As expected, the decomposed NDVI series for herbaceous vegetation in the Creosotebush Core Site reflects significant growth peaks for the cycles 2006-07, 2007-08 and 2008-09, with high summer monsoonal rainfall (Fig. 5a). This is not a particular characteristic of our site, but a common feature of arid shrublands. In fact, the growth of non-dominant herbaceous vegetation is also reflected in the analysis of NDVI-rainfall relationships of other dry shrublands, for example in Mulga landscapes in central Australia (Moreno de las Heras et al., 2012). We have updated the text in the results and the discussion sections to clarify this point:
Page 15, lines 10-14 (Results section): "For the Creosotebush Core Site (with dominant shrub vegetation and subordinated forbs and grasses), the short-term, 57-day antecedent rainfall series $ARain_{hv}$ also has an important impact on the strength of the NDVI-rainfall relationship, particularly for three consecutive growing cycles with strong summer precipitation (2006-07,

2007-08 and 2008-09, summer precipitation for the period is 40% above the long-term mean)"

Page 19, lines 4-16 (Discussion section): "*Olr* variations in the reference SEV LTER Core Sites may, therefore, be expressed as a function of the dominant vegetation types (Fig. 3): the strong and quick responses of greenness to short-term precipitation (*ARain$_{hv}$*) in the grass-dominated Black Grama Core Site characterize herbaceous growth for the area, while the slow responses of NDVI to medium-term precipitation (*ARain$_s$*) in the shrub-dominated Cresotebush Core Site define the characteristic pattern of vegetation growth for shrubs in the ecotone. The high correlation between *ARain$_{hv}$* and NDVI values in the shrub-dominated Creosotebush Core Site (Fig. 3b) can be explained by the growth of non-dominant herbaceous vegetation (mainly forbs), which can be especially important during wet years (Muldavin et al., 2008; Baez et al., 2012). Similarly, Moreno-de las Heras et al. (2012) in dry open-shrublands of central Australia (*Olr$_s$* values about 220 days) found the emergence of secondary *Olr$_{hv}$* metrics on the study of local NDVI-rainfall relationships (approx. 85 days antecedent rainfall length) caused by the growth of non-dominant herbaceous vegetation".

Both the theoretical model and the semi-empirical NDVI-decomposition procedure applied in this study are consistent with the idea that shrub green biomass (or greenness) can show a higher persistence along dry periods than herbaceous vegetation green biomass (or greenness). The low mortality rates of the shrubs in our model cause a longer persistence of shrub green biomass along dry periods than for herbaceous vegetation. The ARain function (eq. 4) of our NDVI decomposition method also captures this effect. The NDVI response of herbaceous vegetation is dependent on short-term antecedent rainfall (*ARain$_{hv}$*, 57-days series for our site) which causes a sharp reduction of the decomposed herbaceous signal during dry periods. Conversely, the NDVI response of shrubs is dependent on longer-term precipitation (*ARain$_s$*, 145-days series for the studied ecotone), which makes the decomposed shrub signal much more flexible and persistent during dry periods.

Overall, our semi-empirical NDVI decomposition approach correctly partitions the remote-sensed signal into the herbaceous and shrub components for our site, and this is clearly evidenced by the results of our study. A clear sign of the good performance of our approach is the strong agreement we obtained between the decomposed NDVI series for herbaceous and shrub vegetation and the ground-based ANPP estimations (R^2>0.65, *P*<0.00; Fig. 5b), which constitutes a great achievement bearing in mind the very important spatial variability that affects the small-scale ANPP estimations obtained in the field for this study. Another evidence of the good performance of our study approach is the very strong agreement obtained between our landscape-type classification and the spatial distribution of vegetation types measured in the field (R^2 approx. 0.90, *P*<0.00; Fig. 4).

Comment 9: "*NDVI decomposition approach. The performance of the model decomposing NDVI time series should be clearly presented. How much of the observed NDVI variance is captured by model 3? In addition, an examination of the magnitude, spatial and temporal distribution of the residuals should be conducted. I also would like to know the sensitivity of model outputs to parameter uncertainty (growth rate, mortality rate, lag)?*"

Response to Comment 9:
Additive sums of the decomposed signals for herbaceous vegetation, shrubs and background soil equal 100% of the original MODIS NDVI signal for any t_i. This is not a particular trait of our NDVI-decomposition procedure. All NDVI-partition procedures published in the literature decompose the 100% NDVI signal for any t_i into different field attributes. A first evaluation criterion for the method is the agreement between the annual sums of decomposed

NDVI for herbaceous and shrub vegetation and their ground ANPP estimations. Agreement (explained variance) excess 65% in the cases studied (Fig. 5b), which constitutes a great achievement for any NDVI decomposition procedure in dryland sites with patchy vegetation. We have modified Fig. 5 to include further details, particularly the root mean square error (RMSE) and normalized root mean square error (NRMSE) of our remote-sensing ANPP estimations. RMSE and NRMSE for our estimations are 26 g m^{-2} and 12%, respectively. This low degree of error is, at least, comparable with the errors reported for the most popular NDVI decomposition methodologies (for example, Roderick et al., 1999; DeFries et al., 2000, Hansen et al., 2002; Lu et al., 2003; with reported NRMSE values ranging 10-17%). Error-evaluation details have been added to the text in the results and discussion sections:

Page 16, lines 14-17 (Results): "The annual sums of herbaceous and shrub NDVI components for the reference Core Sites show a strong linear agreement ($R^2 \geq 0.65$; $P<0.001$) with ground-based measurements of ANPP (Fig. 5b), while the remote-sensing ANPP estimations yield a root mean square error of 26 g m^{-2} (NRMSE 12%, Fig. 5c)".

Page 20, lines 20-29 (Discussion): "Although affected by data dispersion, the annual sums of decomposed NDVI strongly agree with field estimations of ANPP for herbaceous and shrub vegetation ($R^2 \geq 0.65$, Fig. 5b), resulting in a small root mean square error for our remote-sensing ANPP estimates (26 g m^{-2}, NRMSE 12%, Fig 5c) that is within the lower limit of reported errors by other NDVI decomposition studies (for example, Roderick et al., 1999; DeFries et al., 2000, Hansen et al., 2002; Lu et al., 2003; with NRMSE ranging 10-17%)".

We did not apply any plant-growth or mortality rates in our NDVI decomposition method. The method is based on the use of vegetation-type optimal antecedent rainfall series $ARain_{hv}$ and $ARain_s$ (see pages 12-13, lines 23-19). Provided that the responses of herbaceous and shrub vegetation to antecedent precipitation are well-discriminated (for example, in our case the responses are clearly different: optimal length of rainfall accumulation for the shrubs is more than 2.5 larger than for herbaceous vegetation) the results of the NDVI decomposition do not depend on delicate tuning of rainfall accumulation length for the $ARain_{hv}$ and $ARain_s$ series (Olr_{hv} and Olr_s values, respectively).

Comment 10: *"Is there any significant change in the cover of shrubs over the examined period? Is the proposed method able to track these changes in areas where significant shrub encroachment has been reported over the last decade?"*

Response to Comment 10:
There is little evidence in other studies that shrub-encroachment for the Sevilleta LTER has been particularly active in the last decades. For example, a recent study on creosotebush plant architecture and age structure for our area indicates that the most important pulses of shrub encroachment in this site took place as a consequence of several large droughts between 1950 and 1970 (Allen et al., 2008). Droughts subsequently may have had a lesser impact because of the end of grazing in the mid-1970s for the area.

Our methods are not directed to determine vegetation *cover*, but herbaceous and shrub ANPP, as stated in the title of the paper. However, we can use our results to evaluate whether there is any directional change along the studied period using the contribution of shrubs to total ANPP. We have generated a new figure (Fig. 6) with detailed analysis of the temporal trends of herbaceous and shrub ANPP for our four types of landscapes (grass-dominated, grass-transition, shrub-transition and shrub-dominated). We have found significant (although very weak) positive correlations between shrub contribution to total ANPP and time for the grass-transition and shrub-transition landscapes along the studied period (Fig. 6b). The same

analysis at the individual pixel level, however, did not show any significant correlations, which overall suggests that shrub encroachment has not been particularly active in the area for the 2000-13 period. Overall, these results agree with and extend the findings of Allen et al. (2008) for our site. This information has been added to both the results and discussion sections:

Page 17, lines 4-7 (Results): "Analysis of the temporal evolution of shrub contribution to total ANPP along 2000-13 reflects significant (although very weak) positive correlations with time for the grass- and shrub transition landscapes (Fig. 6b). The same analysis at the individual pixel level, however, does not show any significant correlations between shrub contribution to total ANPP and time".

Page 23, lines 7-11 (Discussion): "Our results suggest that shrub encroachment has not been particularly active in the studied ecotone for 2000-13 (Fig. 6b). Accordingly, Allen et al. (2008) in a recent study on creosotebush plant architecture and age structure indicated that the most important pulses of shrub encroachment for this area took place between 1950 and 1970".

Comment 11: *"Another way of calibrating and/or validating model 3 is to use high resolution imagery and apply segmentation methods to precisely estimate the cover of shrubs. This could be discussed"*.

Response to Comment 11:
Again, we did not apply our NDVI decomposition method to estimate *cover* but to estimate ANPP. Precise estimation of shrub cover for the site using high-resolution imagery probably would not be very useful for validation purposes of our ANPP estimations, although this type of data (optimally a few high resolution images distributed along the studied period) would constitute a very useful input for precisely testing the activity of the shrub-encroachment process in the area. The following information has been added to the discussion (Page 23, lines 11-14): "Precise estimation of shrub cover applying segmentation methods in time series of high-resolution imagery could help to accurately determine the intensity of the shrub-encroachment phenomenon under the present variability in precipitation for our grassland-shrubland ecotone".

Comment 12: *"A very simple and empirical way to classify land cover based on NDVI time series is to conduct an ordination or a partitioning of the matrix of correlation between NDVI time series. I would be curious to compare the outcome of this analysis with that shown in figure 4"*.

Response to Comment 12:
We are not sure about the particular characteristics of the alternative approach indicated by the referee. A common vegetation classification approach that has been applied using NDVI data since the late-1980s with variable results (i.e. very good in some cases but poor in some others) is based on ordination of phenology metrics (e.g. maximun and mininmum NDVI values, start and end of growing cycles, etc.). For example, A.J. Peters et al. applied this approach in the '90s to classify the Jornada LTER site (New Mexico) into areas dominated by a variety of vegetation types (e.g. grasslands, evergreen shrubs, deciduous shrubs). Those studies (Peters et al., 1995, 1997) are already cited in our paper. Particular application of that approach will not provide any new information for this study (we offer a high-quality and ground-validated classification of landscape types in our study that would not be easily improved by other classification methods based on the use of time series of coarse NDVI

data) and would break the coherence of the study, which is based on the analysis of NDVI-rainfall relationships.

Comment 13: *"Is the change of ANPP along the ecotone consistent with the decrease of ANPP that has been associated with shrub encroachment in dry areas (Knapp & al. Global Change Biology 2008)?"*

Response to Comment 13:
We have generated a new figure (Fig. 6) with details of the temporal variation of both grass and shrub ANPP along the studied period for the different landscape types in our ecotone. Differences in remote-sensed ANPP for the landscape types are tested using repeated-measures ANOVA. The change in ANPP along our ecotone is consistent with the results reported by Knapp et al. (2008) and in other studies carried out in similar Chihuahuan sites (Jornada LTER, Huenneke et al. 2002). The grass-dominated landscapes generally support higher levels of ANPP, although it is quite variable from year to year (Fig. 6a). Differences are clear for highly productive years, but for growing cycles with low primary production we found no significant differences or reversed differences (i.e. higher production in the shrub-dominated sites). The text in the paper has been updated with the following information in the results and discussion sections:
Pages 16-17, lines 25-3 (Results): "Remote-sensed estimations of ANPP are significantly impacted by landscape type ($F_{3, 334}$=48.6, P<0.01), with grass-dominated sites supporting in general higher levels of vegetation production (Fig. 6a). However, landscape-type effects are variable in time (landscape type x time interaction: $F_{14, 1515}$=57.2, P<0.01). Year-to-year variability of ANPP is particularly large for the grass-dominated sites, which show higher levels of ANPP than the transition and shrub-dominated landscapes for highly productive years (Fig. 6a). For growing cycles with low primary production there are no significant ANPP differences or the differences are reversed, with shrub-dominated sites showing higher production than grass-dominated sites (e.g. 2003-04 cycle, Fig. 6a)".
Page 21, lines 11-16 (Discussion): "Analysis of the spatiotemporal dynamics of ANPP in our ecotone indicates that grass-dominated sites, although very importantly affected by year-to-year variability, generally support higher primary production than transition and shrub-dominated landscapes, particularly for wet years with high ANPP levels (Fig. 6a). This result is consistent with other shrub-encroachment studies which have found associations between shrub proliferation and ANPP reductions in dry American grasslands (Huenneke et al., 2002; Knapp et al., 2008)".

Comment 14: *"Is the year-to-year variability in ANPP higher for grass-dominated sites? Coefficient of variation in yearly ANPP along the ecotone could be reported"*.

Response to Comment 14:
Year-to-year variability in ANPP is higher for the grass-dominated sites (as evidenced by Fig. 6), which also agrees with results obtained in other grassland-shrubland desert ecotones (for example, Huenneke et al. 2002, Knapp et al. 2008). Text modifications in our study for this comment are detailed in the above response to Comment 13.

Comment 15: *"To complete figure 5, add panels showing the relative contribution of grass and shrubs to total ANPP. This figure could be divided into two"*.

Response to Comment 15:

We have added a panel in that figure (Fig. 5e) showing the relative contribution of shrubs and herbaceous vegetation to total ANPP.

Comment 16: *"Figure 1 should present the soil moisture dynamics"*.

Response to Comment 16:
We disagree with this suggested change. The paper is based on the analysis of NDVI-rainfall relationships for the study of grassland-shrubland ecotone dynamics, deliberately because there are no soil-moisture data available across the whole extent of the study. Nor would there be in most areas where the technique could be applied. We have not applied (or discussed) any soil-moisture data in this study as they would have to be modelled and we do not have any spatial data to validate them to any degree of confidence. We believe that the presentation of soil-moisture dynamics in our modelling results does not add any critical information for our study and, at the same time, would be very confusing for the readers.

Comment 17: *"Typos. Capital letters for panels in legend of figures"*.

Response to Comment 17:
Now, all the panels in figures (as well as in legends and text citations) are indicated (cited) using lower-case letters.

Comment 18: *"Typos. Variables in fig 4B"*.

Response to Comment 18:
We have corrected the typo.

Comment 19: *"Figure 5C and 5B should show increasing values of ANPP from left to right in the color palette"*.

Response to Comment 19:
Scale bars now show increasing values from left to right.

References cited in this response letter that are not cited in the revised paper:
Alonso-Sanz, R., Martin, M. 2004, Three-state one-dimensional cellular automata with memory, Chaos, Solitons and Fractals, 21: 809-834.

Parton, W.J., 1978. Abiotic section of ELM. In: G.S. Innis (Editor), Grassland Simulation Model. Ecological Studies 26. Springer-Verlag, New York.P.31-53.

Parton, W.J., Hartman, M.D., Ojima, D.S., Schimel, D.S., 1998. DAYCENT: Its land surface sub-model: description and testing. Glob. Planet. Chang. 19, 35-48.

Wainwright, J., Parsons, A. J., Müller, E. N., Brazier, R. E., Powell, D. M., Fenti, B. 2008, A transport-distance approach to scaling erosion rates: 1. Background and model development, Earth Surface Processes and Landforms 33, 813–826.

Responses to Anonymous Referee#2's comments

We would like to thank Reviewer 2 for his/her interest in our study and helpful comments, which have largely contributed to improve our manuscript. We detail below a point-by-point response to all his/her comments/suggestions. Modifications to adapt the paper to Referee2's comments can be tracked in the marked MS submitted as supporting information for this response.

Point-by-point reply:

General comment 1: "*Vegetation structure and the associated dynamics in recent years is key to the understanding of terrestrial carbon cycle and prediction of future climate change. In an arid/semi-arid environment, it is particularly important, as land degradation is phenomenal and largely irreversible. In this paper, the authors used the latest satellite data derived from the MODIS sensor, as well as field-based measurements of climate and vegetation characteristics, and performed a theoretically correct, but empirically complex analysis over the study area in the Chihuahuan Desert in New Mexico, USA. It clearly shows the linkage between the vegetation change and one major environmental driver in this region – precipitation. In my opinion, the paper is well written in the introduction part and the theoretical basis, with a complete set of references and a simplified but clear process-based model description. That means, the paper lays out the question quite well. However, the methodology and consequently the results have quite a few confusing points, and that limits my understanding of this paper. Overall, I recommend reconsider the paper after major revisions. The authors need to make more efforts on clearly explain the methods, use simple and concise words, with the help of equations and diagrams*".

Response to General comment 1:
We really appreciate the positive evaluation of the scope and contents of our study. We have carried out important modifications in the manuscript with the purpose to make points more succinct, simplify concepts and clarify all the confusing points indicated by Referee 2 in the below detailed comments and responses to the comments.

General comment 2: "*Concepts should be concise instead of wordy descriptions. For example, what are the reference NDVI-rainfall signatures (section 3.3)? Even after reading the entire paper, I was still confused by this concept. Is this the optimal RaL (in days) that maximizes Pearson's R (NDVI vs antecedent total rainfall for observations from 2000 to 2013)? I suppose it should be a simple variable and probably is 57 days for herbs and 145 days for shrubs as shown in Figure 3b. Why not use a simple term, such as ORaL (for optimal length of rainfall accumulation)? Or a symbol?*"

Response to General comment 2:
We have made every effort to simplify concepts and avoid wordy descriptions. Referee 2 is right, the concept "NDVI-rainfall signature" (or RaL) resulted confusing and uninformative. Following his/her recommendations, we have excised the term "NDVI rainfall signature" from the text, which has been replaced by *Olr* (for optimal length of rainfall accumulation). *Olr* is now defined in the introduction (Page 4 lines 7-9: "The length (or number of days) of antecedent rainfall that best explains the NDVI (or green biomass) dynamics of dryland vegetation (hereafter optimal length of rainfall accumulation, *Olr*) appears to…") and used consistently in our conceptual model and the rest of the paper (for example, in figures 1 and 3).

