

## Response to reviewer #1:

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Dear reviewer,

**Thank you very much for your positive, critical and constructive comments on our manuscript. Please see our responses to your comments point-by-point as follows.**

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This paper uses a DGVM to examine how ecosystem productivity and biome distributions respond to hypothetical changes in the intensity and frequency of daily rainfall events as well as wet season duration, all without changing mean annual rainfall. Simulations span all of Africa, covering a wide range of annual rainfall conditions. Results show increased productivity with greater frequency and lower intensity, or with longer wet seasons but reduced frequency or intensity of daily events. Biome shifts are evident in some regions, though remain largely modest over the whole of the continent for simulations spanning plus and minus 20% of the current climatology. The use of a model to identify sensitivities within model assumptions is reasonable, as is the approach to synthetic weather generation for driving the model and generating scenarios. Overall, I judge this to be a good study on a worthwhile and understudied topic of importance, but the paper could use some improvement as recommended below.

**Response: Thank you very much for your positive assessment of our work! Please see the following responses to your specific comments.**

1) Mechanistic explanation of why GPP increases or decreases, and why biomes shifts occur is largely lacking. This is particularly disappointing given that the study uses a model, and thus it is possible to fully document why the observed dynamics emerge in the way they do. Specifically, new analysis of the reduction in productivity from a maximal rate due to soil water stress should be added, with daily and cumulative time series similar to those shown schematically in Figure 7 but with real data from your simulations, and also with extension to GPP, not just soil water.

**Response: This work aims to study the impact of intra-seasonal rainfall variability on ecosystem function (e.g. GPP) and biome distribution. We mainly use soil moisture changes to explain the shifts in GPP and biome distribution. For example, Figure 5 (in the original manuscript) presents the soil moisture change and GPP change in pair for each experiment; from which, we can see that the pattern of soil moisture change can largely explain the changes in GPP in woodlands and savannas, consistent with the previous literature. Figure 7 (in the original manuscript) is a summary of the hydrological mechanisms derived from the original time series. These mechanisms are consistent with the existing ecohydrological knowledge (e.g. Rodrigues-Iturbe and Porporato, the book "Ecohydrology of Water-Controlled Ecosystem", 2004), and also expand beyond to include the impact of rainy season length.**

**In the revised manuscript, we directly used soil moisture status to explain the GPP pattern. We feel that the revised manuscript has presented the mechanisms for the changes in GPP and biomes with enough evidence. We agree that our presentation may cause some confusion**

**and misunderstanding, and we have significantly revised and improved in the updated manuscript (see the updated manuscript attached at the end).**

2) The rigidity of rainfall regime assumptions is rather disappointing, mainly the lack of multiple wet seasons (as important in East Africa) and the lack of seasonal variability beyond a binary, wet versus dry season set of statistics. While the realism could be improved here, I must admit that it is unlikely to have a major impact on the qualitative dynamics that are demonstrated with the current approach.

**Response: We fully agree with your assessment, as we have discussed these limitations in the section 4.1. We agree that our rainfall model can be significantly improved by incorporating the month-to-month variation in rainfall frequency and intensity. Though in this work we decide to keep the original approach, as the whole simulation is very costly for the computational time, and we also agree with your assessment that the qualitative patterns would not change.**

3) In Figure 2 please reiterate what the symbols represent, either in the caption or in the figure itself ( $\lambda$  = daily rainfall frequency,  $\alpha$  = daily rainfall depth,  $T_w$  = wet season duration).

**Response: We deleted Figure 2 in the revised manuscript as the other reviewer suggested that this figure is not very useful.**

4) The writing is quite poor throughout the manuscript, riddled with errors of grammar, syntax, diction, tense, accord, use of plural/singular, etc., making the paper rather frustrating to read. It is beyond the responsibility of a reviewer to edit the manuscript but it really should be thoroughly improved before it can be considered for final publishing. The authors should either pay for copy-editing or do it themselves.

**Response: Thanks for pointing this out. In the revised manuscript, all the coauthors have helped improving the language and presentation. Please refer to the updated manuscript attached at the end of this reply.**

5) L88: This statement is not true. Croplands have greater sensitivity to hydrological variability than grasslands, according to recent synthesis of global flux tower data.

**Response: We agree with your comments. We revised the text to reflect the actual meaning: "Grasslands have the largest sensitivity to hydrological variabilities among all natural ecosystems"**

6) L173: "fine-scale" is vague and should be clarified.

**Response: “fine-scale” in the SEIB-DGVM is defined as individual plant level. We have clarified this point in the revised manuscript. Please see the following revised text:**

**“This model follows the traditional “gap model” concept (Shugart, 1998) to explicitly simulate the dynamics of ecosystem structure and function for individual plants at a set of virtual vegetation patches, and uses results at these virtual patches as a surrogate to represent large-scale ecosystem states.”**

7) L348: “negative impact” in what sense? Grasslands are not bad, so an expansion of grasslands at the expense of woodlands is not a negative impact. Please rephrase this.