General comment 3: "*Figures and methods should be linked to explain the concepts better. Still in section 3.3, terms ARain_hv and ARain_S appear for the first time. But I did not understand what it was, until I saw it again in Figure 4. So are these in fact the green and red lines in Fig. 3b (for empirical results), and theoretically it should be the curves in Fig. 1b? Once the terminology is created, please use them consistently in the paper. Why not use them starting from Fig. 1?*"

Response to General comment 3:
We have added direct links between our concepts and the figures displayed in the study. For example, the *Olr* term is defined in the introduction, and further determinations of *Olr* values for herbaceous and shrub vegetation (i.e. Olr_{hv} and Olr_s, respectively) are graphically detailed for both the theoretical model simulations (Fig. 1) and the empirical results (Fig. 3).

Unlike *Olr*, *ARain* is not a single value but a temporal series of values (i.e. a temporal series of antecedent precipitation with *Olr* rainfall accumulation length). Now the $ARain_{hv}$ and $ARain_s$ series are detailed in both the modelling section and the empirical results of the study with graphical representation in figures 1 and 3. Concept definitions for $ARain_{hv}$ and $ARain_s$ now appear for the first time in the modelling section, and are directly linked to Fig. 1 (Page 7, lines 1-3): "Here, $ARain_{hv}$ and $ARain_s$ are defined as the antecedent rainfall series that optimize those vegetation-type specific relationships (i.e. time series of precedent rainfall with accumulation lengths Olr_{hv} for herbaceous vegetation and Olr_s for shrubs, Fig. 1a)".

General comment 4: "*One of the major flaws I found in this paper is the decomposition of NDVI (section 3.5). It is true that the signal can be partitioned into several contributions from pure pixels. However, I do not agree that the soil background contribution can be subtracted as a constant value. If the authors did not account for the contribution of soil underneath vegetation, the contribution of soil should be a linear function of vegetation cover. For example, if a pure pixel of soil has an NDVI value of 0.12, then the contribution of soil for a pixel covered by 80% vegetation should be only 0.12*0.2 = 0.024*".

Response to General comment 4:
$C_{bs}(t)$ in equation 3 of the NDVI decomposition method describes the whole soil background contribution to the NDVI signal and not just the bare soil component. We erroneously transcribed this term in our study (as bare soil) from the original description of the equation by Lu et al. (2003), who defined the term as "the baseline or contribution from the background soil" and applied a constant value across time to remove the soil NDVI signal. Similarly, Montandon and Small (2008) in their field study determined for our site "soil background NDVI values" (rather than bare soil contributions). We apologize for the misunderstanding we could have caused with our wrong reproduction of the equation and concepts. We have modified the text to correct the errors: "Time series of NDVI at any specific location reflects additive contributions of background soil and the herbaceous and woody shrub components of vegetation (C_{bs}, C_{hv}, and C_s, respectively) for that particular site (Lu et al., 2003)" (Page 12, lines 1-5), "Montandon and Small (2008) carried out in situ measurements of field spectra convolved by the MODIS bands to determine the background soil contribution to NDVI in the SNWR. They obtained a soil NDVI value of 0.12 for Turney sandy loam soils, which are broadly distributed across the McKenzie Flats" (Page 12, lines 7-10), and "Therefore, a constant value of 0.12 was applied to subtract the background soil baseline (C_{bs}) from the NDVI time series, obtaining a new set of soil-free series ($NDVI_O$)" (Page 12, lines 19-21).

Our approach is consistent with the standardization method proposed by Carlson and Ripley (1997), which probably constitutes the most common NDVI normalization technique for the estimation of vegetation biophysical properties (e.g. cover, LAI, NPP). Carlson & Ripley's NDVI normalization method consists on the re-scaling of NDVI values as a function of local maximum values of NDVI time-series (usually obtained at peak vegetation growth in irrigated agricultural fields for the region) after removing the soil background contribution as a constant value (e.g. generally estimated as the minimum value of the time series of NDVI or determined in the field using *in situ* NDVI measurements). Provided that soil NDVI does not change importantly with soil moisture levels (this is only true for bright sandy and sandy-loam soils as the desert soils found in our study site, Huete et al. 1985) and that spatial variations in soil characteristics (i.e. soil texture and chiefly colour) are not very important (in our sites and at the scale of analysis the soils are homogeneous Turney sandy loams; see page 8, lines 19-20), the application of a unique and constant soil NDVI value offers an efficient approach for removing the background soil contribution (Huete et al. 1985, Montandon and Small 2008, Choler et al. 2010). In fact, some of the most popular NDVI decomposition methods apply a constant value to remove the background soil NDVI baseline (for example, Roderick et al. 1999, Lu et al. 2003). Coherency with those studies is now detailed in the text (Page 12, lines 12-15): "Application of reference soil values in NDVI decomposition and normalization methodologies provides an efficient standardization approach for characterizing the background soil baseline, particularly in areas with homogeneous soils (Carlson and Ripley, 1997; Roderick et al., 1999; Lu et al., 2003; Choler et al. 2010)".

Specific comment 1: "*Abstract: "We use these relationships to (a) classify landscape types as a function of the spatial distribution of dominant vegetation, and to (b) decompose the NDVI signal into partial primary production components for herbaceous vegetation and shrubs across the study site." I cannot understand this sentence. Overall, I think the authors need to put more results in the abstract rather than lots of introduction*".

Response to Specific comment 1:
We have reworded the abstract, reducing the introductory information and extending the results (Pages 1-2, lines 12-9): "Climate change and the widespread alteration of natural habitats are major drivers of vegetation change in drylands. In the Chihuahuan Desert, large areas of grasslands dominated by perennial grass species have transitioned over the last 150 years to shrublands dominated by woody species, accompanied by accelerated water and wind erosion. Multiple mechanisms drive the shrub-encroachment process, including precipitation variations, land-use change, and soil erosion-vegetation feedbacks. In this study, using a simple ecohydrological modelling framework, we show that herbaceous (grasses and forbs) and shrub vegetation in drylands have different responses to antecedent precipitation due to functional differences in plant growth and water-use patterns. Therefore shrub encroachment may be reflected in the analysis of landscape-scale vegetation-rainfall relationships. We analyze the structure and dynamics of vegetation at an 18 km^2 grassland-shrubland ecotone in the northern edge of the Chihuahuan Desert (McKenzie Flats, Sevilleta National Wildlife Refuge, NM, USA) by investigating the relationship between decade-scale (2000-13) records of remotely sensed vegetation greenness (MODIS NDVI) and antecedent rainfall. NDVI-rainfall relationships show a high sensitivity to spatial variations on dominant vegetation types across the grassland-shrubland ecotone, and provide ready biophysical criteria to (a) classify landscape types as a function of the spatial distribution of dominant vegetation, and to (b) decompose the NDVI signal into partial components of annual net primary production (ANPP) for herbaceous vegetation and shrubs. Analysis of remote-sensed ANPP dynamics across the study site indicates that plant growth for herbaceous vegetation is

particularly synchronized with monsoonal summer rainfall. For shrubs, ANPP is better explained by winter plus summer precipitation, overlapping the monsoonal period (June to September) of rain concentration. Our results suggest that shrub encroachment has not been particularly active in this Chihuahuan ecotone for 2000-13. However, future changes in the amount and temporal pattern of precipitation (i.e. reductions in monsoonal summer rainfall and/or increases in winter precipitation) may enhance the shrub-encroachment process, particularly in the face of expected upcoming increases in aridity for desert grasslands of the American Southwest".

Specific comment 2: "*Page 58, Line 13: "a set of plausible parameters obtained from literature". Why are these parameters not dependent on vegetation type? In particular W0 and k?*"

Response to Specific comment 2:
We retrieved parameter values from previous studies that have applied theoretical modelling frameworks with a similar structure (e.g. one-layer models) to explore shrub-herbaceous dry ecosystems (for example, Rietkerk et al., 2002; Ogle and Reynolds, 2004; Gilad et al., 2007; Saco and Moreno-de las Heras, 2013). Those studies indicated very important differences between herbaceous and shrub vegetation types for the plant growth and mortality rates (g_{max} and m parameters), although in general they did not apply clear differences for the other parameters. Consequently, we preferred to keep other parameter values constant for the simulations of both the herbaceous and shrub dynamics.

In order to test whether variations in the values of model parameters W_0, k_w, c, k_i, i_0 and r_w can impact the simulated Olr values (and therefore our interpretations of the modelled herbaceous and shrub dynamics) we have applied a model sensitivity analysis that is now available in the supporting information for the revised paper (Supplementary Fig. 1). Most parameters, and particularly W_0 and k_w, have a negligible effect on simulated Olr_{hv} and Olr_s values. The only two parameters that can impact Olr values significantly are i_0 (infiltration rate in bare soil) and r_w (loss of soil moisture by direct evaporation and/or deep drainage) that, in any case, do not depend on vegetation density or vegetation type. Reductions in bare soil infiltration and increases in evaporation/deep drainage can increase Olr. This effect is more important for simulated Olr_s values than for Olr_{hv}. Therefore, variations in i_0 and r_w can ultimately amplify the Olr differences we obtained for herbaceous and shrub vegetation (i.e. the difference between Olr_{hv} and Olr_s).

The main results of our model sensitivity analysis are now summarized in the text (Page 7, lines 7-11): "Sensitivity analysis of Olr to other model parameters (Supplementary Fig.1 in the online supporting information of this study) indicates that W_0, k_w, k_i, and c have negligible effects on simulated Olr values. Reductions on bare soil infiltration (i_0) and increases on water loss by direct evaporation and/or deep drainage (r_w) can impact Olr_{hv} and Olr_s values, ultimately amplifying the differences we obtained between vegetation types".

Specific comment 3: "*Page 59, Line 3: "These modelling results illustrate conceptually the distinct dependence of the relationship between plant biomass and antecedent precipitation on vegetation type". This is the major contribution from the simplified model, and serves the purpose of this study pretty well. It would be even better to emphasize with one or two sentences describing the particular circumstances/assumptions where the "simplified" version can be applied*".

4

Response to Specific comment 3:
We are very pleased with the positive evaluation of our model simulations and the conceptual set-up of our study. We have expanded the model information with the above discussed model sensitivity analysis (please, see our response to the Specific comment 2), and we have added also some details on the potential limitations of the model and how these limitations can affect our simulated results (Page 7, 11-14): "Other factors not explicitly considered in our simple model, such as differences in root structure, may also reinforce herbaceous and shrub differences in time-scale plant responses to antecedent precipitation (Reynolds et al., 2004; Collins et al., 2014)".

We have added also a sentence to emphasize the utility of the model for the study of dryland systems (Page 7, lines 15-19): "The simple model presented in this study provides a good starting point for addressing general differences in plant responses to antecedent precipitation for different vegetation types in drylands. Overall, our modelling results illustrate conceptually the distinct dependence of the relationship between plant biomass and antecedent precipitation on vegetation type, particularly when comparing the dynamics of dryland herbaceous and shrub vegetation".

Specific comment 4: "*Page 63, Line 15 and 19: "Exploratory data analysis. . ." and "Preliminary analysis". Why not put these analyses as supplementary materials?*"

Response to Specific comment 4:
Those analyses are already integrated in the results section. For example, linearity between NDVI, NPP and precipitation is explicit in Figs. 5b and 7. Similarly, the emergence of secondary Olr_{hv} values for the Creosotebush Core Site during wet years with strong herbaceous production is detailed in Fig. 3 and Supplementary Fig. 2, both cited in the results section (Page 15, lines 5-17). Citation of those analyses in the methods is unnecessary and probably quite confusing for the readers. Therefore, we have deleted those citations in the Methods.

Specific comment 5: "*Page 63, Line 23: "In order to avoid confounding effects (i.e. the mixing of the dominant-shrub and non-dominant herbaceous responses to precipitation) on the identification of the local NDVI-rainfall signatures, correlations between NDVI and antecedent precipitation series (of different rainfall accumulation lengths) were determined independently for each annual cycle of vegetation growth (April–March)." Wordy, and no cause-and-effect relationship*".

Response to Specific comment 5:
We agree with Referee 2 that that sentence is wordy and confusing. We have re-worded the whole paragraph to simplify the text and improve description of cause-and-effect relationship (Page 10, lines 26-31): "Growth of non-dominant herbaceous vegetation in arid shrublands can make the detection of the shrub-specific NDVI-rainfall metrics (i.e. Olr_s) difficult due to the emergence of secondary Olr_{hv} values, particularly in wet years with strong herbaceous production (Moreno-de las Heras et al., 2012). We applied detailed analysis of the NDVI-rainfall relationships in the Core Sites for each annual cycle of vegetation growth to facilitate discrimination of the Olr_{hv} and Olr_s metrics".

Specific comment 6: "*Page 64, Line 2: "The reference vegetation-type characteristic antecedent rainfall series (ARainhv and ARains for herbaceous vegetation and shrubs, respectively)". Please refer to figures here*".

Response to Specific comment 6:
Following the recommendations, $ARain_{hv}$ and $ARain_s$ are now referenced to figures 1 and 3 for the modelling and empirical results sections, respectively (see also the above response to General comment 3 for more details).

Specific comment 7: "*Page 64, Line 15: "Conversely, a low strength on the NDVI-rainfall relationship consistently obtained across the 2000–2013 cycles of vegetation growth for a specific vegetation-characteristic antecedent rainfall series will locally evidence a low activity of the analyzed vegetation type for the study period." Not a necessary sentence, and hard to understand*".

Response to Specific comment 7:
Following the recommendations, we have deleted that sentence.

Specific comment 8: "*Page 64, starting from Line 20: This paragraph is hard to understand. I suppose that the authors have used PCA due to high dimensionality (28 variables). However, PCA analysis makes the study scene-dependent. How could it be applied to other regions, when the 1st dimension of PCA is not dominated by herbaceous/shrub fractions?*"

Response to Specific comment 8:
Referee 2 is right on the purpose of our PCA. We have applied PCA to reduce data dimensionality. We have simplified the paragraph to reflect correctly this point (Page 11, lines 23-26): "In order to reduce data dimensionality, we applied Principal Component Analysis (PCA) using the calculated correlation coefficients as variables for analysis (28 variables resulting from the two vegetation-specific antecedent rainfall series and the 14 growing cycles)".

PCA extracts data variability in a set of orthogonal components that are ordered in terms of absorbed or explained variance (i.e. the first component accounts for as much of the variability in data as possible). In our application, PCA summarizes the intensity of herbaceous and shrub activity (or growth) for all the MODIS pixels in our grassland-shrubland ecotone across 2000-13, and the first component reflects accurately the spatial distribution of herbaceous/shrub fractions across the ecotone. Applications in other simple grassland-shrubland ecotones (or other single ecotones between two vegetation types with contrasted plant growth patterns) will lay very similar results. As far as the plant-growth patterns of the two vegetation types are different, the first component will undoubtedly reflect those differences. The only case we can picture that probably will not offer a good discrimination of vegetation types in the first PCA component is a very large-scale application of this method in areas with a variety of vegetation types and ecotones. For example, in a very extent area where, instead of a single ecotone with two contrasted vegetation types, there are various transitions between multiple vegetation types (e.g. grasslands, evergreen shrublands, deciduous shrublands, and open forests) the information explained by the first component will probably not differentiate all the vegetation types. In this case, accurate discrimination of all the vegetation types will require the use of the first two or three PCA components (and not just the first component of the analysis).

Specific comment 9: "*Page 67, Line 1: "Explorative comparisons revealed that this simple two-step procedure outperformed other more complex NDVI-decomposition methodologies". When this is being said, better to provide evidence (e.g., results of comparisons)*".

6

Response to Specific comment 9:
We applied and compared a variety of NDVI-decomposition methodologies with different levels of complexity. The simple method presented in our study outperformed, for example, the application of artificial neural network and autoregressive modeling, which notably inflated the error of the remote sensing ANPP estimations (see below the section "Comparison of NDVI-decomposition methodologies" for details). Those explorative comparisons facilitated the selection of a simple and efficient methodology for this paper, although we do not think that they provide any sort of critical information for the readers of this study. Actually, we believe that full presentation of those details in the paper would unnecessarily increase the complexity of our study, so we have decided to delete the reference in the text to the explorative work detailed below in this response letter.

Specific comment 10: "*Figure 5: When the core sites were used as reference pure pixels for herbs/shrubs, how can the NDVI series in panel A still show 2 components?*"

Response to Specific comment 10:
We did not use the Core Sites as pure pixels for herbs/shrubs, but as reference sites with dominant herbaceous/shrub vegetation. The Creosotebush and Black Grama Core Sites are dominated by shrubs and perennial grasses, respectively. However, they do not represent areas with pure herbaceous or shrub vegetation. Actually no MODIS pixel for the area (pixel size is 230 x 230 m^2) represents just one pure vegetation type (nor would any pixel size beyond a few cm given the patchy nature of the vegetation). The ground pictures of the sites in Fig. 2 (bottom panels in figure 2) clearly show that in the Black Grama Core Site (right bottom panel) there are scattered shrubs (i.e. the scattered dark green plants in the picture), while in the Creosotebush Core Site (left bottom panel) there are also some perennial grasses and variable amounts of annual forbs and grasses (i.e. the standing dry plants/spikes and stubble in the picture). Accordingly, the decomposed NDVI series in Fig. 5a show: (i) for the Black Grama Core Site a dominant component of herbaceous vegetation and a non-dominant component of shrub vegetation, and (ii) for the Creosotebush Core Site a dominant shrub component and a non-dominant component of herbaceous vegetation.

To avoid misinterpretations, we have carefully checked (and corrected as necessary) vegetation descriptions in the manuscript. Both, dominant and non-dominant components of vegetation for the grassland and shrubland sites are explicitly described in the description of the study area (Page 8, lines 9-19: "This study area extends over two LTER core sites established in 1999 (Fig. 2c): a desert shrubland (Creosotebush SEV LTER Core Site) dominated by creosotebush, and a grassland (Black Grama SEV LTER Core Site) dominated by black grama (…) The abundance of creosotebush (*Larrea tridentata*) in the grasslands is generally low, although smaller shrubs and succulents (e.g. *Gutierrezia sarothrae*, *Ephedra torreyana*, *Yucca glauca*, *Opuntia phaeacantha*) can be common. The abundance of perennial grass species decreases to the southern and southwestern parts of the study area, where creosotebush stands are widely distributed with in general low (although variable in time) amounts of annual forbs and grasses"), and further emphasized in other parts of the manuscript (for example, Page 15, lines 10-11: "For the Creosotebush Core Site (with dominant shrub vegetation and subordinate forbs and grasses)…").

Comparison of NDVI-decomposition methodologies:

(1)   Methods:
We applied and evaluated two variations of the simple NDVI decomposition method presented in the paper (Reference method) using two more complex approaches (SOLO and AutRes methods):

SOLO: This methodological variation consisted on the application of an artificial neural network (ANN) modelling algorithm (SOLO, Self-organizing Linear Output Map, Hsu et al. 2002) for refining the relationship between soil free NDVI ($NDVI_0$) and the herbaceous and shrub optimal antecedent rainfall series $ARain_{hv}$ and $ARain_s$ (eq. 5 in the manuscript):

$$NDVI_0(t) = h\, ARain_{hv}(t) + s\, ARain_s(t)$$

SOLO classifies input data (i.e. the $NDVI_0$ temporal series) into different groups with similar temporal properties (e.g. homogeneous sections of the temporal series with increasing values, decreasing values, plateaus, etc.) and further applies first-order least-squares optimization of the target NDVI-rainfall equation independently for the different data groups established in the classification.

AutRes: This methodological variation consisted on the application of an autoregressive model instead of first-order optimization of the above simple equation. $NDVI_0$ for any $t+\Delta t$ in the autoregressive model is expressed as the partial contribution of herbaceous and shrub vegetation (C_{hv} and C_s, respectively) in t plus their variation in time (to $t+\Delta t$) in response to changes on antecedent precipitation:

$$NDVI_{0\,(t+\Delta t)} = C_{h\,(t)} + h\,\Delta ARain_{hv\,(t\rightarrow t+\Delta t)} + C_{s\,(t)} + s\,\Delta ARain_{s\,(t\rightarrow t+\Delta t)}$$

where, *h* and *s* represent vegetation-type specific rainfall-NDVI conversion coefficients for the herbaceous and shrub components.

This autoregressive approach requires reference information on the contribution of shrub and herbaceous vegetation to NDVI in, at least, a discrete *t* to propagate the relationships along the NDVI temporal series. Evergreen shrubs in the area (e.g. creosotebush) permanently maintain green leaves during all seasons, while herbaceous vegetation generally does not show photosynthetic activity at the end of winter. We assumed that $NDVI_0$ at the end of the cycles of vegetation growth (late March) was fully represented by shrubs, using these values as reference points to propagate the autoregressive model along the time series.

Following the procedure detailed in the paper, we applied the estimated coefficients *h* and *s* to determine the weight of the herbaceous and shrub fractions on the time series. In order to preserve the observed seasonality of the original time series, the predicted weights (or percentage contributions) were reassigned to the input $NDVI_0$ series obtaining the final components for herbaceous vegetation and shrubs (C_{hv} and C_s, respectively).

(2)   Results:
NDVI partitions obtained using the reference decomposition method yield for the Black Grama Core Site a clearly dominant herbaceous component (below Fig. R1a). Conversely, the decomposed shrub NDVI signal strongly prevails over the decomposed herbaceous component in the shrub-dominated Creosotebush Core site. SOLO and AutRes

decomposition methods, however, do not reproduce the expected dominances for the reference grassland and shrubland sites, particularly for the shrub-dominated Creosotebush Core Site where the decomposed signal for herbaceous vegetation exceeds the shrub component for a variety of periods (Figs. R1 d and g).

Agreement between field ANPP levels and the annual sums of the decomposed herbaceous/shrub NDVI series is markedly stronger for the reference NDVI decomposition method ($R^2 \geq 0.65$) than for SOLO and AutRes decomposition methods ($R^2 \leq 0.55$ and 0.53, respectively; Figs. R1 b, e and h). Accordingly, SOLO and AutRes NDVI decomposition methods notably inflate the error of the remote sensing ANPP estimations, when compared with the results generated by the reference NDVI decomposition method applied in our study (normalized error is 12%, 18% and 26% for the reference, SOLO and AutRes methods, respectively; Figs. R1 c, f and i).

Overall these explorative results reveal that the simple NDVI decomposition procedure applied in our study (the reference method) outperforms other more complex methodologies based on artificial neural network and autoregressive modeling (SOLO and AutRes methods) for the decomposition and transformation of the NDVI signal into herbaceous and shrub NPP components.

(3)   References:
Hsu, K., Gopta, H. V., Gao, X., Sorooshian, S., and Iman, B. 2002. Self-organizing linear output map (SOLO): an artificial neural network suitable for hydrologic modelling analysis, Water Resources Research, 38, 1302.
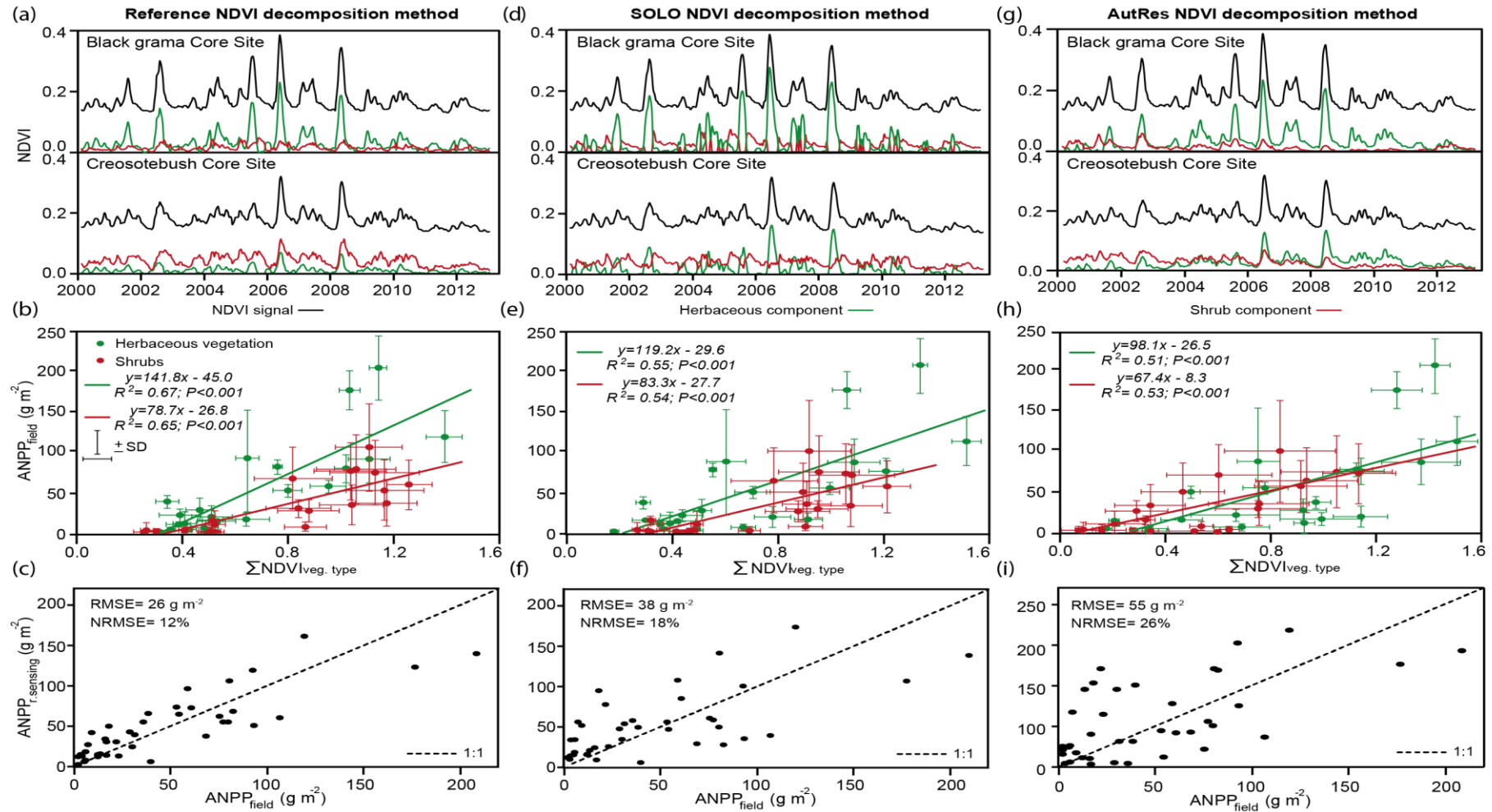
Figure R1. NDVI decomposition comparisons between three methods: (a-c) Reference decomposition method applied in our study, (b) SOLO method, and (c) AutRes method. Plots (a, d, and g) show the decomposed NDVI time series of herbaceous and shrub vegetation for the Black Grama and Creosotebush Core sites. Plots (b, e, and h) show the agreement between the annual sums of decomposed herbaceous/shrub NDVI and field ANPP. Plots (c, f and i) show the root mean square error (RMSE) and normalized error (NRMSE) of the herbaceous and shrub ANPP estimates derived from the application of the different NDVI decomposition methods.

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1 Assessing vegetation structure and ANPP dynamics in a

2 grassland-shrubland Chihuahuan ecotone using NDVI-

3 rainfall relationships

4

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10

11 Abstract

12 Climate change and the widespread alteration of natural habitats are major drivers of

13 vegetation change in drylands. In the Chihuahuan Desert, large areas of grasslands dominated

14 by perennial grass species have transitioned over the last 150 years to shrublands dominated

15 by woody species, accompanied by accelerated water and wind erosion. Multiple mechanisms

16 drive the shrub-encroachment process, including precipitation variations, land-use change,

17 and soil erosion-vegetation feedbacks. In this study, using a simple ecohydrological

18 modelling framework, we show that herbaceous (grasses and forbs) and shrub vegetation in

19 drylands have different responses to antecedent precipitation due to functional differences in

20 plant growth and water-use patterns. Therefore, shrub encroachment may be reflected in the

21 analysis of landscape-scale vegetation-rainfall relationships. We analyze the structure and

22 dynamics of vegetation at an 18 km^2 grassland-shrubland ecotone in the northern edge of the

23 Chihuahuan Desert (McKenzie Flats, Sevilleta National Wildlife Refuge, NM, USA) by

24 investigating the relationship between decade-scale (2000-13) records of remotely sensed

25 vegetation greenness (MODIS NDVI) and antecedent rainfall. NDVI-rainfall relationships

26 show a high sensitivity to spatial variations on dominant vegetation types across the

27 grassland-shrubland ecotone, and provide ready biophysical criteria to (a) classify landscape

28 types as a function of the spatial distribution of dominant vegetation, and to (b) decompose

29 the NDVI signal into partial components of annual net primary production (ANPP) for

Deleted: A classic case of vegetation change is the shrub-encroachment process that has been taking place over the last 150 years i

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Deleted: (black grama, *Bouteloua eriopoda*, and blue grama, *B. gracilis*)

Deleted: (creosotebush, *Larrea tridentata*, and mesquite, *Prosopis glandulosa*)

Deleted: exogenous triggering factors such as

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Deleted: precipitation

Deleted: Spatial evaluation of NDVI-rainfall relationship at the studied ecotone indicates that herbaceous vegetation shows quick growth pulses associated with short-term (previous 2 months) precipitation, while shrubs show a slow response to medium-term (previous 5 months) precipitation. We use these relationships to

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herbaceous vegetation and shrubs. Analysis of remote-sensed ANPP dynamics across the study site indicates that plant growth for herbaceous vegetation is particularly synchronized with monsoonal summer rainfall. For shrubs, ANPP is better explained by winter plus summer precipitation, overlapping the monsoonal period (June to September) of rain concentration. Our results suggest that shrub encroachment has not been particularly active in this Chihuahuan ecotone for 2000-13. However, future changes in the amount and temporal pattern of precipitation (i.e. reductions in monsoonal summer rainfall and/or increases in winter precipitation) may enhance the shrub-encroachment process, particularly in the face of expected upcoming increases in aridity for desert grasslands of the American Southwest.

1   Introduction

Land degradation is pervasive across many dryland regions, which cover over 40% of the Earth's surface and account for about 30% of global terrestrial net primary productivity, globally supporting about 2.5 billion inhabitants (Millennium Ecosystem Assessment, 2005). Over recent decades these dryland regions have experienced growing human and climatic pressures. The most dramatic landscape alterations resulting from these pressures are those associated with desertification, which are perceived as catastrophic and largely irreversible changes that can ultimately lead to relatively barren ecosystem states (Schlesinger et al., 1990; Okin et al., 2009). A common form of vegetation change in drylands involves the encroachment of desert shrub species into arid and semi-arid grasslands, which has already affected more than 250 million hectares worldwide throughout the US, South America, Southern Africa and Australia (D'Odorico et al., 2012; Turnbull et al., 2014).

A classic case of vegetation shift is the shrub-encroachment process that has been taking place over the last 150 years in the Chihuahuan Desert in south-western USA and northern Mexico, where large areas of grasslands dominated by C_4 perennial grass species (black grama, *Bouteloua eriopoda*, and blue grama, *B. gracilis*) have been replaced by shrublands dominated by C_3 desert shrub species (mainly creosotebush, *Larrea tridentata*, and honey mesquite, *Prosopis glandulosa*). These changes in vegetation have been accompanied by accelerated water and wind erosion (for example, Schlesinger et al., 1990; Wainwright et al., 2000; Mueller et al., 2007; Turnbull et al., 2010a; Ravi et al., 2010). A complex range of mechanisms have been suggested to explain the occurrence of this vegetation transition, including external drivers that initiate the transition, and endogenous soil erosion-vegetation

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1 feedbacks that further drive vegetation change (Turnbull et al., 2012). These internal

2 feedbacks strongly alter the organization and distribution of both vegetation and soil resources

3 (i.e. substrate, soil moisture and nutrients), strengthening the vegetation-change process (Okin

4 et al., 2009; Turnbull et al., 2010b, 2012; Stewart et al., 2014).

5 The onset of the grassland-shrubland transition in the Chihuahuan Desert is thought to have

6 started with the introduction of large numbers of domestic grazers, which may have favored

7 the establishment of pioneer shrubs via the creation of gaps (Buffington and Herbel, 1965;

8 van Auken, 2000; Webb et al., 2003) and via a reduction in the frequency and intensity of

9 natural wildfires (D'Odorico et al., 2012). Changing rainfall amount and frequency has also

10 been invoked as one of the major external drivers of shrub encroachment, which may

11 contribute to vegetation change by shifting competitive plant physiological advantages of

12 grass and desert shrub species (Gao and Reynolds, 2003; Snyder and Tartowsky, 2006;

13 Throop et al., 2012). However, there remains a lack of consensus regarding changes in rainfall

14 in the southwest USA over recent decades. Whilst Petrie et al. (2014) found no significant

15 changes in precipitation at the Sevilleta Long Term Ecological Research Site in central New

16 Mexico, other studies have reported significant increases in both annual and winter

17 precipitation at the Jornada Experimental Range in southern New Mexico, but concurrent

18 decreases in the size of discrete precipitation events (Wainwright, 2006; Turnbull et al.,

19 2013).

20 Comprehensive understanding of how desert grasslands are responding to the present

21 variability on both climate and land use is critical for environmental management, especially

22 in consideration of uncertainty regarding future climate change across many dryland regions.

23 Remote sensing of vegetation provides a valuable source of information for landscape

24 monitoring and forecasting of vegetation change in drylands (Okin and Roberts, 2004;

25 Pennington and Collins, 2007; Moreno-de las Heras et al., 2012). Satellite-derived

26 chlorophyll-sensitive vegetation indices, such as the Normalized Difference Vegetation Index

27 (NDVI), provide important information on vegetation structure (e.g. surface cover,

28 aboveground green biomass, vegetation type) and dynamics over broad spatial domains

29 (Anderson et al., 1993; Peters et al., 1997; Weiss et al., 2004; Pettorelli et al., 2005; Choler et

30 al., 2010; Forzieri et al., 2011).

31 In drylands, where vegetation dynamics are particularly well coupled with rainfall patterns,

32 the relationship between time series of NDVI and precipitation provides specific information

Deleted: Long-term records suggest that the current grassland-shrubland transition in the Chihuahuan Desert

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Deleted: Once the shrub-encroachment phenomenon is initiated, the process is further amplified by internal soil erosion-vegetation feedbacks. These internal feedbacks strongly alter the organization and distribution of both vegetation and soil resources (i.e. substrate, soil moisture and nutrients), strengthening the vegetation-change process (Okin et al., 2009; Turnbull et al., 2010a, 2012; Stewart et al., 2014).

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Deleted: Multi-temporal series of coarse- and medium-resolution NDVI, now routinely and freely available from several satellite-borne sensors (e.g. the Advanced Very High Resolution Radiometer, NOAA-AVHRR, the Moderate Resolution Imaging Spectro-radiometer, MODIS), offer powerful tools for the analysis of the impacts of environmental change on the distribution and dynamics of arid and semi-arid vegetation (Huete et al., 2002; Holm et al., 2003; Weiss et al., 2004; Pennington and Collins, 2007; Forzieri et al., 2011).

1 on the use of water for the production and maintenance of plant biomass (Pennington and

2 Collins, 2007; Notaro et al., 2010; Veron and Paruelo, 2010). Investigations of the

3 relationships between NDVI and rainfall suggest that arid and semi-arid vegetation responds

4 to antecedent (or preceding cumulative) precipitation rather than to immediate rainfall, since

5 plant growth is affected by the history of available soil moisture (Al-Bakri and Suleiman,

6 2004; Schwinning and Sala, 2004; Evans and Geerken, 2004; Moreno-de las Heras et al.,

7 2012). The length (or number of days) of antecedent rainfall that best explains the NDVI (or

8 green biomass) dynamics of dryland vegetation (hereafter optimal length of rainfall

9 accumulation, Olr) appears to be site-specific and strongly dependent on vegetation type

10 (Evans and Geerken, 2004; Prasad et al., 2007; Garcia et al., 2010). Herbaceous vegetation

11 (i.e. grass and forb life-forms) and shrubs usually show important differences in the patterns

12 of vegetation growth and water-use, which mediate the responses of plant biomass to rainfall

13 in drylands (Ogle and Reynolds, 2004; Gilad et al., 2007; Pennington and Collins, 2007;

14 Forzieri et al., 2011; Stewart et al., 2014). Thus, the study of the relationship between the

15 NDVI and rainfall may offer important clues for detecting broad-scale landscape changes

16 involving grassland-shrubland transitions in arid and semi-arid landscapes.

17 The aim of this study is to analyze vegetation structure and dynamics at a Chihuahuan

18 grassland-shrubland ecotone (McKenzie Flats, Sevilleta National Wildlife Refuge, New

19 Mexico, USA). To fulfil this aim we explore the relationship between decade-scale (2000-13)

20 records of remote-sensed vegetation greenness (MODIS NDVI) and rainfall. Our analysis is

21 based on a new approach that examines characteristic NDVI-rainfall relationships for

22 dominant vegetation types (i.e. herbaceous vegetation and woody shrubs) to investigate the

23 organization and dynamics of vegetation as a way of evaluating how the shrub-encroachment

24 process occurs.