**Response: Here “negative impact” refers to a GPP decrease. We have clarified here by the following:**

**“Experiment  $S_{\text{FREQ-INT}}$  shows that the simulated biome distributions have a small portion of regions converting from woodlands to grasslands at low rainfall regime (~500 mm/year), corresponding to the decrease of GPP resulted from increased rainfall frequency in these regions.”**

8) L540: To suggest that this modeling study solves the noted debate is surely stretching what is possible with a model. This should be rephrased to better reflect the nature of the study and its methods.

**Response: We accepted the reviewer’s comments. Please see the following revised text:**

**“In this modeling study we provide a plausible answer to possibly resolve the previous debate about whether increasing rainfall intensity (or equivalently decreasing rainfall frequency, i.e.  $\text{FREQ} \downarrow$ ,  $\text{INT} \uparrow$ ) has positive or negative impacts on above-ground primary productivity with a fixed annual rainfall total.”**

9) L571: This first sentence in section 4.3 is incorrect. The study did not fully demonstrate importance of rainfall seasonality. Seasonality is treated in this study in such a simplistic way that it is a misrepresentation and overstatement to make this claim.

**Response: We fully agree with your comments, as we have recognized in section 4.1 “Limitation of the methodology”. We revised the manuscript as follows:**

**“Our results involving rainy season length (i.e.  $S_{\text{TW-FREQ}}$  and  $S_{\text{TW-INT}}$ ) provide evidence for the ecological importance of rainfall seasonality.”**

10) L585: The focus on phase and magnitude seems to miss the potential influence of seasonality beyond the simplistic treatment adopted here toward, for example, month-specific probabilities of daily rainfall. Depth and frequency statistics can vary over shorter intervals of

the year than simply being static for wet versus dry season. This notion should also be drawn out here.

**Response: We accepted the reviewer's suggestions and these shortcomings have been discussed in section 4.1:**

**"We only consider rainy season length for rainfall seasonality, and neglect the possible temporal phase change; in reality, rainfall seasonality change usually has length and phase shifts in concert. These rainfall-model-related limitations can be possibly overcome by simulating smaller intervals of rainfall processes (e.g. each month has their own  $\alpha$  and  $\lambda$ ) rather than simulating the whole wet or dry season using one fixed set of  $\alpha$  and  $\lambda$ ."**

**Also we add the following text to the discussion in section 4.3:**

**"Cautions are required that our simplified treatment rainy season length may overestimate its importance, and we did not consider the rainfall phase information here."**

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**Again, thank you very much for taking your precious time in reviewing our manuscript and providing constructive comments! Please let us know whether you are satisfied with our responses, and we will try our best to address any extra concerns and suggestions.**

**Best wishes,**

**Kaiyu Guan, on behalf of all the authors**

## Response to reviewer #2:

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Dear reviewer,

**We appreciate your constructive comments for our manuscript. We address your comments point-by-point in the following response.**

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The manuscript presents results from a modelling exercise to study how the delivery of annual rainfall impacts ecosystems. The Authors used scenarios of given annual rainfall amounts occurring at different rates (and thus different amounts per event) and with different durations of the rainy season; the scenarios are applied to Africa, focusing on biomass productivity (GPP) and soil moisture, which, as I understood, is interpreted to be the key driver of GPP. Even though the manuscript addresses a topic that is likely of interest to the audience of Biogeosciences, it is not well written; there are several grammatical errors and some parts (especially the methods) were not very clear. I have listed below specific comments as they appeared in the text.

**Response: Thank you very much for your positive assessment and constructive comments. As this work aims to study the impact of intra-seasonal rainfall variability on ecosystem function (e.g. GPP) and biome distribution, we did use soil moisture pattern to explain the shifts in GPP and biome distribution.**

**In the revised manuscript, all the coauthors have helped improving the language and presentation. Please refer to the updated manuscript attached at the end of this reply.**

- Page 7577, Line 11: it is not clear what the Author meant with 'second-order climate statistics'.

**Response: We change it to "intra-seasonal climate variabilities".**

- P7580, L10-15: the Authors mention here that MAP is given by the product of 3 rainfall characteristics, but in reality they define MAP as a product of 4 parameters,  $\alpha$ ,  $\lambda$ ,  $T_w$ , and  $f_w$ . I do not think that the term 'normalized' used in the context of ' $f_w$ ' is correct here. I think it should also be said here that the rainfall statistics in the wet and dry season are not different (now, this is said at P7592). This part should be better explained.

**Response: We realize that the writing in the previous manuscript causes the confusion, and we have clarified this point in the revised manuscript. Please see the following revised text:**

**“We manipulate rainfall changes through a stochastic weather generator based on a parsimonious model of rainfall processes (Rodriguez-Iturbe et al., 1984). We model the total amount of rainfall during wet season as a product of the three intra-seasonal rainfall characteristics for the wet season, rainfall frequency ( $\lambda$ , event/day), rainfall intensity ( $\alpha$ , mm/event), and rainy season length ( $T_w$ , days) (More details in section 2.3).”**

**We actually treat wet and dry season separately for their frequency and intensity, which has been explained in detail in section 2.3. We also revised that section to make it clearer to follow:**

**“The stochastic rainfall model can be expressed as  $MAP = \alpha \lambda T_w / f_w$ , and we set  $f_w$  to be 0.9, i.e. the period including 90% of total annual rainfall is defined as “rainy season” (exchangeable with “wet season” hereafter). In particular, we first use Markham (1970)’s approach to find the center of the rainy season, and then extend the same length to both sides of the center until the total rainfall amount in this temporal window (i.e. “rainy season”) is equal to 90% of the total annual rainfall. Rainy season and dry season have their own rainfall frequency and intensity. Two seasons are separately modeled based on the Market Poisson Process. Here we only focus on and manipulate rainy-season rainfall characteristics in our study, as rainy-season rainfall accounts for almost all the meaningful rainfall inputs for plant use. Thus in the following paper, whenever we mention  $\alpha$  or  $\lambda$ , we refer to the rainy season.”**

- P7580, L19: this line repeats exactly what said 3 lines before.

**Response: We revised this part as follows:**

**“The SEIB-DGVM also allows the development of annual and perennial grasses as well as multiple life cycles of grass at one year based on environmental conditions. Multiple life cycles of tree growth per year are possible in theory but rarely happen in simulations (Sato and Ise, 2012). Soil moisture status is a predominant factor to determine the optimum LAI of the grass layer, which influences maximum daily production and leaf phenology.”**

- P7581, L12: what is the rooting depth adopted in the model. Did it vary spatially?

**Response: Each plant-functional-type (PFT) in the SEIB-DGVM model has its own inherent rooting depth. Thus rooting depths vary explicitly in space based on the biome distribution, resulted from vegetation dynamics and competition. Different rooting depth also means that each plant simulated in the SEIB-DGVM has different capacity to use soil moisture at different layers of soil. We clarify this point in the revised manuscript.**

- P7581, L17: the Authors mention here that ‘other environmental conditions’ affect Lai and so NPP. What are these other conditions? The Authors focus on soil moisture, which is considered

the main variable and it is used to interpret the data. However, I think it would be better to report also other variables and explain why their role is not as important as soil moisture.

**Response: We tended to be more inclusive and that is why we wrote “other environmental conditions”. In reality, the soil moisture pattern can explain most changes of GPP in woodlands and savannas (Figure 5). The only divergence happens in the tropical forests (Figure 5a and 5b), which is mostly due to the reason that tropical forests in SEIB-DGVM are not water-limited but radiation-limited. Thus, though soil moisture increases with increased rainfall frequency in tropical forests (Figure 5a), GPP instead decreases due to increased cloudiness (Figure 5b), as we have already discussed in Section 3.1 (specifically Pattern 1.3).**

For the relevant text, we have changed it as follows:

**“Soil moisture status is the predominant factor to determine LAI of the grass layer, which influences maximum daily productivity and leaf phenology. When LAI exceeds 0 for 7 continuous days, dormant phase of perennial grass layer changes into growth phase. While when LAI falls below 0 for 7 continuous days, growth phase switches to dormant phase (Sato et al, 2007).”**

- P7582, L3-5: please, re-phrase this part.

**Response: This part has been revised as follows:**

**“Two plant function types (PFTs) of tropical woody species are simulated by the SEIB-DGVM in Africa: tropical evergreen trees and tropical deciduous trees. The distribution of these two woody types is largely determined by hydro-climatic environments in the model. Tropical evergreen trees only develop in regions where water resources are sufficient all year around, so they can maintain leaves for all seasons; otherwise, tropical deciduous trees could survive and dominate the landscape as they can shed leaves if there is no sufficient water supply in its root zone during the dry season (Sato and Ise, 2012).”**

- P5782, L11: how were 30 years used to drive the 2000-year warm-up period?

**Response: We repeatedly use the 30-year climate forcing for 2000 years for the spin-up period. We have clarified this point in the revised manuscript.**

- P7583: daily rainfall is generated using a marked Poisson process with frequency of daily rainfall and daily rainfall depths exponentially distributed. According to Fig. 1, it seems that this approximation is not realistic. I think the Authors should justify this assumption.

**Response: We recognize the reviewer’s concern, though we are afraid that there is a misunderstanding here. Figure 1 provides the spatial patterns of rainfall frequency, intensity**

and rainy season length, and these spatial patterns do not reflect the temporal feature of the rainfall distribution at a single point.

The Market Poisson process has been validated and widely used as a stochastic rainfall model in the past (see the following references [1]-[4] have been cited in the manuscript too). Thus, we feel that citing these references may be sufficient here for the methods, and we have also clarified the text to make it easier to follow.

#### References:

[1] Rodríguez-Iturbe, I. and Porporato, A.: *Ecohydrology of Water-Controlled Ecosystems: Soil Moisture And Plant Dynamics*, Cambridge University Press, Cambridge, United Kingdom, 2004.

[2] Porporato, A., Laio, F., Ridolfi, L., and Rodríguez-Iturbe, I.: Plants in water-controlled ecosystems: active role in hydrologic processes and response to water stress – III. Vegetation water stress, *Adv. Water Resour.*, 24, 725–744, 2001.

[3] Rodríguez-Iturbe, I., Gupta, V. K., and Waymire, E.: Scale considerations in the modeling of temporal rainfall, *Water Resour. Res.*, 20, 1611–1619, 1984.

[4] Rodríguez-Iturbe, I., Porporato, A., Ridolfi, L., Isham, V., and Cox, D. R.: Probabilistic modeling of water balance at a point: the role of climate, soil and vegetation, *P. Roy. Soc. A-Math. Phy.*, 10 455, 3789–3805, 1999.