25 This paper is organized in two parts. First, we present the conceptual underpinning and

26 theoretical basis of our study, by using a simple, process-based ecohydrological model to

27 illustrate the biophysical control of the relationship between plant biomass dynamics and

28 antecedent rainfall for dryland herbaceous and shrub vegetation. Secondly, we empirically

29 determine reference optimal lengths of rainfall accumulation (in days) for herbaceous and

30 shrub vegetation (Olr_{hv} and Olr_s) in a 18 km^2 Chihuahuan ecotone, and use these vegetation-

31 type specific NDVI-rainfall metrics to (i) analyze the spatial organization and dynamics of net

32 primary production (NPP) for herbaceous vegetation and shrubs, and to (ii) explore the impact

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of inter-annual variations in seasonal rainfall on the dynamics of vegetation production at the grassland-shrubland ecotone.

2 Theoretical basis: herbaceous and shrub plant biomass-rainfall relationships in drylands

Dryland herbaceous vegetation (i.e. grass and forb life-forms) and shrubs usually exhibit important differences in the patterns of vegetation growth and water-use. Herbaceous vegetation typically shows quick and intense growth pulses synchronized with major rainfall events, while the dynamics of plant biomass for shrubs is generally less variable in time (Sparrow et al., 1997; Lu et al., 2003; Garcia et al., 2010). These dissimilar growth responses are controlled biophysically by the different plant growth and mortality rates associated with herbaceous vegetation and shrubs. While grasses and forbs are associated with high rates of plant growth and mortality, shrubs are associated with comparatively lower plant growth and mortality rates (Ogle and Reynolds, 2004; Gilad et al., 2007).

We use a simplified version of the dynamic ecohydrological model developed by Rietkerk et al. (2002) to illustrate conceptually how the vegetation-specific rates of plant growth and mortality control the relationship between the dynamics of aboveground biomass and antecedent rainfall for herbaceous vegetation and shrubs in drylands. The model consists of two interrelated differential equations; one describing the dynamics of vegetation (aboveground green biomass, B, g m^{-2}) and the other describing soil-moisture dynamics (soil-water availability, W, mm).

Changes in plant biomass are controlled by plant growth and mortality:

$$\frac{dB}{dt} = g_{max} \frac{W - W_0}{W + k_w} B - mB, \tag{1}$$

where plant growth is a saturation function of soil-moisture availability, and is determined by the maximum specific plant-growth rate (g_{max}, day^{-1}), the permanent wilting point or minimum availability of soil moisture for vegetation growth (W_0, mm), and a half saturation constant (k_w, mm). Plant senescence (biomass loss) is controlled by a plant-specific mortality coefficient (m, day^{-1}).

Soil-water dynamics are controlled by rainfall infiltration, plant transpiration, and soil-moisture loss due to both deep drainage and direct evaporation:

5

$$\frac{dW}{dt} = P\frac{B+k_i \cdot i_0}{B+k_i} - c g_{max}\frac{W-W_0}{W+k_w}B - r_w W,\tag{2}$$

where water infiltration is modelled as a saturation function of plant biomass, characterized by the minimum proportion of rainfall infiltration in the absence of vegetation (i_0, dimensionless), a half saturation constant (k_i, g m^{-2}) and daily precipitation (P, mm day^{-1}). Plant transpiration is controlled by plant growth, and is modulated by a plant-water-consumption coefficient (c, l g^{-1}). Finally, water losses to both deep drainage and direct evaporation are modeled as a linear function of soil-water availability, with a rate r_w (day^{-1}). A Maple 9.5 (Maplesoft, Waterloo, Canada) code for this model is available for download as online supporting material of this article (Code 1).

Two sets of plant-growth and mortality coefficients were applied to this model to simulate vegetation dynamics for a herbaceous species (g_{max}=0.32 day^{-1}, m=0.05 day^{-1}) and a shrub (g_{max}=0.12 day^{-1}, m=0.03 day^{-1}), following criteria established in previous studies (Ogle and Reynolds, 2004; Gilad et al., 2007). Plant-biomass dynamics for these two vegetation types (Fig. 1a) were modelled using a north Chihuahuan Desert 15-year daily precipitation series obtained at the Sevilleta National Wildlife Refuge (Sevilleta LTER, http://sev.lternet.edu/data/sev-1; mean annual rainfall 238 mm) and a set of parameters obtained from literature suited to dryland environments: W_0= 0.05 mm, k_w= 0.45 mm, k_i = 180 g m^{-2}, i_0= 0.20, c= 0.1 l g^{-1}, r_w= 0.1 day^{-1} (Rietkerk et al., 2002; Gilad et al., 2007; Saco and Moreno-de las Heras, 2013).

Using this model, we explored the strength of the plant biomass-precipitation relationship as a function of the length of rainfall accumulation (Fig 1b). We have applied Pearson's R correlation between the simulated plant biomass for both the herbaceous and the shrub species and antecedent rainfall series using various lengths of rainfall accumulation; i.e. for any time t_i in the plant biomass series, the rainfall in the preceding day (t_{i-1}), the cumulative rainfall in the two preceding days ($t_{i-1:i-2}$), in the three preceding days ($t_{i-1:i-3}$) and so on. Modelling results show that the plant biomass-rainfall correlation is maximized at 52 days of cumulative rainfall for the simulated herbaceous species (Olr_{hv} = 52 days) and is maximized at 104 days of cumulative rainfall for the modeled shrub species (Olr_s = 104 days; Fig. 1b). This result indicates that the simulated herbaceous species responds to short-term (~ two months) antecedent rainfall for the production of plant biomass whilst the simulated shrub species responds to a longer period of antecedent precipitation to support plant dynamics. Here,

$ARain_{hv}$ and $ARain_s$ are defined as the antecedent rainfall series that optimize those vegetation-type specific relationships (i.e. time series of precedent rainfall with accumulation lengths Olr_{hv} for herbaceous vegetation and Olr_s for shrubs, Fig. 1a). Further analysis using a range of plausible values for the plant-mortality and maximum plant-growth coefficients (Fig. 1c) indicates that Olr increases largely by reducing the characteristic plant-mortality and growth rates of vegetation, and therefore suggests a strong influence on vegetation type. Sensitivity analysis of Olr to other model parameters (Supplementary Fig.1 in the online supporting information of this study) indicates that W_0, k_w, k_i, and c have negligible effects on simulated Olr values. Reductions on bare soil infiltration (i_0) and increases on water loss by direct evaporation and/or deep drainage (r_w) can impact Olr_{hv} and Olr_s values, ultimately amplifying the differences we obtained between vegetation types. Other factors not explicitly considered in our model, such as differences in root structure, may also reinforce herbaceous and shrub differences in time-scale plant responses to antecedent precipitation (Reynolds et al., 2004; Collins et al., 2014).

The simple model presented in this study provides a good starting point for addressing general differences in plant responses to antecedent precipitation for different vegetation types in drylands. Overall, our modelling results illustrate conceptually the distinct dependence of the relationship between plant biomass and antecedent precipitation on vegetation type, particularly when comparing the dynamics of dryland herbaceous and shrub vegetation.

In the following part of this study, we empirically determine and use metrics of reference vegetation-type specific relationships between aboveground green biomass and antecedent rainfall (i.e. optimal Olr_{hv} and Olr_s lengths, and corresponding $ARain_{hv}$ and $ARain_s$ series) to explore the spatial organization and NPP dynamics of herbaceous and shrub vegetation at a semi-arid grassland-shrubland ecotone.

3 Materials and methods

3.1 Study area

This study is conducted in the Sevilleta National Wildlife Refuge (SNWR), central New Mexico, USA, the location of the Sevilleta Long Term Ecological Research (LTER) site. The SNWR is located in the northern edge of the Chihuahuan Desert, and is a transition zone between four major biomes: the Chihuahuan Desert, the Great Plains grasslands, the Colorado

Plateau steppe, and the Mogollon coniferous woodland (Fig. 2a). Livestock grazing has been excluded from the SNWR since 1973, following 40 years of rangeland use. Due to the biome-transition nature of the SNWR, minor variations in environmental conditions and/or human use can result in large changes in vegetation composition and distribution at the refuge (Turnbull et al., 2010b). Analysis of aerial photographs and soil-carbon isotopes indicate that the extent of desert shrublands has considerably increased over the grasslands in regions of the SNWR over the last 80 years (Gosz, 1992; Turnbull et al., 2008).

Our study area is an 18 km^2 grassland-shrubland ecotone within the McKenzie Flats, an area of gently sloping terrain on the eastern side of the SNWR (Fig. 2b). This study area extends over two LTER Core Sites established in 1999 (Fig. 2c): a desert shrubland (Creosotebush SEV LTER Core Site) dominated by creosotebush, and a grassland (Black Grama SEV LTER Core Site) dominated by black grama. The central and northeastern parts of the study area are mixed black and blue grama (*Bouteloua eriopoda* and *B. gracilis*, respectively) grasslands. The abundance of creosotebush (*Larrea tridentata*) in the grasslands is generally low, although smaller shrubs and succulents (e.g. *Gutierrezia sarothrae*, *Ephedra torreyana*, *Yucca glauca*, *Opuntia phaeacantha*) can be common. The abundance of perennial grass species decreases to the southern and southwestern parts of the study area, where creosotebush stands are widely distributed with in general low (although variable in time) amounts of annual forbs and grasses. Soils are Turney sandy loams (Soil Survey Staff, 2010) with about 60% sand and 20% silt content (Muldavin et al., 2008; Turnbull et al., 2010b). The climate is semi-arid, with mean annual precipitation of ~240 mm that is made up of 57% falling in the form of high-intensity convective thunderstorms during the summer monsoon (June to September) and the remainder being received as low-intensity frontal rainfall and snow (October to May). Mean annual daily temperature is 14°C, with a winter average of 6°C and a summer average of 24°C. Daily air temperature rises over 10°C in the beginning of April, leading to the onset of the yearly cycles of vegetation growth (Weiss et al., 2004). Vegetation growth in the study area generally peaks between July and September, coinciding with the summer monsoon (Muldavin et al., 2008).

3.2 Vegetation measurements (remote sensed and ground based) and rainfall data

We use temporal series of NDVI as a proxy of aboveground green biomass in our study area. NDVI is a remote-sensed chlorophyll-sensitive vegetation index that correlates with green

1   biomass in semi-arid environments (Anderson et al., 1993; Huete et al., 2002; Veron and

2   Paruelo, 2010). Differences in soil background brightness can generate important

3   uncertainties in relating NDVI levels to dryland vegetation, especially when vegetation cover

4   is low and soil type is heterogeneous in space (Okin et al., 2001). Despite these uncertainties,

5   multiple studies have demonstrated the usefulness of NDVI for examining primary production

6   and vegetation structure in arid and semi-arid ecosystems (for example, Weiss et al., 2004;

7   Choler et al., 2010; Moreno-de las Heras et al., 2012), and particularly in Chihuahuan

8   landscapes with sparse vegetation (30-50% cover) similar to those included in this study

9   (Peters and Eve, 1995; Peters et al., 1997; Pennington and Collins, 2007; Notaro et al., 2010).

10 We compiled decade-scale (2000-13) series of NDVI with a 16-day compositing period from

11 the MODIS Terra satellite (MOD13Q1 product, collection 5, approx. 250 m resolution). We

12 used the NASA Reverb search tool (NASA EOSDIS, http://reverb.echo.nasa.gov/) to

13 download the corresponding MODIS tiles. The data were re-projected to UTM WGS84 and

14 further resampled to fit our 18-km^2 study area (335 pixels; 231.5 m pixel resolution after re-

15 projection to UTM coordinates). We checked the reliability layer of the acquired MODIS

16 products and discarded those NDVI values that did not have the highest quality flag value

17 (less than 1 % of data). Missing values were interpolated using a second order polynomial. To

18 reduce inherent noise, the NDVI time series were then filtered by applying a Savitzky-Golay

19 smoothing algorithm, as recommended by Choler et al. (2010).

20 To validate remote sensing analysis of the spatial distribution of vegetation types, the

21 dominance of herbaceous vegetation, shrubs, perennial grass, forbs, and creosotebush plants

22 was recorded at a set of 27 control points (Fig. 2c) using the point-intercept method (Godin-

23 Alvarez et al., 2009). Vegetation presence/absence of the aforementioned vegetation types

24 was recorded every metre using a 2-cm diameter, 1.2-m tall, metal rod pointer along five 50-

25 m long linear transects that were laid at each control point at random directions (without

26 overlapping). Dominance was determined as the relative abundance of a particular vegetation

27 type in relation to the total amount of vegetated points found per linear transect.

28 Reference information on aboveground net primary production (NPP) was obtained from a

29 pre-existing, decade-scale (2000-11) dataset (Sevilleta LTER, http://sev.lternet.edu/data/sev-

30 182). This dataset was recorded in a set of 10 sampling webs distributed within the Black

31 Grama and Creosotebush SEV LTER Core Sites (five webs per Core Site, Fig. 2c). Each

32 sampling web consisted of four 25-m^2 square sub-plots located in each cardinal direction

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1 around the perimeter of a 200-m diameter circle, with four 1-m^2 quadrats spatially distributed

2 in the internal corners of the 25-m^2 sub-plots. A detailed description of the methods that were

3 applied for the development of the SEV LTER field NPP dataset can be found in Muldavin et

4 al. (2008). Briefly, species-specific plant standing biomass was estimated three times per year

5 (in February-March, May-June and September-October) using allometric equations, and NPP

6 was calculated seasonally for spring (the difference in plant biomass form March to May),

7 summer (from June to September), and fall/winter (from October to February). For this study,

8 we have used lumped records of annual net primary production (ANPP) for herbaceous

9 vegetation and shrubs that were spatially averaged at the Core Site scale. ANPP for each

10 yearly cycle of vegetation growth has been calculated as the sum of the seasonal NPP records

11 (i.e. spring + summer + fall/winter).

12 Daily rainfall information for this study was obtained from an automated meteorological

13 station located in the study site (the Five Points weather station, SEV LTER, Fig. 2c; Sevilleta

14 LTER, http://sev.lternet.edu/data/sev-1). The meteorological station is equipped with a rain

15 gauge that records precipitation on a 1-minute basis during periods of rain.

3.3 Reference NDVI-rainfall metrics for herbaceous vegetation and shrubs

17 We explored reference NDVI-rainfall relationships for herbaceous vegetation and shrubs in

18 the Black Grama and Creosotebush SEV LTER Core Sites (where vegetation is dominantly

19 herbaceous and shrub, respectively) using the 2000-13 NDVI time series (averaged from five

20 MODIS pixels in each site, covering a total of 1200 m^2 per site). Pearson's correlations

21 between NDVI and antecedent precipitation series were calculated for the two sites using

22 various lengths of rainfall accumulation (1-300 days). Optimal length of rainfall accumulation

23 for herbaceous vegetation and shrubs (Olr_{hv} and Olr_s, respectively) were then determined as

24 the length of rainfall accumulation (in days) of the antecedent precipitation series that

25 maximized the correlations between NDVI and rainfall in the black grama- and the

26 creosotebush-dominated Core Sites, respectively. Growth of non-dominant herbaceous

27 vegetation in arid shrublands can make the detection of shrub-specific NDVI-rainfall metrics

28 (i.e. Olr_s) difficult due to the emergence of secondary Olr_{hv} values, particularly in wet years

29 with strong herbaceous production (Moreno-de las Heras et al., 2012). We applied detailed

30 analysis of the NDVI-rainfall relationships in the Core Sites for each annual cycle of

31 vegetation growth to facilitate discrimination of the Olr_{hv} and Olr_s metrics. Our approach

32 assumes linearity between rainfall and both NDVI values and green biomass, which has been

broadly demonstrated to occur for dryland vegetation (Evans and Geerken, 2004; Choler et al., 2010; Notaro et al., 2010; Veron and Paruelo, 2010; Moreno-de las Heras et al., 2012) and particularly in our grassland-shrubland desert ecotone (Pennington and Collins, 2007; Muldavin et al., 2008).

The optimal antecedent rainfall series determined in the Core Sites for herbaceous vegetation ($ARain_{hs}$, with Olr_{hv} length of rainfall accumulation) and shrubs ($ARain_s$, with Olr_s rainfall accumulation length) were further used in our 18-km^2 ecotone to classify landscape types and to decompose local NDVI signals into greenness components for herbaceous and shrub vegetation.

3.4 Spatial distribution of vegetation types and landscape classification

We applied analysis of the relationship between local series of NDVI and the reference $ARain_{hv}$ and $ARain_s$ antecedent rainfall series to determine the spatial distribution of dominant vegetation and classify landscape types over our 18-km^2 ecotone study area. This analysis builds on the assumption that spatial variations in the NDVI-rainfall relationship reflect spatial differences in the dominance of vegetation types. We assume that areas dominated by herbaceous vegetation (or shrubs) will show a strong NDVI-rainfall relationship for the herbaceous-characteristic $ARain_{hv}$ (or the shrub-characteristic $ARain_s$) antecedent rainfall series along the study period.

The strength of the relationship between NDVI and rainfall (quantified using Pearson's R correlation between NDVI and antecedent precipitation) was calculated for every MODIS pixel in the study area using the reference $ARain_{hv}$ and $ARain_s$ antecedent rainfall series. Correlation values were determined for each cycle of vegetation growth (April-March) in 2000-13. In order to reduce data dimensionality, we applied Principal Component Analysis (PCA) using the calculated correlation coefficients as variables for analysis (28 variables resulting from the two vegetation-specific antecedent rainfall series and the 14 growing cycles). We studied further the relationship between the main PCA factors and ground-based dominance of vegetation types using the reference vegetation distribution dataset (27 control points). Finally, we used the empirical relationships between vegetation dominance and the main PCA factors to discriminate differentiated landscape types across the study area: grass-dominated (GD), grass-transition (GT), shrub-transition (ST) and shrub-dominated (SD) landscapes.