- P7584, L28: from P7583 L6-7 and L14, it looks like  $T_w$  is a stochastic variable; how was the fix value defined in Exp 1 simulations? Specifically, in sections 3.2 and 3.3 the Authors refer to values of  $T_w$  (not its statistics) and comment on the large impact that this parameter has on the results. This is an important point and it needs to be clear how this parameter was determined in order to understand the results.

**Response: Thanks for pointing this out. We have revised the relevant text as follows:**

“The stochastic rainfall model can be expressed as  $MAP = \alpha \lambda T_w / f_w$ , and we set  $f_w$  to be 0.9, i.e. the period including 90% of total annual rainfall is defined as “rainy season” (exchangeable with “wet season” hereafter). In particular, we first use Markham (1970)’s approach to find the center of the rainy season, and then extend the same length to both sides of the center until the total rainfall amount in this temporal window (i.e. “rainy season”) is equal to 90% of the total annual rainfall. Rainy season and dry season have their own rainfall frequency and intensity. Two seasons are separately modeled based on the Market Poisson Process. Here we only focus on and manipulate rainy-season rainfall characteristics in our study, as rainy-season rainfall accounts for almost all the meaningful rainfall inputs for plant use. Thus in the following paper, whenever we mention  $\alpha$  or  $\lambda$ , we refer to the rainy season.”

Also see:

“All the necessary parameters to fit for the stochastic rainfall (including the mean and variance of rainfall frequency, intensity and length of wet and dry seasons) were derived from the satellite-gauge-merged rainfall measurement from TRMM 3b42V7 (Huffman et al., 2007) for the period of 1998 to 2012, based on the above assumptions for the rainfall process. Specifically, we applied our definition of “rainy season” to each year of the TRMM rainfall data for per pixel, and calculated the mean and variance of the “rainy season length”, using which we fitted the beta distribution for  $T_w$ . For rainfall frequency and intensity, we lumped all the wet or dry season rainfall record together to derive their parameters.”

- P7586, L6-7: rainfall intensity is defined as 1 mm, which is a depth. It should be 1mm day<sup>-1</sup> or it should be referred to as rainfall depth per event.

**Response:** We revised the unit for rainfall intensity as: mm/event; the unit for rainfall frequency as: events/day. Thanks for pointing this out.

- P7587, L13-16: this phrase was not clear to me. Please, re-phrase.

**Response:** We revised the text as follows:

“The relationship of GPP sensitivity to MAP and rainfall intensity (Fig. 6c) is complex and has no clear patterns as previous ones, mostly because the GPP sensitivity space that most pixels cluster (Fig. A4c) also contains large uncertainties (Fig. A4d, shown as large variance in the data). Thus we will not over-interpret the pattern in Fig. 6c.”

- P7588, L3: how is  $s^*$  defined?

**Response:** We put the following text under the Equation (2) in the revised manuscript:

“Figure 2 provides a schematic diagram of “water stress factor” from the SEIB-DGVM, and we also include an approximated linear model that has been widely adopted elsewhere (e.g. Milly, 1992; Porporato et al., 2001). The linear model uses an extra variable  $S^*$ , so called “critical point” of soil moisture: when  $S > S^*$ , there is no water stress (water stress factor =1); and when  $S < S^*$ , water stress factor linearly decreases with the decrease of  $S$ . Though SEIB-DGVM adopts a quadratic form for “water stress factor”, it essentially functions similarly as the linear model, such that  $S^*$  distinguishes two soil moisture regimes that below which there is a large sensitivity of water stress to soil moisture status, and above which there is little water stress. Understanding how this “water stress factor” functions is the key to explain the following results.”

- P7591, L24: I do not think that the term ‘understand’ is correct here. Considering the limitations of the model, the model is used for interpretation more than understanding.

**Response: We accept the reviewer's suggestion, and change "understand" to be "interpret".**

- P7592, L11-12: I would erase the word 'still' (' : : in reality they have seasonal variations').

**Response: We accept the reviewer's suggestion and have made the corresponding revision.**

- P7593, L12: a rainfall frequency of 0.35 day<sup>-1</sup> is not very low.

**Response: We change to the following text:**

**"We identify that negative GPP sensitivity with increased rainfall frequency is possible at very low MAP range (~400 mm year<sup>-1</sup>) with relatively low rainfall frequency (<0.35 events/day) (Fig. 6a)".**

- P7594, L15-16: I thought  $\alpha$  and  $\lambda$  also described the dry season. This is confusing.

**Response: We agree that our text is confusing and we made the changes to clarify it.**

**In the rainfall model, we have wet season (including 90% of the total annual rainfall) and dry season (having 10% of the total annual rainfall). Wet season and dry season have their own rainfall frequency and intensity, derived from the TRMM rainfall data. In the experiments we only apply the changes of rainfall frequency/intensity for wet season, while always use the climatological value for dry season. For example, if we need to increase rainfall frequency by 10% in one experiment, we only apply the change to the wet-season rainfall frequency, and keep the dry-season rainfall frequency unchanged, and then we use the Market Poisson Process to simulate the daily rainfall for wet and dry season separately.**

**Thus when we use "rainfall frequency" and "rainfall intensity" in the manuscript, we refer to the values during wet-season, as dry-season rainfall characteristics are fixed at the climatological values. Besides, dry-season also only accounts for 10% of the total rainfall, and has little importance for the ecosystem changes.**

**We have clarified this point in the revised manuscript as follows:**

**"The stochastic rainfall model can be expressed as  $MAP = \alpha \lambda T_w / f_w$ , and we set  $f_w$  to be 0.9, i.e. the period including 90% of total annual rainfall is defined as "rainy season" (exchangeable with "wet season" hereafter). In particular, we first use Markham (1970)'s approach to find the center of the rainy season, and then extend the same length to both sides of the center until the total rainfall amount in this temporal window (i.e. "rainy season") is equal to 90% of**

the total annual rainfall. Rainy season and dry season have their own rainfall frequency and intensity. Two seasons are separately modeled based on the Market Poisson Process. Here we only focus on and manipulate rainy-season rainfall characteristics in our study, as rainy-season rainfall accounts for almost all the meaningful rainfall inputs for plant use. Thus in the following paper, whenever we mention  $\alpha$  or  $\lambda$ , we refer to the rainy season.”

- Fig. 1: panel b: rainfall intensity should be depth. Panels e-h do not look like histograms; how were they normalized?

**Response:** Thanks for pointing this out. They are normalized histogram that the areas of the histogram should be added up to 1, but we forgot to provide the bins of x-axis for each data in the figure caption. We attached the bins for the histogram in the revised manuscript:

“e-f: Normalized histograms of the rainfall characteristics in two savanna regions of West and Southwest Africa. e-MAP (bin width for the x-axis: 100 mm/year); f-rainfall intensity (bin width for the x-axis: 1 mm/event); g-rainfall frequency (bin width for the x-axis: 0.1 event/day); h-rainy season length (bin width for the x-axis: 20 days).”

- Fig. 2: I would remove this figure.

**Response:** We accept the reviewer’s suggestion and have removed this figure in the revised manuscript.

- Fig. 3: this figure is not very useful. The linearized model and  $s^*$  are not used here.

**Response:** We decide to keep this figure as it helps the explanations of the hydrological mechanism. We also added the explanation of  $S^*$  under the Equation (2):

“Figure 2 provides a schematic diagram of “water stress factor” from the SEIB-DGVM, and we also include an approximated linear model that has been widely adopted elsewhere (e.g. Milly, 1992; Porporato et al., 2001). The linear model uses an extra variable  $S^*$ , so called “critical point” of soil moisture: when  $S > S^*$ , there is no water stress (water stress factor =1); and when  $S < S^*$ , water stress factor linearly decreases with the decrease of  $S$ . Though SEIB-DGVM adopts a quadratic form for “water stress factor”, it essentially functions similarly as the linear model, such that  $S^*$  distinguishes two soil moisture regimes that below which there is a large sensitivity of water stress to soil moisture status, and above which there is little water stress. Understanding how this “water stress factor” functions is the key to explain the following results.”

Also, I believe that this is not a water stress factor as defined in Porporato et al. (2001), but is more a reduction function for transpiration. The water stress is lower at high soil moisture and increases as soil moisture decreases.

**Response: The reviewer's assessment is correct that Equation (1) and (2) provide a reduction function for transpiration; what we are saying here is that this concept is similar as Porporato et al. (2001), which is basically the reversed form of Equation (2).**

**We clarified this point in the revised manuscript.**

Fig. 6: it would be nice to have more explanation in the text on how this figure is generated.

**Response: We have added the following text in the revised manuscript:**

**"Figure 6 further shows the difference of simulated GPP as a function of MAP and a perturbed rainfall characteristic in the corresponding experiment, to explore how MAP and these rainfall characteristics affect the simulated GPP. We term Figure 6 as "GPP sensitivity space", and "positive GPP sensitivity" means that GPP changes at the same direction with MAP or rainfall characteristics, and vice versa for "negative GPP response". These "GPP sensitivity spaces" are generated based on the aggregated mean GPP in each bin of the rainfall properties. The bin size for MAP, rainfall frequency, rainfall intensity and rainy season length are 100 mm/year, 0.05 event/day, 1 mm/event and 15 days respectively. We also provide the standard error (SE) of GPP in each bin to assess the uncertainties of the "GPP sensitivity spaces", with higher SE**

**meaning larger uncertainties.  $SE = \frac{\sigma}{\sqrt{n}}$ , where  $\sigma$  and  $n$  refer to the standard deviation of GPP values and the sample size in each bin respectively."**

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**Again, thank you very much for taking your precious time in reviewing our manuscript and providing constructive comments! Please let us know whether you are satisfied with our responses, and we will try our best to address any extra concerns and suggestions.**

**Best wishes,**

**Kaiyu Guan, on behalf of all the authors**

**The attached files:**

- 1) revised manuscript with all the editing marks**
- 2) final revised manuscript without any marks**

1     **Continental-scale impacts of intra-seasonal rainfall variability**  
2                     **on simulated ecosystem responses in Africa**

3  
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25     Running title: Ecological Impacts of Intra-Seasonal Rainfall Variability