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Preliminary analysis in this study revealed important mixing effects for the creosotebush-dominated core site, where quick and strong pulses of non-dominant herbs and grasses during wet years masked the shrub-specific NDVI-rainfall signature over the period of analysis. In order to avoid confounding effects (i.e. the mixing of the dominant-shrub and non-dominant herbaceous responses to precipitation) on the identification of the local NDVI-rainfall signatures, correlations between NDVI and antecedent precipitation series (of different rainfall accumulation lengths) were determined independently for each annual cycle of vegetation growth (April-March). We identified the reference signatures for herbaceous and shrub vegetation by determining the series of antecedent precipitation that consistently best explained the NDVI dynamics for the Black Grama and Creosotebush Core Sites across the 2000-13 yearly growing cycles. The reference vegetation-type characteristic antecedent rainfall series ($ARain_{hv}$ and $ARain_s$ for herbaceous vegetation and shrubs, respectively) that were determined in the core sites

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Deleted: Conversely, a low strength on the NDVI-rainfall relationship consistently obtained across the 2000-13 cycles of vegetation growth for a specific vegetation-characteristic antecedent rainfall series will locally evidence a low activity of the analyzed vegetation type for the study period.

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3.5 NDVI decomposition and transformation into herbaceous and shrub ANPP components

Time series of NDVI at any specific location reflects additive contributions of background soil and the herbaceous and woody shrub components of vegetation (C_{bs}, C_{hv}, and C_s, respectively) for that particular site (Lu et al., 2003):

$$NDVI(t) = C_{bs}(t) + C_{hv}(t) + C_s(t), \qquad (3)$$

Montandon and Small (2008) carried out *in situ* measurements of field spectra convolved by the MODIS bands to determine the background soil contribution to NDVI in the SNWR. They obtained a soil NDVI value of 0.12 for Turney sandy loam soils, which are broadly distributed across the McKenzie Flats. Analysis of the local MODIS NDVI time series revealed that this soil-background reference value broadly matches the minimum NDVI values for our study area. Application of reference soil values in NDVI decomposition and normalization methodologies provides an efficient standardization approach for characterizing the background soil baseline, particularly in areas with homogeneous soils (Carlson and Ripley, 1997; Roderick et al., 1999; Lu et al., 2003; Choler et al. 2010). Soil background NDVI may change with soil-moisture content (Okin et al., 2001). Although this effect can be especially important for dark organic-rich soils, soil-moisture variations have shown a little impact in desert-type bright sandy and sandy-loam soils, as those represented in the study area (Huete et al., 1985). Therefore, a constant value of 0.12 was applied to subtract the background soil baseline (C_{bs}) from the NDVI time series, obtaining a new set of soil-free series ($NDVI_O$):

$$NDVI_O(t) = C_{hv}(t) + C_s(t), \qquad (4)$$

We applied the reference herbaceous- and shrub-characteristic antecedent rainfall series, $ARain_{hv}$ and $ARain_s$, to partition single time series of soil-free NDVI ($NDVI_O$) into separate contributions for herbaceous vegetation (C_{hv}) and woody shrubs (C_s) across our study area. This approach is based on the assumption that the primary determinant of the dynamics of both NDVI and green biomass in Chihuahuan landscapes is the rainfall pattern (Huenneke et al., 2002; Weiss et al., 2004; Muldavin et al., 2008; Pennington and Collins, 2007; Notaro et al., 2010; Forzieri et al., 2011), and therefore the partial contributions of herbaceous vegetation and shrubs to NDVI can be estimated as a function of their characteristic dependency on antecedent rainfall. In other words, we assume that C_{hv} and C_s for any t_i are

1 proportional to $ARain_{hv}$ and $ARain_s$. The NDVI components for herbaceous vegetation and

2 shrubs were partitioned using the following two-step NDVI-decomposition procedure (Maple

3 9.5 code for analysis provided as online supporting material of this article; Code 2).

4 First, we applied first-order least-squares optimization of the relationship between soil-free

5 NDVI ($NDVI_O$) and the vegetation-type specific antecedent rainfall series ($ARain_{hv}$ and

6 $ARain_s$ for herbaceous vegetation and shrub, respectively):

7 $$NDVI_O(t) = h\,ARain_{hv}(t) + s\,ARain_s(t), \tag{5}$$

8 where, h and s represent vegetation-type specific rainfall-NDVI conversion coefficients for

9 the herbaceous and shrub components.

10 Secondly, we used the determined coefficients h and s to calculate the weights of C_{hv} and C_s

11 on the time series (i.e. the predicted percentage contribution of each vegetation type over the

12 predicted totals for any t_i). Seasonal variations in other environmental factors (e.g.

13 temperature, day length) may influence NDVI dynamics for Chihuahuan vegetation, shaping

14 the responses of vegetation to precipitation (Weiss et al., 2004; Notaro et al., 2010). In order

15 to preserve the observed seasonality of the original NDVI time series in the decomposed

16 signals for herbaceous and shrub vegetation, the predicted weights (or percentage

17 contributions) of the fitted vegetation components were reassigned to the NDVI levels of the

18 original time series, obtaining the final NDVI components for herbaceous vegetation and

19 shrubs (C_{hv}, and C_s, respectively).

20 The 2000-13 time series of NDVI were decomposed into separate contributions of herbaceous

21 vegetation and shrubs for the Black Grama and Cresotebush SEV LTER Core Sites. We used

22 the reference 2000-11 field NPP dataset to study the relationship between the decomposed

23 NDVI time series and ground-based estimates of herbaceous and shrub NPP for the Core

24 Sites. The sum of the herbaceous and the shrub NDVI components ($\sum NDVI_{veg.type}$) were

25 calculated for each growing cycle of vegetation (April-March). We further determined the

26 relationships between field ANPP estimates of herbaceous and shrub vegetation and

27 $\sum NDVI_{veg.type}$. Finally, we applied the signal-decomposition procedure to every single NDVI

28 time series of the 335 MODIS pixels contained within our study area. The established Core

29 Site NDVI-ANPP relationships were used to estimate herbaceous and shrub ANPP across the

30 18 km^2 study site.

Deleted: Explorative comparisons revealed that this simple two-step procedure outperformed other more complex NDVI-decomposition methodologies (e.g. artificial neural network, autoregressive and non-linear modeling). In order to facilitate the application of this NDVI-decomposition procedure by other users, the Maple 9.5 (Maplesoft, Waterloo, Canada) code that we developed is available for download as online supporting material of this article.¶

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3.6 Spatiotemporal dynamics of vegetation production and impact of seasonal precipitation on herbaceous and shrub ANPP

We used the remotely sensed ANPP estimations and landscape-type classification (GD, grass-dominated, GT, grass-transition, ST, shrub-transition, and SD, shrub-dominated landscapes) to analyze the spatiotemporal dynamics of ANPP along our study grassland-shrubland ecotone, applying repeated-measures ANOVA with time as within subjects factor and landscape type as between subjects factor. Departures from sphericity were corrected using the Greenhouse-Geisser F-ratio method for repeated-measures ANOVA (Girden, 1992). 2000-13 activity of the shrub-encroachment phenomenon for the established landscape types (GD, GT, ST and SD) was explored applying Pearson's R correlation between shrub contribution to total ANPP and time.

We used three different seasonal precipitation metrics to analyze the impact of inter-annual variations in seasonal precipitation on the production of herbaceous and shrub vegetation at our ecotone: (i) preceding non-monsoonal rainfall ($Rain_{PNM}$, from October to May) that takes place before the summer peak of vegetation growth, (ii) summer monsoonal precipitation ($Rain_{SM}$, from June to September), and (iii) late non-monsoonal rainfall ($Rain_{LNM}$, from October to March) that takes place at the end of the annual cycles of vegetation growth. The effects of seasonal precipitation on herbaceous and shrub ANPP for the established landscape types (grass-dominated, grass-transition, shrub-transition and shrub-dominated landscapes) were explored by applying Pearson's R correlation. Effect significance and size was determined using a general linear model (GLM) that includes the different sources of seasonal precipitation ($Rain_{PNM}$, $Rain_{SM}$, and $Rain_{LNM}$) as covariates, landscape type (LT) as a factor, and the interaction terms between landscape type and seasonal precipitation (LT:$Rain_{PNM}$, LT:$Rain_{SM}$, and LT:$Rain_{LNM}$).

4 Results

4.1 Patterns of greenness and reference NDVI-rainfall metrics in the Core Sites

Inter- and intra-annual variations of NDVI show similar patterns of vegetation greenness for both the Black Grama and the Creosotebush Core Sites (Fig. 3a). The signal generally peaks slightly in spring (May) and strongly in summer (July-September). The lowest NDVI values

are observed between February and April. Summer peaks in NDVI values are, however, less marked in the Creosotebush Core Site. In addition, the NDVI signal for the creosotebush-dominated site generally shows an autumn (October-November) peak that is especially important during particular growing cycles (2000-01, 2001-02, 2004-05, 2007-08, 2009-10).

Correlations between NDVI and antecedent precipitation using rainfall-accumulation lengths of 1-300 days indicate that an optimal short-term cumulative rainfall period of 57 days best explains the NDVI variations for the dominant herbaceous vegetation of the grassland site ($ARain_{hv}$ antecedent rainfall series, with Olr_{hv} accumulation length; Fig. 3, see also Supplementary Fig. 2 in the online supporting information of this study for details on the annual cycles of vegetation growth). For the Creosotebush Core Site (with dominant shrub vegetation and subordinate forbs and grasses), the short-term, 57-day antecedent rainfall series $ARain_{hv}$ also has an important impact on the strength of the NDVI-rainfall relationship, particularly for three consecutive growing cycles with strong summer precipitation (2006-07, 2007-08 and 2008-09, summer precipitation for the period is 40% above the long-term mean). However, the NDVI-rainfall correlation in this shrub-dominated site generally peaks using a much longer optimal cumulative rainfall period of nearly 145 days ($ARain_s$ series, with Olr_s length).

4.2 Spatial distribution of vegetation types and landscape classification

PCA analysis of the NDVI-rainfall correlation coefficients (per growing cycle) for the reference 57- and 145-day antecedent rainfall series (i.e. $ARain_{hv}$ and $ARain_s$ with Olr_{hv} and Olr_s rainfall accumulation lengths, respectively for all MODIS pixels contained within our study area) shows that PCA factor 1 (about 40% of total data variance) reflects a landscape gradient that discriminates the two reference responses of vegetation greenness to antecedent rainfall (Figs. 4a and 4b). The correlation between the NDVI and the short-term antecedent rainfall series $ARain_{hv}$ increases to the negative side of factor 1 (particularly for growing cycles 2001-02, 2002-03, 2005-06, and 2012-13), while the correlation with the 145-day antecedent rainfall series ($ARain_s$) increases to the positive side of the this factor (particularly for cycles 2000-01, 2002-03, 2005-06, and 2006-07, Fig. 4b). Analysis of the relationship between PCA factor 1 and vegetation dominance for the ground-based set of control points indicates that this landscape gradient is explained by the field distribution of dominant vegetation types since the dominance of herbaceous vegetation and shrubs increases to the negative and positive side of PCA factor 1, respectively (R^2 approx. 0.90, Fig. 4c).

15

Four different landscape types (GD, GT, ST and SD) are defined in the 18-km^2 study area as determined by the spatial projection of the relationship between PCA factor 1 and field dominance of herbaceous and shrub vegetation (Figs. 4c and 4d). SD, ST and GT landscapes are distributed in the southwestern part of the study site, while GD landscapes are located in the central and northeastern parts of the area (Figs. 4d and 4e).

4.3   NDVI transformation into herbaceous and shrub ANPP components

Temporal decomposition of NDVI into partial herbaceous and shrub vegetation components results in very different outputs for the reference Black Grama and Creosotebush Core Sites (Fig. 5a). The herbaceous component (which is derived from the relationship between NDVI and the reference 57-day antecedent rainfall series, $ARain_{hv}$) prevails in the grass-dominated reference site, whilst the shrub component (which is function of the reference 145-day antecedent rainfall series, $ARain_s$) comprises the leading NDVI fraction in the shrub-dominated reference site.

The annual sums of herbaceous and shrub NDVI components for the reference Core Sites show a strong linear agreement ($R^2 \geq 0.65$; $P<0.001$) with ground-based measurements of ANPP (Fig. 5b), while the remote-sensing ANPP estimations yield a root mean square error of 26 g m^{-2} (NRMSE 12%, Fig. 5c).

Spatial projection of the reference NDVI-ANPP relationships across the 18 km^2 study area displays a contrasted distribution of mean 2000-13 ANPP for herbaceous and shrub vegetation (Figs. 5d and 5e). Herbaceous ANPP is mainly distributed in the central and northeastern parts of the study site, contributing to >80% total ANPP. Conversely, shrub ANPP is concentrated in the southwestern edge of the study area.

4.4   ANPP spatiotemporal dynamics and impact of seasonal precipitation on herbaceous and shrub primary production

Remote-sensed estimations of ANPP are significantly impacted by landscape type ($F_{3,\,334}=48.6$, $P<0.01$), with grass-dominated sites supporting in general higher levels of vegetation production (Fig. 6a). However, landscape-type effects are variable in time (landscape type x time interaction: $F_{14,\,1515}=57.2$, $P<0.01$). Year-to-year variability of ANPP is particularly large for the grass-dominated sites, which show higher levels of ANPP than the transition and shrub-dominated landscapes for highly productive years (Fig. 6a). For growing

cycles with low primary production there are no significant ANPP differences or the differences are reversed, with shrub-dominated sites showing higher production than grass-dominated sites (e.g. 2003-04 cycle, Fig. 6a).

Analysis of the temporal evolution of shrub contribution to total ANPP along 2000-13 reflects significant (although very weak) positive correlations with time for the grass- and shrub transition landscapes (Fig. 6b). The same analysis at the individual pixel level, however, does not show any significant correlations between shrub contribution to total ANPP and time.

Exploratory analysis of the influence of seasonal precipitation on remote-sensed estimations of ANPP indicates different responses for herbaceous and shrub vegetation (Fig. 7). Herbaceous ANPP strongly correlates with monsoonal summer precipitation for all landscape types (Fig. 7a). The slope of the relationship between herbaceous ANPP and monsoonal summer (June-September) precipitation decreases for the shrub-transition and shrub-dominated landscapes. Conversely, shrub ANPP strongly correlates with both preceding non-monsoonal (October-May) and monsoonal summer (June-September) precipitation for all landscape types (Fig. 7b).

General linear model results confirm the exploratory observations of the relationships between remote-sensed estimations of ANPP and seasonal precipitation (Table 1). Model results identify both monsoonal summer precipitation ($Rain_{SM}$) and the interaction between $Rain_{SM}$ and landscape type as the most important contributors (effect size, $\eta^2 > 10\%$; $P<0.001$) to the total variance comprised in ANPP data for herbaceous vegetation. Similarly, non-monsoonal summer precipitation ($Rain_{PNM}$) and monsoonal summer precipitation ($Rain_{SM}$) are identified as the leading contributors to shrub ANPP.

5 Discussion

5.1 Vegetation-growth pattern and reference NDVI-rainfall metrics for herbaceous and shrub vegetation

Analysis of time series of NDVI provides important information on the dynamics of vegetation growth in drylands (Peters et al., 1997; Holm et al., 2003; Weiss et al., 2004; Choler et al., 2010). NDVI trends in the grass-dominated site show strong peaks centered in the summer season (Fig. 3a), which agrees with both field and remote-sensed observations of

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the dynamics of aboveground biomass for desert grasslands dominated by *Bouteoula eriopoda* and *B. gracilis* in the area (Peters and Eve, 1995; Huenneke et al., 2002; Muldavin et al., 2008; Notaro et al., 2010). For the shrub-dominated site, summer peaks in the NDVI signal are smaller, and for particular years both spring and late-autumn peaks can exceed summer greenness. Accordingly, the timing of plant growth for *Larrea tridentata* (which dominates the reference shrubland site) has been shown to vary from year to year, since this species has the ability to shift the temporal patterns of vegetation growth to take advantage of changes in resource availability (Fisher et al., 1988; Reynolds et al., 1999; Weiss et al., 2004; Muldavin et al., 2008).

The analysis of the relationships between NDVI and precipitation provide further insights on plant water-use patterns and, hence, on vegetation function and structure (Pennington and Collins, 2007; Veron and Paruelo, 2010; Notaro et al., 2010; Garcia et al., 2010; Forzieri et al., 2011; Moreno-de las Heras et al., 2012). Temporal trends in NDVI for the reference grass- and shrub-dominated SEV LTER sites are explained by antecedent (or preceding cumulative) rainfall amounts, reflecting the coupling of the history of plant-available soil moisture with vegetation growth (Fig. 3). Correlations between NDVI and precipitation indicate that plant growth pulses for the grass-dominated site are associated with short-term antecedent rainfall (*ARain$_{hv}$* series; 57 days optimal length, *Olr$_{hv}$*). For the shrub-dominated landscape, vegetation greenness shows a strong association with longer-term antecedent precipitation (*ARain$_s$* series; 145 days optimal length, *Olr$_s$*), although importantly, NDVI dynamics for this site also correlate with the 57-day cumulative rainfall series. Previous work on the analysis of NDVI-rainfall relationships found similar variations in the length of the antecedent rainfall series that best explain the dynamics of vegetation greenness, suggesting that such differences result from site variations in dominant vegetation (Evans and Geerken, 2004; Prasad et al., 2007; Garcia et al., 2010).

Given the strong relationship between time-integrated NDVI values and ground-based ANPP estimations for our site (Fig. 5b), our herbaceous and shrub exploratory modeling results provide a biophysical explanation for the range of variations found in the NDVI-rainfall relationships (Fig. 1). The length of the cumulative precipitation series that optimizes the relationship between plant biomass and antecedent rainfall (*Olr*) appears to be a function of the characteristic water-use and plant growth pattern of dryland vegetation, that are largely influenced by the plant-growth and mortality rates of vegetation (Fig. 1c). Vegetation growth

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1 and water use strongly differ for herbaceous and shrub life-forms in drylands (Sparrow, 1997;

2 Ogle and Reynolds, 2004; Gilad et al., 2007; Garcia et al., 2010), in which case plant biomass

3 dynamics respond to short-term and long-term antecedent precipitation, respectively (Figs.