26  
27     Submitted to *Biogeosciences*

28

29 **Abstract:**

30 Climate change is expected to ~~result in an increase change of~~ intra-seasonal rainfall  
31 variability, ~~which has arisen~~ arising from ~~concurrent~~ shifts in rainfall frequency,  
32 intensity and seasonality. ~~These intra-seasonal C~~ changes in intra-seasonal rainfall  
33 ~~variability~~ are likely to have important ecological impacts ~~for on~~ terrestrial  
34 ecosystems. ~~Yet, and~~ quantifying these impacts across biomes and large climate  
35 gradients is ~~required largely missing~~. This gap hinders our ability to for a better  
36 ~~prediction of~~ ecosystem services and their responses to climate change, esp. for arid  
37 and semi-arid ecosystems. Here we use a synthetic weather generator and an  
38 ~~independently validated~~ advanced vegetation dynamic model (SEIB-DGVM) to  
39 virtually conduct a series of “rainfall manipulation experiments” to study how  
40 changes in the intra-seasonal rainfall variability affect continent-scale ecosystem  
41 responses across Africa. We generated different rainfall scenarios with fixed total  
42 annual rainfall but shifts in: i) frequency vs. intensity, ii) rainy season length ~~seasonality~~  
43 vs. frequency, iii) intensity vs. rainy seasonality ~~season length~~. These scenarios were  
44 fed into ~~the~~ SEIB-DGVM to investigate changes in biome distributions and ecosystem  
45 productivity. We find a loss of ecosystem productivity with increased rainfall  
46 frequency and decreased intensity at very low rainfall regimes (<400 mm/year) and  
47 low frequency (<0.3 ~~day<sup>-1</sup> event/day~~); beyond these very dry regimes, most  
48 ecosystems benefit from increasing frequency and decreasing intensity, except in the  
49 wet tropics (>1800 mm/year) where radiation limitation prevents further productivity  
50 gains. This finding result reconciles seemingly contradictory findings in previous field  
51 studies ~~on the direction of~~ rainfall frequency/intensity impacts on ecosystem  
52 productivity. We also find that changes in rainy season length can yield more dramatic  
53 ecosystem responses compared with similar percentage changes in rainfall frequency  
54 or intensity, with the largest impacts in semi-arid woodlands. This study demonstrates  
55 that not all rainfall regimes are ecologically equivalent, and that intra-seasonal rainfall  
56 characteristics play a significant role in influencing ecosystem function and structure  
57 through controls on ecohydrological processes. Our results also suggest that shifts in  
58 rainfall seasonality have potentially large impacts on terrestrial ecosystems,

59 ~~something that~~ and these understudied impacts should be explicitly examined in future  
60 studies of climate impacts.

61 **Keywords:** rainfall frequency, rainfall intensity, rainfall seasonality, biome  
62 distribution, Gross Primary Production (GPP), Africa

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64

65 **1. Introduction**

66 Due to increased water holding capacity in the atmosphere as a consequence of global  
67 warming (O’Gorman and Schneider, 2009), rainfall is projected to ~~vary~~ change in  
68 intensity and frequency across much of the world (Easterling et al., 2000; Trenberth et  
69 al., 2003; Chou et al., 2013), in conjunction with complex shifts in rainfall seasonality  
70 (Feng et al., 2013; Seth et al., 2013). ~~These changes possibly~~ is indicates a large  
71 increase in the frequency of extreme events and variability in rainfall (Easterling et al.,  
72 2000; Allan and Soden, 2008), and many of these changes may be accompanied with  
73 little changes in total annual rainfall (Knapp et al., 2002; Franz et al., 2010).  
74 Meanwhile, regions sharing similar mean climate state may have very different  
75 intra-seasonal ~~dynamics~~ variabilities, and the ecological significance of intra-seasonal  
76 ~~climate variabilities~~ second-order climate statistics has been largely overlooked  
77 previously in terrestrial biogeography (Good and Caylor, 2011). For example,  
78 ecosystems in West Africa and Southwest Africa (Figure 1) share similar total annual  
79 rainfall, but West Africa has much more intense rainfall events within a much shorter  
80 rainy season, while Southwest Africa has a longer and less intense rainy season. The  
81 same amount of total rainfall can come in very different ways, which may cause  
82 distinctive ecological-ecosystem responses and landscapestructure. Understanding the  
83 impacts of these regional differences in intra-seasonal rainfall variability and their  
84 possible future changes on terrestrial ecosystems is critical for maintaining ecosystem  
85 services and planning adaptation and mitigation strategies for ecological and social  
86 benefits (Anderegg et al., 2013).

87

88 [insert Figure 1]

89

90 The changes in intra-seasonal rainfall characteristics, specifically frequency,  
91 intensity and seasonality, have critical significance to ecosystem productivity and  
92 structure (Porporato et al., 2001; Weltzin et al., 2003; Williams and Albertson, 2006;  
93 Good and Caylor, 2011; Guan et al., 2014), but previous studies on this topic  
94 (summarized in Table 1) have their limitations in the following aspects. First, existing

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95 relevant field studies ~~on this topic~~ mostly focus on a single ecosystem, *i.e.* grasslands,  
96 and subsequently only low rainfall regimes have been examined to date (mostly below  
97 800mm/year, see Table 1). Grasslands have the largest sensitivity to hydrological  
98 variabilities among all natural ecosystems (Scanlon et al., 2005; Guan et al., 2012),  
99 however inferences drawn from a single ecosystem are limited in scope and difficult  
100 to apply to other ecosystems ~~and rainfall regimes~~. Second, even within grasslands,  
101 different studies have seemingly contradictory findings (see Table 1), and there is a  
102 lack of a comprehensive framework to resolve these inconsistencies. Specifically,  
103 whether increased rainfall intensity with decreased rainfall frequency has positive  
104 (Knapp et al., 2002; Fay et al., 2003; Robertson et al., 2009; Heisler-White et al., 2009)  
105 or negative impacts (Heisler-White et al., 2009; Thomey et al., 2011) on grassland  
106 productivity is still under debateable. Third, previous relevant studies mostly focus on  
107 the impacts of rainfall frequency and intensity (Table 1 and Rodríguez-Iturbe and  
108 Porporato, 2004), and largely ~~neglect-overlook~~ the possible changes in rainfall  
109 seasonality. Rainfall frequency and intensity mostly describe rainfall characteristics  
110 within the rainy season, but do not account for the impacts of interplay between rainy  
111 season length and dry season length (Guan et al., 2014). For ecosystems  
112 predominately controlled by water availability, rainy season length constrains the  
113 temporal niche for active plant physiological activities (van Schaik et al., 1993;  
114 Scholes and Archer, 1997), and large variations in rainfall seasonality can lead to  
115 significant shifts in biome distribution found from paleoclimate pollen records (e.g.  
116 Vincens et al., 2007). Given changes in rainfall seasonality have been found in various  
117 tropical regions (Feng et al., 2013) and have been projected in future climate (Biasutti  
118 and Sobel, 2009; Shongwe et al., 2009; Seth et al., 2013), studies investigating their  
119 impacts on terrestrial ecosystems are relatively rare, and very few field studies are  
120 designed to address this aspect (Table 1, Bates et al., 2006; Svejcar et al., 2003; Chou  
121 et al., 2008). Finally, there is an increasing trend of large-scale studies addressing  
122 rainfall variability and ecological responses using satellite remote sensing (Fang et al.,  
123 2005; Zhang et al., 2005; Good and Caylor, 2011; Zhang et al., 2013; Holmgren et al.,  
124 2013) and flux network data (Ross et al., 2012). These large-scale studies are able to

125 expand analyses to more types of ecosystems and different climate conditions, and  
126 provide valuable observation-based insights. However there are very few theoretical  
127 modeling works to corroborate this effort. All these above issues call for a  
128 comprehensive modeling study to investigate different aspects of intra-seasonal  
129 rainfall variability on terrestrial ecosystems spanning large environmental gradients  
130 and various biomes.

131 In this paper, we aim to study ecological impacts of intra-seasonal rainfall  
132 variability on terrestrial ecosystems. In particular, we design virtual “rainfall  
133 manipulation experiments” to concurrently shift intra-seasonal rainfall characteristics  
134 without changing total annual rainfall. We focus on the impacts of these different  
135 rainfall scenarios on ecosystem productivity (e.g. Gross Primary Production, GPP)  
136 and biome distributions in the African continent, simulated by an advance  
137 independently validated dynamic vegetation model SEIB-DGVM (Sato and Ise, 2012).  
138 Previous modeling approaches in this topic (Gerten et al., 2008; Hély et al., 2006)  
139 designed various rainfall scenarios by rearranging (halving, doubling or shifting) the  
140 rainfall amount based on the existing rainfall observations. In contrast to these  
141 approaches, we design a weather generator based on a stochastic rainfall model  
142 (Rodríguez-Iturbe et al., 1999), which allows us to implement a series of experiments  
143 by synthetically varying two of the three rainfall characteristics (rainfall intensity,  
144 rainfall frequency, and rainy season length) while fixing total annual rainfall at the  
145 current climatology. We choose Africa as our test-bed mostly because the following  
146 two reasons: (1) the rainfall regimes and biomes have large gradients varying from  
147 extremely dry grasslands to highly humid tropical evergreen forests, ~~and thereby~~  
148 ~~provide a large pool of different biomes~~; (2) Africa is a continent usually assumed to  
149 have few temperature constraints (Nemani et al., 2003), which will help to isolate the  
150 impacts of precipitation from temperature, as one challenge in attributing climatic  
151 controls on temperate ecosystems or Mediterranean ecosystems is the superimposed  
152 influences from both temperature and precipitation. The overarching science question  
153 we will address is: **How do African ecosystems respond to possible changes in**  
154 **intra-seasonal rainfall variability (i.e. rainfall frequency, intensity and rainy**

155 **season length)?**

156

157 [insert Table 1]

158

## 159 **2. Materials and Methods:**

### 160 **2.1 Methodology overview**

161 Table 1 summarizes previous field-based rainfall manipulation experiments, such as

162 ~~the one that Knapp et al. (2002) did in a grassland~~ that concurrently increasing rainfall  
163 frequency and decreasing rainfall intensity while fixing total rainfall ~~for a grassland.~~