4 1a-b). Olr variations in the reference SEV LTER Core Sites may, therefore, be expressed as a

5 function of the dominant vegetation types (Fig. 3): the strong and quick responses of

6 greenness to short-term precipitation ($ARain_{hv}$) in the grass-dominated Black Grama Core Site

7 characterize herbaceous growth for the area, while the slow responses of NDVI to medium-

8 term precipitation ($ARain_s$) in the shrub-dominated Cresotebush Core Site define the

9 characteristic pattern of vegetation growth for shrubs in the ecotone. The high correlation

10 between $ARain_{hv}$ and NDVI values in the shrub-dominated Creosotebush Core Site (Fig. 3b)

11 can be explained by the growth of non-dominant herbaceous vegetation (mainly annual

12 forbs), which can be especially important during wet years (Muldavin et al., 2008; Baez et al.,

13 2012). Similarly, Moreno-de las Heras et al. (2012) in dry open-shrublands of central

14 Australia (Olr_s values about 220 days) found the emergence of secondary Olr_{hv} metrics on the

15 study of local NDVI-rainfall relationships (approx. 85 days antecedent rainfall length) caused

16 by the growth of non-dominant herbaceous vegetation. Overall, Olr values determined for

17 herbaceous and shrub vegetation in this work are in agreement with the range of characteristic

18 antecedent rainfall series reported in other studies to best describe green biomass dynamics

19 for arid and semi-arid grasslands (1-3 months) and woody shrublands (4-8 months) (Evans

20 and Geerken, 2004; Munkhtsetseg et al., 2007; Garcia et al., 2010; Moreno-de las Heras et al.,

21 2012).

22 **5.2 Spatial distribution and net primary production of herbaceous vegetation**

23 **and shrubs**

24 Our results indicate that the relationship between temporal series of remotely sensed NDVI

25 and antecedent precipitation is highly sensitive to spatial differences in dominant vegetation

26 (Fig. 4). The main PCA factor (explaining about 40% variance in data) extracted using the

27 annual NDVI responses (i.e. the Pearson's R coefficients) to the reference 57- and 145-day

28 characteristic antecedent rainfall series ($ARain_{hv}$ and $ARain_s$ series, respectively) accurately

29 discriminates the behavior of herbaceous and shrub vegetation for the 18 km^2 study area

30 (Figs. 4b-c), hence providing a robust approach for classifying landscapes as a function of the

31 dominance of vegetation types using coarse-grained remotely sensed data (Fig. 4d). This

32 parsimonious approach offers a practical alternative to other more complex remote-sensing

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1 methodologies for the analysis of the spatial distribution of vegetation types in mixed

2 systems, such as Spectral Mixture Analysis (SMA, Smith et al., 1990), which may be difficult

3 to apply in this Chihuahuan case study since both the mixed nature and fine-grained

4 distribution of vegetation in the area (patches of grass and shrubs are typically <1 m^2 and 0.5-

5 5 m^2, respectively; Turnbull et al. 2010b) can impose serious drawbacks on the detection of

6 reference spectral signatures for pure herbaceous and shrub vegetation using coarse-grained

7 MODIS data. Implementing SMA-based approaches for the analysis of vegetation distribution

8 and landscape classification in drylands using medium- and coarse-grained data is very

9 challenging since it requires significant amounts of ancillary data (e.g. laboratory-based or

10 field multi-date spectra for vegetation types) to solve data uncertainties generated by surface

11 heterogeneity, which is often not feasible (Somers et al. 2011).

12 The relationships of vegetation greenness to $ARain_{hv}$ and $ARain_s$ also provide criteria for

13 decomposing and transforming the NDVI signal into structural components of primary

14 production for this study. Lu et al. (2003) applied seasonal trend decomposition to partition

15 NDVI into (cyclic) herbaceous and (trend) woody vegetation in Australia. They assumed a

16 long-term weak phenological wave and a strong annual response for determining the shrub

17 and herbaceous components of vegetation, respectively. Our approach relies on the use of

18 differences in biophysical properties of herbaceous and shrub vegetation related to the

19 coupling between vegetation growth and precipitation for decomposing the NDVI signal,

20 rather than apparent differences in the seasonality of vegetation greenness alone. As expected,

21 signal decomposition outcomes indicate that the herbaceous component of the NDVI leads the

22 temporal trends for the grass-dominated reference Black Grama Core Site, while the shrub

23 component largely dominates the NDVI signal for the Creosotebush Core Site (Fig. 5a).

24 Although affected by data dispersion, the annual sums of decomposed NDVI strongly agree

25 with field estimations of ANPP for herbaceous and shrub vegetation ($R^2 \geq 0.65$, Fig. 5b),

26 resulting in a small root mean square error for our remote-sensing ANPP estimates (26 g m^{-2},

27 NRMSE 12%, Fig 5c) that is within the lower limit of reported errors by other NDVI

28 decomposition studies (for example, Roderick et al., 1999; DeFries et al., 2000, Hansen et al.,

29 2002; Lu et al., 2003; with NRMSE ranging 10-17%). Other dryland studies have found

30 important levels of data dispersion when relating fine-grained field ANPP to coarse-scale

31 NDVI values (Lu et al., 2003; Holm et al., 2003; Pennington and Collins, 2007; Veron and

32 Paruelo, 2010). Major sources of data dispersion for this study are most likely associated with

the high spatial variability of ANPP in the analyzed systems. For instance, field estimations have shown that ANPP for both grass- and shrub-dominated Chihuahuan landscapes are affected by important levels of spatial variability, primarily due to the patchiness of vegetation cover (Huenneke et al., 2002; Muldavin et al., 2008).

5.3 Spatiotemporal dynamics of ANPP and impact of seasonal precipitation on herbaceous and shrub primary production

Cross-scale interactions between vegetation composition, individual plant characteristics and climatic drivers (e.g. variations in precipitation amount and seasonality) have an important role on determining primary production patterns in arid and semi-arid ecosystems (Peters, 2002; Snyder and Tartowsky, 2006; Pennington and Collins, 2007; Notaro et al., 2010; Baez et al., 2013). Analysis of the spatiotemporal dynamics of ANPP in our ecotone indicates that grass-dominated sites, although very importantly affected by year-to-year variability, generally support higher primary production than transition and shrub-dominated landscapes, particularly for wet years with high ANPP levels (Fig. 6a). This result is consistent with other shrub-encroachment studies which have found associations between shrub proliferation and ANPP reductions in dry American grasslands (Huenneke et al., 2002; Knapp et al., 2008).

Our results suggest that primary production is differently controlled by seasonal precipitation for herbaceous and shrub vegetation across the 18-km^2 Chihuahuan Desert ecotone (Fig 7, Table 1). Monsoonal summer precipitation (June-September) controls ANPP for herbaceous vegetation (Fig. 7a), while ANPP for shrubs is better explained by the preceding year's non-monsoonal (October-May) plus the summer monsoonal precipitation in the present year (Fig 7b). Accordingly, field observations of ANPP for Chihuahuan landscapes found that grassland primary production is particularly coupled with monsoonal rainfall, while desert shrublands appear to be less dependent on summer precipitation (Fisher et al., 1988; Reynolds et al., 1999; Huenneke et al., 2002; Muldavin et al., 2008; Throop et al., 2012).

Differences in the distribution of rainfall types, soil-moisture dynamics, and rooting habits of dominant plant species may explain the variable impact of seasonal precipitation on herbaceous and shrub ANPP for the studied Chihuahuan landscapes. Monsoonal summer precipitation (July-September, approx. 60% annual precipitation) generally takes place in the form of high-intensity thunderstorms that infiltrate shallow soil depths (top 15-35 cm) (Snyder and Tartowsky, 2006). Summer soil-water resources for plant production are

1 ephemeral and strongly affected by evapotranspiration, which typically reduces soil moisture

2 to pre-storm background levels in 4-7 days after rainfall (Turnbull et al., 2010a). C_4 grasses

3 (*Bouteloua eriopoda* and *B. gracilis*), which dominate herbaceous vegetation in the analyzed

4 ecotone, concentrate active roots in the top 30 cm of the soil and intensively exploit

5 ephemeral summer soil moisture for plant growth (Peters, 2002; Muldavin et al., 2008).

6 Preferential spatial redistribution of runoff to grass patches following summer storms further

7 enhances plant production for black and blue grama (Wainwright et al., 2000; Pockman and

8 Small, 2010; Turnbull et al., 2010b).

9 Non-monsoonal precipitation (about 40% annual precipitation, primarily from November to

10 February) typically falls in the form of long-duration low-intensity frontal rainfall that often

11 percolates to deep soil layers (Snyder and Tartowsky, 2006). *Larrea tridentata*, the dominant

12 C_3 shrub in the studied ecotone, has a bimodal rooting behavior that facilitates the use of both

13 shallow and deep soil moisture for plant production (Fisher et al., 1988; Reynolds et al., 1999;

14 Ogle and Reynolds, 2004). Deep creosotebush roots (70-150 cm depth) may acquire winter-

15 derived soil-water resources that are unavailable to grass species, while active roots near the

16 surface (20-40 cm depth) may serve to access summer-derived shallow soil moisture for plant

17 growth (Gibbens and Lenz, 2001). The observed reduction in summer rain-use efficiency of

18 herbaceous vegetation for the shrub-transition and shrub-dominated landscapes (i.e. variations

19 on the slope of the relationship between herbaceous ANPP and summer precipitation, Fig. 7a)

20 suggests competitive effects of creosotebush for the use of shallow water sources, probably

21 associated to the large spatial extent of near-surface active roots (the radial spread of which

22 typically ranges between 2-6 m, Gibbens and Lenz, 2001). Alternative, landscape changes

23 induced by shrub encroachment (i.e. increased runoff and erosion) may reduce the ability of

24 grass patches to capitalize on horizontal redistribution of runoff for plant growth after summer

25 storms (Wainwright et al., 2000; Turnbull et al., 2012; Stewart et al. 2014).

26 Conceptual and mechanistic models of vegetation change suggest that vegetation composition

27 in arid and semi-arid landscapes is likely to be highly sensitive to climate change, and point at

28 variations in the amount and distribution of precipitation as a major driver of shrub

29 encroachment into desert grasslands (Peters, 2002; Gao and Reynolds, 2003; Snyder and

30 Tartowsky, 2006). Overall our results agree with those findings and suggest that changes in

31 the amount and temporal pattern of precipitation comprising reductions in monsoonal summer

32 rainfall and/or increases in winter precipitation may enhance the encroachment of

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creosotebush into desert grasslands dominated by black and blue grama. Analysis of long-term rainfall series indicates that winter precipitation has increased during the past century in the northern Chihuahuan Desert, particularly since 1950, probably associated with the more frequent occurrence of ENSO events for that period (Dahm and Moore, 1994; Wainwright, 2006). This pattern of precipitation change may be responsible, at least in part, of past increase in woody shrub abundance over desert grasslands in the American Southwest (Brown et al., 1997; Snyder and Tartowsky, 2006; Webb et al., 2003). Our results suggest that shrub encroachment has not been particularly active in the studied ecotone for 2000-13 (Fig. 6b). Accordingly, Allen et al. (2008) in a recent study on creosotebush plant architecture and age structure indicated that the most important pulses of shrub encroachment for this area took place between 1950 and 1970. Precise estimation of shrub cover applying segmentation methods in time series of high-resolution imagery could help to accurately determine the intensity of the shrub-encroachment phenomenon under the present variability in precipitation for our grassland-shrubland ecotone.

Climate-change projections for the area suggest a general picture of increased aridity in the next 100 years, with increased evaporation due to higher summer temperatures, and increased drought frequency (Christensen and Konikicharla, 2013). The capacity of *L. tridentata* to switch between different soil-water sources (i.e. summer-derived ephemeral shallow soil moisture and more stable deep soil-water reserves derived from winter rainfall) and adapt the timing of vegetation growth to take advantage of changes in resource availability make this C_3 shrub less susceptible to predicted increases in aridity than C_4 grasses that are strongly dependent on summer precipitation (Reynolds et al., 1999; Throop et al., 2012; Baez et al., 2013). Current increases in atmospheric CO_2 concentrations may also contribute to reduce the competitiveness of C_4 grasses for the use of soil-water resources against C_3 desert shrubs (Polley et al., 2002). Remaining desert grasslands in the American Southwest may, therefore, be increasingly susceptible to shrub encroachment under the present context of changes in climate and human activities.

6   Conclusions

In this study we applied a new analytical methodology for the study of the organization and dynamics of vegetation at a grassland-shrubland Chihuahuan ecotone with variable abundance of grasses (primarily *Boutelua eriopoda* and *B. gracilis*) and shrubs (mainly *Larrea*

23

tridentata), based on the exploration of the relationship between time series of remote-sensed vegetation greenness (NDVI) and precipitation. Our results indicate that the characteristics of the NDVI-rainfall relationships are highly dependent on differences in patterns of water use and plant growth of vegetation types. In fact, NDVI-rainfall relationships show a high sensitivity to spatial variations on dominant vegetation types across the grassland-shrubland ecotone, and provide ready biophysically based criteria to study the spatial distribution and dynamics of net primary production (NPP) for herbaceous and shrub vegetation. The analysis of the relationship between NDVI and precipitation offers, therefore, a powerful methodology for the study of broad-scale vegetation shifts comprising large changes in the dominance of vegetation types in drylands using coarse-grained remotely sensed data, and could be used to target areas for more detailed analysis and/or the application of mitigation measures.

Analysis of remote-sensed NPP dynamics at the grassland-shrubland ecotone reflects a variable performance of dominant vegetation types. Herbaceous production is synchronized with monsoonal summer rainfall, while shrub NPP shows a flexible response to both summer and winter precipitation. Overall our results suggest that changes in the amount and temporal pattern of precipitation (i.e. reductions in summer precipitation and/or increases in winter rainfall) may intensify the shrub-encroachment process in the studied desert grasslands of the American Southwest, particularly in the face of predicted general increases in aridity and drought frequency for the area.

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1 **Table 1.** Main effects and interactions of seasonal precipitation (preceding non-monsoonal

2 rainfall, October-May; monsoonal summer rainfall, June-September; late non-monsoonal

3 rainfall, October-March) and landscape type (4 levels: grass-dominated, grass-transition,

4 shrub-transition, and shrub-dominated landscapes) on remote-sensing estimated annual (per

5 growing cycle, April-March) net primary production for herbaceous vegetation and shrubs.

	F	df	P	η^2 (%)
Herbaceous vegetation ANPP$_{r.sensing}$				
Rain$_{PNM (Oct-May)}$	194.2	1	0.000	4.2
Rain$_{SM (June-Sept.)}$	1483.4	1	0.000	**25.4**
Rain$_{LNM (Oct.-March)}$	129.3	1	0.000	2.0
LT	35.9	3	0.000	2.3
LT:Rain$_{PNM (Oct-May)}$	122.4	3	0.000	7.8
LT:Rain$_{SM (June-Sept.)}$	282.4	3	0.000	**16.2**
LT:Rain$_{LNM (Oct.-March)}$	1.1	3	0.326	0.0
Shrubs ANPP$_{r.sensing}$				
Rain$_{PNM (Oct-May)}$	1661.2	1	0.000	**27.7**
Rain$_{SM (June-Sept.)}$	1720.8	1	0.000	**28.4**
Rain$_{LNM (Oct.-March)}$	7.1	1	0.010	0.1
LT	2.9	3	0.030	0.2
LT:Rain$_{PNM (Oct-May)}$	6.6	3	0.000	0.4
LT:Rain$_{SM (June-Sept.)}$	46.2	3	0.000	3.0
LT:Rain$_{LNM (Oct.-March)}$	31.9	3	0.000	2.1

6 Abbreviations: ANPP$_{r.sensing}$, remote-sensed annual net primary production; Rain$_{PNM (Oct-May)}$,
7 preceding non-monsoonal rainfall; Rain$_{SM (June-Sept.)}$, monsoonal summer rainfall; Rain$_{LNM (Oct.-}$
8 $_{March)}$, late non-monsoonal rainfall; LT, landscape type; ':', interaction terms; η^2, eta-squared
9 (effect size).
10 Notes: η^2 values in bold are > 10% (effects that contribute in more than 10% to the total
11 variance comprised in ANPP$_{r.sensing}$).
12

Fig. 1. Simulated dryland biomass-rainfall relationships for herbaceous and shrub vegetation: (**a**) modelled biomass dynamics for an herbaceous (green) and a shrub (red) species, (**b**) strength of the biomass-precipitation relationship (Pearson's R correlation) using different lengths of rainfall accumulation for the simulated herbaceous and shrub species (values above the dotted grey line are significant at $P<0.05$), (**c**) optimal rainfall accumulation length (Olr) as a function of the plant-growth and mortality rates. $ARain_{hv}$ and $ARain_s$ lines in panel (a) represent the antecedent rainfall series that best correlate with the simulated series of herbaceous and shrub biomass, respectively (i.e. time series of precedent rainfall with rainfall accumulation lengths Olr_{hv} for herbaceous vegetation and Olr_s for shrubs). The green and red dots in panel (c) indicate optimal rainfall accumulation lengths obtained for the simulated herbaceous (Olr_{hv}, 52 days) and shrub (Olr_s, 104 days) species, respectively. The (grey) "vegetation extinction" area in panel (c) reflects combined values of plant-growth and mortality rates that do not support long-term vegetation dynamics for the simulated rainfall conditions.

Fig. 2. Study area: (**a**) location of the Sevilleta National Wildlife Refuge (SNWR) and distribution of major New Mexico biomes, (**b**) regional location of the study area (McKenzie Flats, SNWR), (**c**) detailed location of the study site (18-km^2 area) and general view of the reference SEV LTER Black Grama (right) and Creosotebush (left) Core Sites. Map (a) follows the Sevilleta LTER classification of New Mexico biomes (Sevilleta LTER, http://sev.lternet.edu/content/new-mexico-biomes-created-sevlter). Source for background image in panels (b) and (c): 2009 National Aerial Imagery Program (USDA Farm Service Agency).

Fig. 3. Reference NDVI-rainfall relationships at the SEV LTER Black Grama and Creosotebush Core Sites: (**a**) 2000-13 MODIS NDVI time series for the Core Sites, (**b**) strength of the NDVI-rainfall relationship (Pearson's R correlation) for the Core Sites using different lengths of rainfall accumulation (maximum correlations, R_{max}, for the annual cycles of vegetation growth are shown together with the 2000-13 mean trend; detailed correlograms for each growing cycle can be found in Supplementary Fig. 1 as online supporting information for this study). R values above the dotted grey line are significant at $P<0.05$. $ARain_{hv}$ and $ARain_s$ lines in panel (a) represent the antecedent rainfall series that best correlate

34

with the NDVI series for the Black Grama and Creosotebush Core sites (i.e. time series of precedent rainfall with rainfall accumulation lengths Olr_{hv} and Olr_s, respectively). Reference Olr_{hv} and Olr_s values in panel (b) represent the optimal rainfall accumulation lengths for herbaceous vegetation (57 days) and shrubs (145 days), respectively.

Fig. 4. Principal Component Analysis (PCA) of the NDVI-rainfall correlation coefficients for the herbaceous- and shrub-specific antecedent rainfall series $ARain_{hv}$ and $ARain_s$ (57- and 145-day cumulative rainfall series, respectively) and resulting landscape type classification across the 18 km^2 study area: **(a)** PCA projection of cases (MODIS pixels), **(b)** PCA projection of variables (per growing cycle NDVI-antecedent rainfall correlation scores), **(c)** landscape type classification (GD, grass-dominated, GT, grass-transition, ST, shrub-transition, and SD, shrub-dominated landscapes) as a function of the relationship between PCA Factor 1 and field-estimated vegetation dominance for a reference set of 27 control points, **(d)** spatial distribution of landscape types in the study area, **(e)** general view and characteristics of the landscape types. MODIS pixel locations for the ground control points are highlighted in panel (a). Vector labels in panel (b) indicate the dates of the yearly cycles of vegetation growth (April-March). Source for background image in panel (d): 2009 National Aerial Imagery Program (USDA Farm Service Agency).
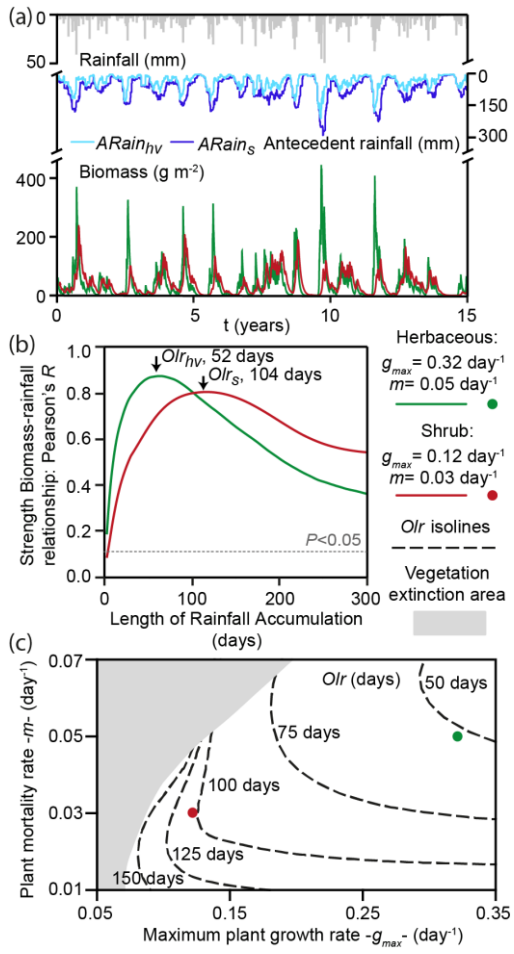
Fig. 5. NDVI decomposition and transformation into partial Annual Net Primary Production (ANPP) components for herbaceous and shrub vegetation: **(a)** decomposed NDVI time series of herbaceous and shrub vegetation for the reference SEV LTER Black Grama and Creosotebush Core Sites, **(b)** relationships between field ANPP and the (per growing cycle) annual integrals of herbaceous and shrub NDVI components for the SEV LTER Core Sites, **(c)** remote-sensed ANPP estimates against field ANPP determinations (root mean square error, RMSE, and normalized error, NRMSE, of the estimates are shown within the plot) **(d)** remote-sensed ANPP estimations of herbaceous and shrub vegetation (mean for the 2000-13 series), and **(e)** herbaceous and shrub contribution to total ANPP (mean for the 2000-13 series) across the 18-km^2 study area.

Fig. 6. Spatiotemporal dynamics of remote-sensed ANPP: **(a)** ANPP differences between landscape types (grass-dominated, grass-transition, shrub-transition, and shrub-dominated landscapes) along 2000-13, **(b)** 2000-13 temporal variations of the shrub contribution to total ANPP for the different landscape types (Pearson's R correlations of shrub ANPP contributions with time). Different letters in panel (a) for each cycle of vegetation growth indicate significant differences between landscape types at $P<0.05$ (tested using repeated-measures ANOVA and post-hoc Tukey HSD tests). Dotted lines in panel (b) represent weak ($R<0.40$) correlations. Displayed correlations are significant at $P<0.05$. Numbers in plot (c) indicate correlation coefficients.

Fig. 7. Scatter plots and correlations (Pearsons's R) between remote-sensed ANPP estimations and seasonal precipitation (preceding non-monsoonal, summer monsoonal, and late non-monsoonal rainfall) for the different landscape types (grass-dominated, grass-transition, shrub-transition, and shrub-dominated landscapes): **(a)** herbaceous ANPP, **(b)** shrub ANPP. Solid and dotted lines represent strong ($R\geq0.40$) and weak ($R<0.40$) correlations, respectively. Displayed correlations are significant at $P<0.05$. Numbers within the plots indicate correlation coefficients.

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Fig. 1.

New Mexico Biomes
- Great Plains Grassland
- Conifer Woodland
- Colorado Plateau Steppe
- Chihuahuan Desert

Study Area
- SEV LTER Black Grama Core Site
- SEV LTER Creosotebush Core Site
- Control Points (vegetation-type distribution) ○
- Field NPP webs (centre coordinates) ●
- Five Points weather Station ●

Fig. 2.

Fig. 3.

(a) PCA projection of cases (MODIS pixels)

PCA Factor 2 (12% variance) vs PCA Factor 1 (38% variance)

Control Points ○

(b) PCA projection of variables (per cycle NDVI-rainfall correlation coefficients)

PCA Factor 2 vs PCA Factor 1

Contributors to Factor 1 (>5% variance) ←
Contributors to Factor 2 (>5% variance) ●—
NDVI-$ARain_{hv}$ correlations
NDVI-$ARain_s$ correlations

2002-03, 2004-05, 2012-13, 2001-02, 2005-06, 2008-09, 2009-10, 2007-08, 2001-02, 2011-12, 2000-01, 2005-06, 2002-03, 2006-07, 2000-01, 2009-10

(c) Dominance of vegetation forms and landscape type classification

Vegetation Dominance (%) vs PCA Factor 1

● Shrubs
● Herbaceous vegetation

$y=84.1 - 5.5x$
$R^2= 0.87; P<0.001$

$y=17.4 + 8.1x$
$R^2= 0.89; P<0.001$

± SD

GD   GT   ST   SD

(d)

2 km

GT   GD   SD   ST

N

(e)

GD *Grass-dominated landscapes*

Dominance:
- Perennial grass > 65%
- Forbs > 20%
- Creosotebush < 30%

GT *Grass-transition landscapes*

Dominance:
- Perennial grass 65-50%
- Forbs 20-15%
- Creosotebush 30-50%

ST *Shrub-transition landscapes*

Dominance:
- Perennial grass 50-35%
- Forbs 20-15%
- Creosotebush 50-70%

SD *Shrub-dominated landscapes*

Dominance:
- Perennial grass < 35%
- Forbs < 15%
- Creosotebush > 70%

Fig. 4.

40

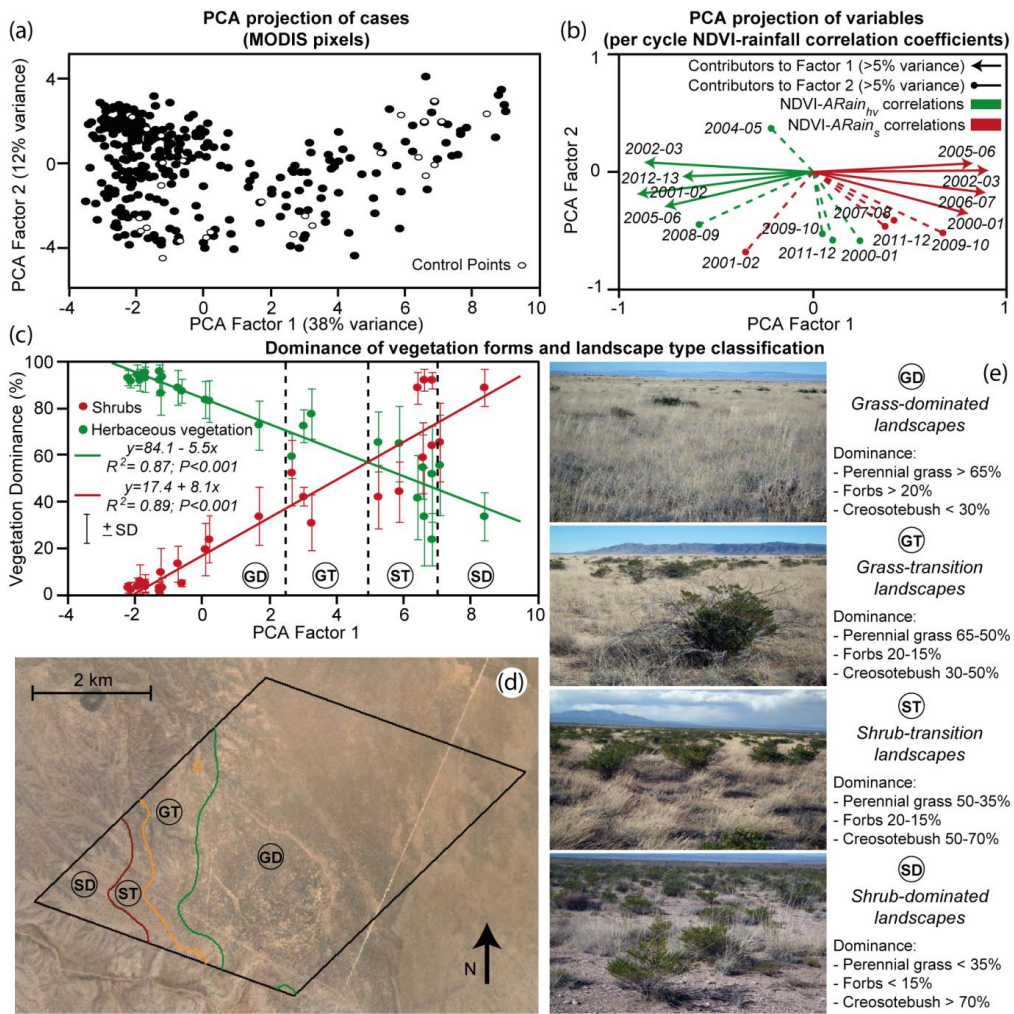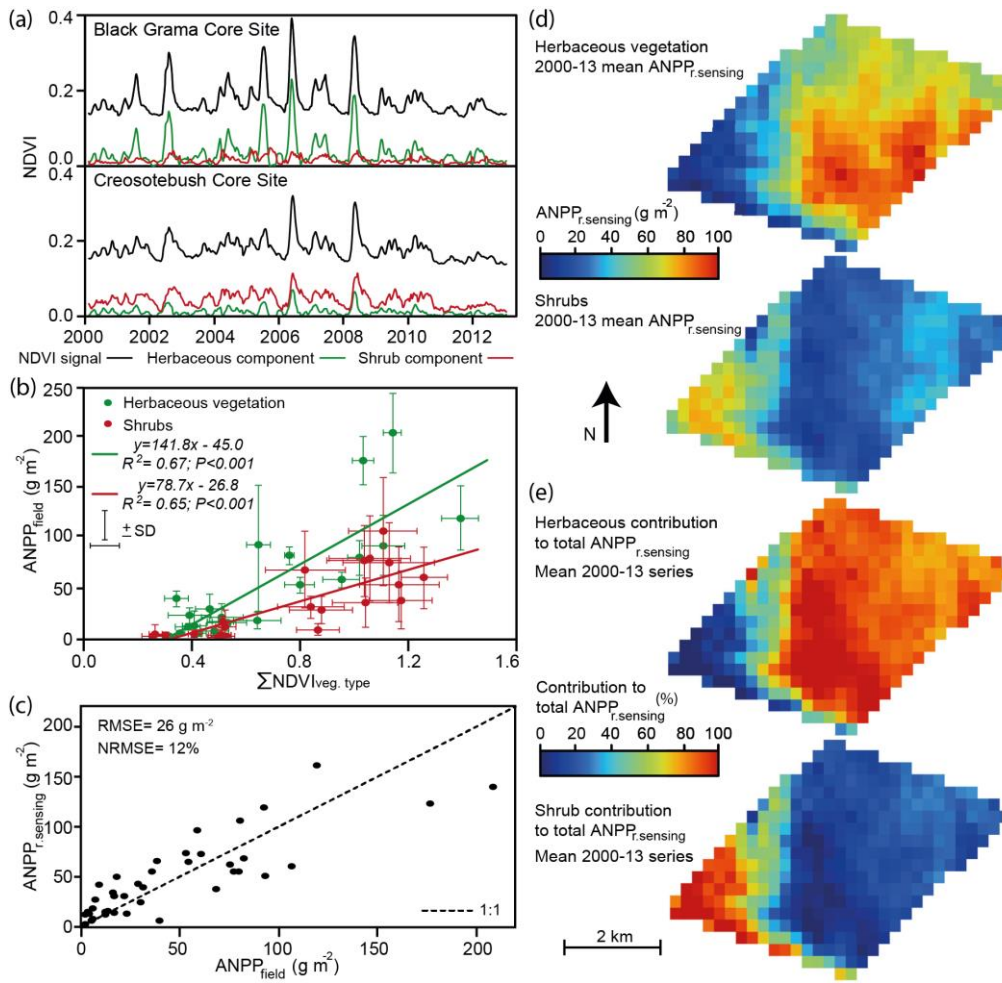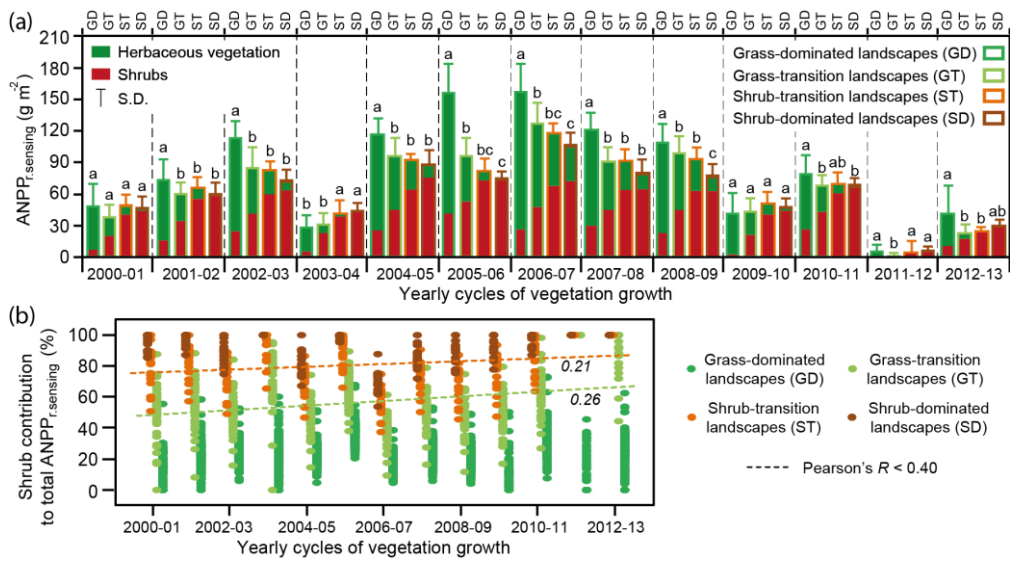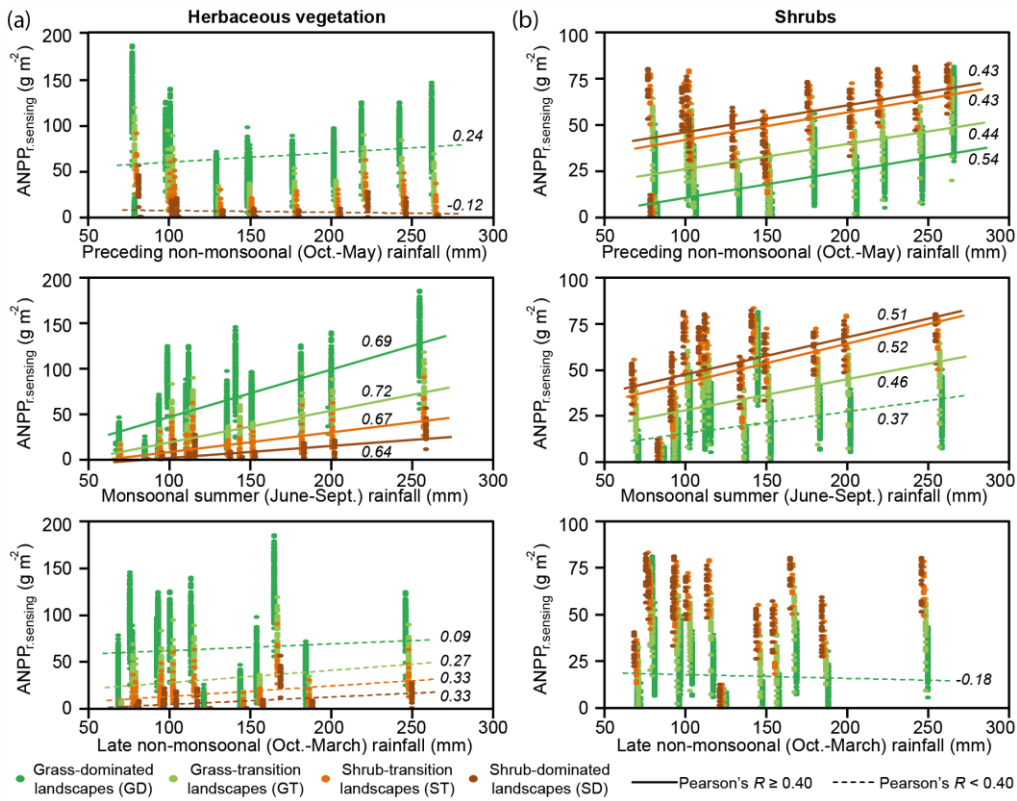**Fig. 5.**

Fig. 6.

1

Fig. 7.

1   In this document we provide the Maple 9.5 (Maplesoft, Waterloo, Canada) codes used in the

2   paper (Code 1) to simulate dryland biomass dynamics for an herbaceous and a shrub species,

3   and (Code 2) to decompose single time series of NDVI into partial components for

4   herbaceous and shrub vegetation applying the reference vegetation-type characteristic

5   antecedent rainfall series for herbs and shrubs ($ARain_{hv}$ and $ARain_s$, respectively). We also

6   provide two supplementary figures: (i) Supplementary Fig. 1 that presents the results of our

7   model sensitivity analysis, and (ii) Supplementary Fig. 2 that presents detailed NDVI-

8   antecedent rainfall correlograms obtained for each growing cycle of vegetation growth (April-

9   March) in the reference Black Grama and Creosotebush SEV LTER Core Sites.

10

11

12

13

14   Contents:

19

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1 **Code 1:   Dynamic Vegetation Model**

2

3 **Input files** (location: C:\DataFolder\)**:**

4 1. Daily rainfall: Rain.txt

5 Data is stored in columns 1 and 2 for dates and rainfall, respectively.

6

7 **Output files** (location: C:\DataFolder\)**:**

8 1. Temporal series of herbaceous and shrub biomass: Biomass.txt

9 Data is stored in columns 1, 2 and 3 for dates, herbaceous and shrub biomass, respectively.

10 2. Temporal series of herbaceous and shrub biomass graph: Biomass.png (green, herbaceous

11 biomass; red, shrub biomass; blue, daily rainfall).

12

13 **Procedure:**

14 *1. We load the Maple packages required for the subsequent calculations.*

15   > with(linalg): with(plots): with(LinearAlgebra): with(Statistics): with(plottools):

16

17 *2. We load the daily rainfall data file.*

18   > droot := "C:\\DataFolder\\":

19   drain := ImportMatrix(cat(droot, "Rain.txt"), source = delimited, delimiter = " ", datatype
20   = anything):

21   dates := ImportMatrix(cat(droot, "Rain.txt"), source = delimited, delimiter = "",
22   datatype=string):

23

24 *3. We define a rainfall function (rainFunct) made by rainfall event pulses.*

25   > rainn := convert(Column(drain, 2), list):

26   revent := [NULL]; raint := 0:

27   for i to nops(rainn) do

28   prec := convert(rainn[i], float):

```
if prec > 0 then

revent := [op(revent), [i, prec]]:

raint := raint+prec:

fi:

od:

rainFunct := t→sum(revent[jjk][2]*(-Heaviside(t-revent[jjk][1])+Heaviside(t-
revent[jjk][1]+1)), jjk = 1 .. nops(revent)):

ndata := nops(rainn);
```

4. We define the model equations.

```
> dB := gmax*(W-W0)*B/(W+kw)-m*B;

dW := P*(B+ki*i0)/(B+ki)-c*gmax*(W-W0)*B/(W+kw)-rw*W;

dsys := subs(W = W(t), B = B(t), [dB, dW]):

ecdif := [diff(B(t), t) = dsys[1], diff(W(t), t) = dsys[2]]:
```

*5. We define a time-evolution function (evolution) that calculates and stores biomass values
for each day, integrating the model equations with the model parameter values.*

```
> evolution := proc (param)

local stot, Biomasst, i:

stot := dsolve({op(subs(P = rainFunct(t), param, ecdif)), B(0) = 50, W(0) = .2}, numeric,
maxfun = 0):

Biomasst := NULL:

for i to ndata do

Biomasst := op([Biomasst]), subs(stot(i), B(t)):

od:

RETURN(Biomasst)
```

1   end proc:

2

3   *6. We define the parameter values and call the time-evolution function.*

4   > herbParam := W0 = 0.05, kw = 0.45, ki = 180, i0 = 0.2, c = 0.1, rw = 0.1, gmax = 0.32,

5   m = 0.05:

6   shrubParam := W0 = 0.05, kw = 0.45, ki = 180, i0 = 0.2, c = 0.1, rw = 0.1, gmax = 0.12, m

7   = 0.03:

8   herbBiomass := evolution({herbParam}):

9   shrubBiomass := evolution({shrubParam}):

10

11   *7. We plot the time series of herbaceous and shrub biomass along with precipitation.*

12   > topl := 700:

13   figherb := pointplot([seq([i, herbBiomass[i]], i = 1 .. nops([herbBiomass]))], connect =

14   true, color = green):

15   figshrub := pointplot([seq([i, shrubBiomass[i]], i = 1 .. nops([shrubBiomass]))], connect =

16   true, color = red):

17   figYears := [NULL]:

18   for iy to 16 do

19   figYears := [op(figYears), pointplot([[365*iy, 0], [365*iy, topl]], color = grey, connect =

20   true, linestyle = 3)]

21   od:

22   figPrecipt := NULL:

23   for i to ndata do if drain[i][2] > 0 then

24   figPrecipt := op([figPrecipt]), pointplot([[i, topl], [i, topl-4*drain[i][2]]], connect = true,

25   color = navy, thickness = 3):

26   fi:

27   od:

```
1    figures:= display(figherb, figshrub, figYears, figPrecipt):

2    display(figures);

3

4    8. We export the output files.

5    fout := cat(droot, "Biomass.txt"):

6    for i to ndata do

7    FileTools[Text][WriteLine](fout, cat(dates[i][1], " ", convert(herbBiomass[i], string), " ",

8    convert(shrubBiomass[i], string))):

9    od:

10   FileTools[Text][Close](fout):

11   plotsetup(png, plotoutput = cat(droot, "Biomass.png")):

12   display(figures);

13   plotsetup(default):

14
```

1   **Code 2:   NDVI Decomposition Procedure**

2

3   **Input files** (location: C:\DataFolder\)**:**

4   1. NDVI experimental data: case.txt

5   Data is stored in column 1.

6   2. Characteristic antecedent rainfall series for herbaceous and shrub vegetation ($ARain_{hv}$ and

7    $ARain_s$, respectively): totalAR.txt

8   Data is stored in columns 1 and 2 for herbaceous and shrub vegetation, respectively.

9   3. Time in days from the initial date: totalT.txt

10   Data is stored in column 1.

11

12   **Output files** (location: C:\DataFolder\)**:**

13   1. Temporal series of herbaceous and shrub NDVI components: HScomponents.txt

14   Data is stored in columns 1 and 2 for herbaceous and shrub biomass, respectively.

15   2. Graph with the temporal series of herbaceous and shrub NDVI, along with the original total

16   NDVI signal: HScomponents.png (black, original signal; green, herbaceous component; red,

17   shrub component).

18

19   **Procedure:**

20   *1. We load the Maple packages required for the subsequent calculations.*

21   > with(ExcelTools): with(plots): with(plottools): with(LinearAlgebra): with(Statistics):

22

23   *2. We define the NDVI bare soil component (0.12) and define a function, pair, to handle data*

24   *lists.*

25   nsoil := 0.12;

26   pair := proc (x, y)

27   [x, y]

28   end proc

1

2. We load the data files and store data as lists. The following data lists are defined:

dataAR1 = antecedent rainfall series for herbaceous vegetation (57-day period, $ARain_{hv}$

series).

dataAR2 = antecedent rainfall series for shrubs (145-day period, $ARain_s$ series).

dataT = time (measured in days from the beginning of the series).

dataNDVI = original NDVI time series.

dataNDVI0 = NDVI data list without the soil base line.

```
> droot := "C:\\ DataFolder \\":
dNDVI := ImportMatrix(cat(droot, "case.txt"), source = delimited, delimiter = "      ",
datatype = anything):
totalAR := ImportMatrix(cat(droot, "TotalAR.txt"), source = delimited, delimiter = "   ",
datatype = anything):
totalT := ImportMatrix(cat(droot, "totalT.txt"), source = delimited, delimiter = " "):
Ndata := op(rtable_dims(dNDVI)[1])[2]:
dataAR1 := [NULL]: dataAR2 := [NULL]: dataAR1N := [NULL]: dataAR2N := [NULL]:
dataT := [NULL]: dataNDVI := [NULL]: dataNDVI0 := [NULL]:
for i to Ndata do
dataAR1 := [op(dataAR1), evalf(totalAR[i][1])]; dataAR2 := [op(dataAR2),
evalf(totalAR[i][2])]; dataT := [op(dataT), evalf(totalT[i][1])]; dataNDVI :=
[op(dataNDVI), evalf(dNDVI[i][1])]; dataNDVI0 := [op(dataNDVI0), evalf(dNDVI[i][1]-
nsoil)]
od:
```

4. We define a first-order least-squares optimization function (linearfit) that fits the partial

contribution of the herbaceous and shrub components to the time series of NDVI (filtered for

the base-line bare soil contribution, dataNDVI0) as a function of the vegetation-type specific

1   *antecedent rainfall series that maximize the NDVI-precipitation relationships for herbaceous*

2   *vegetation (dataAR1, ARain$_{hv}$ series) and for shrubs (dataAR2, ARain$_s$ series).*

3   >linearfit := proc (TAR1, TAR2, Tiemp, NDVIst)

4   local AInput, DOutput, fitlinear, dparam, i, sumres;

5   global Total;

6   AInput := zip(pair, TAR1, TAR2); DOutput := NDVIst;

7   fitlinear := LinearFit([ar1, ar2], AInput, DOutput, [ar1, ar2], output = solutionmodule);

8   dparam := fitlinear:-Results("leastsquaresfunction"); sumres := fitlinear:-

9   Results("residualsumofsquares");

10   Total := [NULL]; for i to Ndata do Total := [op(Total), subs(ar1 = AInput[i][1], ar2 =

11   AInput[i][2], dparam+nsoil)] od:

12   RETURN(dparam, sumres):

13   end proc:

14

15   *5. We define a function that reassigns the predicted weights of the fitted vegetation*

16   *components (i.e. the percentage contribution of each vegetation type over the predicted totals*

17   *for any t$_i$) to match the original shape of the NDVI time series, obtaining the final NDVI*

18   *components for herbaceous vegetation and shrubs.*

19   > linDecomp := proc (TAR1, TAR2, NDVIst, fit)

20   local Ntotal, j, i, pre1, pre2, ratio;

21   global Nherb, Nshrub;

22   Nherb := [NULL]; Nshrub := [NULL]; Ntotal := [NULL];

23   for i to Ndata do

24   pre1 := subs(ar1 = TAR1[i], ar2 = 0, fit); pre2 := subs(ar1 = 0, ar2 = TAR2[i], fit);

25   if $0 <=$ pre1 and $0 <=$ pre2 then ratio := NDVIst[i]/subs(ar1 = TAR1[i], ar2 = TAR2[i], fit);

26   Ngrass := [op(Nherb), pre1*ratio]; Nshrub := [op(Nshrub), pre2*ratio] elif pre1 < 0 and 0

27   $<=$ pre2 then Nherb := [op(Nherb), 0]; Nshrub := [op(Nshrub), NDVIst[i]] elif pre2 < 0

28   and $0 <=$ pre1 then Nherb := [op(Nherb), NDVIst[i]]; Nshrub := [op([Nshrub]), 0] else

29   print(errors); ratio := 1; Nherb := [op(Nherb), 0]; Nshrub := [op(Nshrub), 0] fi;

30   Ntotal := [op(Ntotal), Nherb[nops(Nherb)]+Nshrub[nops(Nshrub)]+nsoil] od;

31   RETURN(Nherb, Nshrub, Ntotal):

32   end proc:

6. We call the fitting and reassigning functions.

```
lfit1 := linearfit(dataAR1, dataAR2, dataT, dataNDVI0);
HerbShrubLineal := linDecomp(dataAR1, dataAR2, dataNDVI0, lfit1[1]):
```

7. We plot the time series of the NDVI signal (figOr), and the final NDVI components for herbaceous vegetation (figHerb) and shrubs (figShrub).

```
figOr := PLOT(CURVES(convert(sort(zip(pair, dataT, dataNDVI)), list))):
figHerb := PLOT(CURVES(sort(sort(zip(pair, dataT, Nherb)))), COLOR(RGB, 0, 1, 0)):
figShrub := PLOT(CURVES(sort(sort(zip(pair, dataT, Nshrub)))), COLOR(RGB, 1, 0, 0)):
display(figOr, figHerb, figShrub);
```

8. We export the output files.

```
fout := cat(droot, "HScomponents.txt"):
for i to Ndata do
FileTools[Text][WriteLine](fout, cat(convert(Nherb[i], string), " ", convert(Nshrub[i],
string))):
od:
FileTools[Text][Close](fout):
plotsetup(png, plotoutput = cat(droot, "HScomponents.png")):
display(figOr, figHerb, figShrub):
plotsetup(default):
```
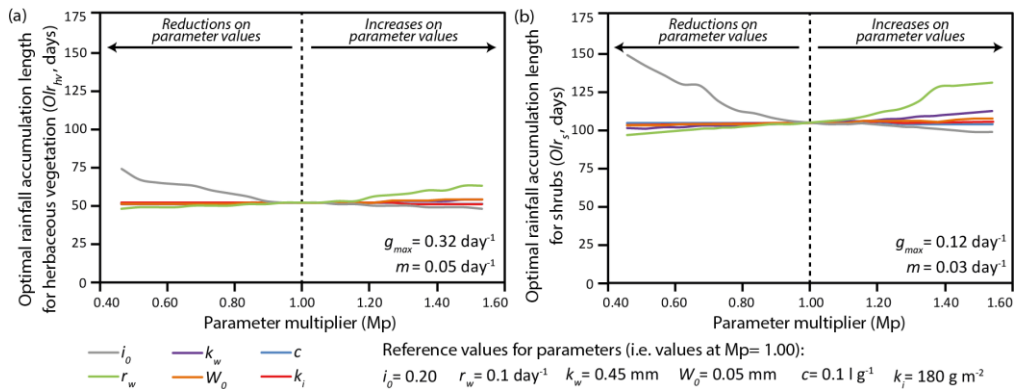
Supplementary Fig. 1. Sensitivity of simulated *Olr* values for herbaceous vegetation (**a**, *Olr$_{hv}$*) and shrubs (**b**, *Olr$_s$*) to variations in model parameters i_0 (bare soil infiltration rate), r_w (soil moisture evaporation/deep drainage rate), k_w (vegetation growth half saturation constant), W_0 (permanent wilting point), c (plant-water-consumption coefficient), and k_i (water infiltration half saturation constant). Parameter values applied in this study are shown in the figure (i.e. reference values). Parameter variations to the reference values are represented by the parameter multiplier (Mp), with Mp values <1 (and >1) showing reductions (and increases) on parameter values. Maximum growth (g_{max}) and mortality (m) rates applied in the study for herbaceous vegetation and shrubs are detailed within the plots.
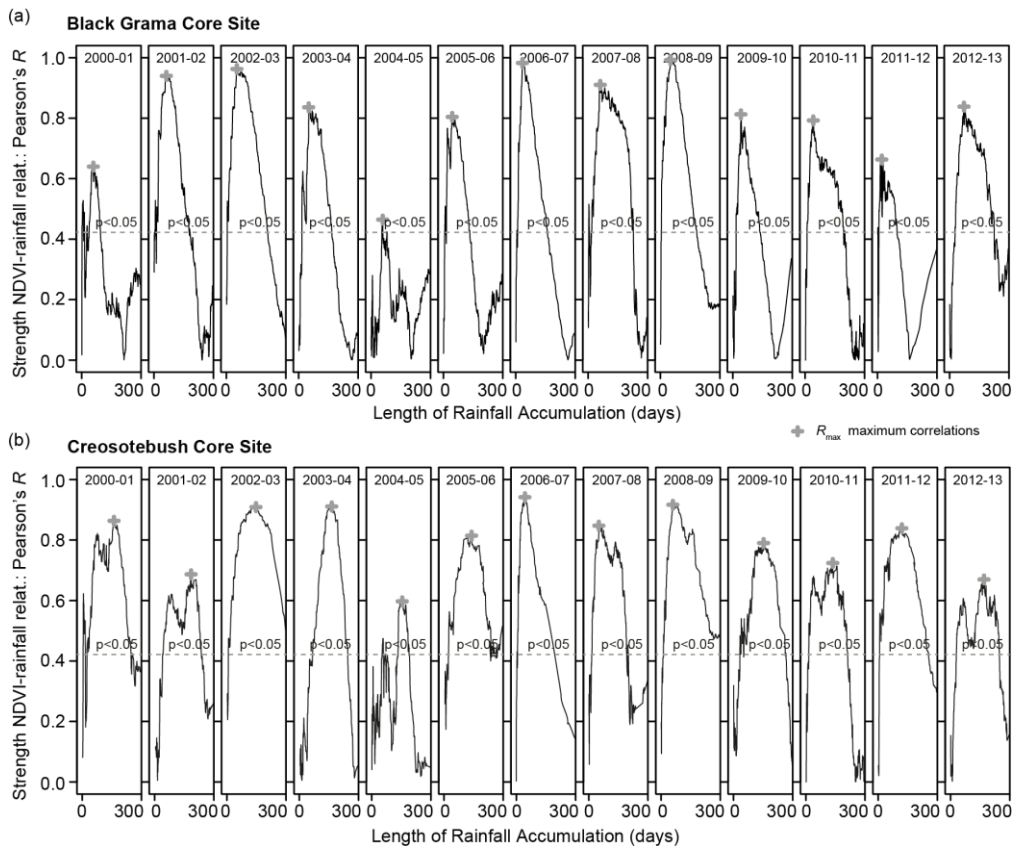
Notes:

Variations on W_0, k_w, k_i, and c values have negligible effects on simulated *Olr*. Reductions on bare soil infiltration (i_0) and increases on water loss by direct evaporation and/or deep drainage (r_w) impact *Olr$_{hv}$* and *Olr$_s$* values, increasing time scale responses of vegetation to antecedent precipitation, and ultimately amplifying the differences we obtained between vegetation types.

Supplementary Fig. 2. Per annual growing cycle (April-March) NDVI-antecedent rainfall

correlograms for the **(a)** Black Grama and **(b)** Creosotebush SEV LTER Core Sites.

Notes:

Correlations between NDVI and antecedent precipitation are maximized using a rainfall

accumulation length of about 57 days for all annual cycles of vegetation growth in the Black

Grama Core Site (Supplementary Fig. 2a).

For the Creosotebush Core Site two different foci that maximize the correlation between

NDVI and antecedent rainfall can be detected: (i) one using a low rainfall accumulation

length (approx. 57 days) and (ii) another using a long rainfall accumulation length (approx.

145 days). The 145 days antecedent rainfall series generally shows a stronger correlation with

the NDVI than the 57 days antecedent rainfall series (cycles 2000-01, 2001-02, 2002-03,

2003-04, 2004-05, 2009-10, 2010-11, 2011-12, 2012-13). However, for three consecutive

annual cycles with strong summer precipitation (2006-07, 2007-08, and 2008-09, summer

precipitation for the period is 40% above the long-term mean) correlation of NDVI to the 57

1   days antecedent rainfall series is stronger than correlation to the 145 days antecedent rainfall

2   series (Supplementary Fig. 2b).