164 The central idea of our study is to design similar rainfall manipulation experiments  
165 but test them virtually in the model domain across large environment gradients. ~~We~~

166 ~~manipulate rainfall changes through a weather generator based on a parsimonious~~  
167 ~~stochastic rainfall model (Rodriguez-Iturbe et al., 1984). We model the total amount~~

168 ~~of rainfall during rainy season as a product of the three intra-seasonal rainfall~~  
169 ~~characteristics for the rainy season, rainfall frequency ( $\lambda$ , event/day), rainfall intensity~~

170 ~~( $\alpha$ , mm/event), and rainy season length ( $T_w$ , days) (More details in section 2.3). We~~  
171 ~~manipulate rainfall changes through a stochastic weather generator based on a~~

172 ~~parsimonious model of rainfall processes: statistically for the daily rainfall record, the~~  
173 ~~mean annual precipitation (MAP) is a product of the three rainfall characteristics for~~

174 ~~the wet season, rainfall frequency ( $\lambda$ , day<sup>-1</sup>), rainfall intensity ( $\alpha$ , mm), and rainy~~  
175 ~~season length ( $T_w$ , days), normalized by  $f_w$  (the fraction of wet season rainfall to the~~

176 ~~MAP) to account for the contribution from dry season rainfall ( $MAP = \alpha \lambda T_w / f_w$ ).~~  
177 Thus it is possible to simultaneously perturb two of the rainfall characteristics away

178 from their climatological values while preserving the mean annual precipitation (MAP)  
179 unchanged (Figure 2). We then feed these different rainfall scenarios into a

180 well-validated dynamic vegetation model (SEIB-DGVM, section 2.2) to study  
181 simulated ecosystem responses. Detailed experiments design is described in section

182 2.5.

183

184 [insert Figure 2]

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185

## 186 2.2 SEIB-DGVM model and its performances in Africa

187 We use a well-validated vegetation dynamic model SEIB-DGVM (Sato et al., 2007)  
188 as the tool to study ecosystem responses to different rainfall variabilities. This model  
189 follows the traditional “gap model” concept (Shugart, 1998) to explicitly simulate the  
190 dynamics of ecosystem structure and function for individual plants ~~the dynamics of~~  
191 ~~fine scale ecosystem structure and function for~~ at a set of virtual vegetation patches,  
192 and uses results at these virtual patches as a surrogate to represent large-scale  
193 ecosystem states. Thus individual trees are simulated from establishment, having  
194 competition with other plants, to death, which creates “gaps” in which for different  
195 plant function types (PFTs) to other plants to occupy and develop. ~~The~~ SEIB-DGVM  
196 includes mechanical-based and empirical-based algorithms for land physical  
197 processes, plant physiological processes, and plant dynamic processes. ~~The~~  
198 SEIB-DGVM contains algorithms that explicitly involve the mechanisms of  
199 plant-related water stress (~~Figure 3~~ Figure 2; Sato and Ise, 2012). With S similar  
200 concepts to previous studies (e.g. Milly, 1992; Porporato et al., 2001), the current  
201 ~~SEIB model~~ SEIB-DGVM implements a continuous “water stress factor” (Equation 2)  
202 based on the soil moisture status (Equation 1), scaling from 0 (most stressful) to 1  
203 (with no stress), which then acts to scale the stomatal conductance for plant  
204 transpiration and carbon assimilation.

$$205 \quad stat_{water} = (S - S_w) / (S_f - S_w) \quad (\text{Equation 1})$$

$$206 \quad \text{Water stress factor} = 2 * stat_{water} - stat_{water}^2 \quad (\text{Equation 2})$$

207 where S, S<sub>w</sub> and S<sub>f</sub> refer to the fraction of volumetric soil water content within the  
208 rooting depth, at the wilting point, and at field capacity, respectively. Figure 2  
209 provides a schematic diagram of “water stress factor” from the SEIB-DGVM, and we  
210 also include an approximated linear model that has been widely adopted elsewhere  
211 (e.g. Milly, 1992; Porporato et al., 2001). The linear model uses an extra variable S\*,  
212 so called “critical point” of soil moisture: when S>S\*, there is no water stress (water  
213 stress factor =1); and when S<S\*, water stress factor linearly decreases with the  
214 decrease of S. Though SEIB-DGVM adopts a quadratic form for “water stress factor”.

215 it essentially functions similarly as the linear model, such that  $S^*$  distinguishes two  
216 soil moisture regimes that below which there is a large sensitivity of water stress to  
217 soil moisture status, and above which there is little water stress. Understanding how  
218 this “water stress factor” functions is the key to explain the following results.

219

220 [insert Figure 2]

221

222 ~~The~~ SEIB-DGVM ~~also~~ allows ~~the~~ development of annual and perennial grasses as  
223 well as multiple life cycles of grass at one year based on environmental conditions ~~;~~  
224 ~~and~~ ~~m~~Multiple life cycles of tree growth per year are possible in theory but rarely  
225 happen in simulations (Sato and Ise, 2012). Soil moisture status is the predominant  
226 factor to determine LAI of the vegetation layer, which influences maximum daily  
227 productivity and leaf phenology. In particular, life cycles of grass are under prominent  
228 control of soil moisture status. The previously defined “water stress factor” and other  
229 environmental conditions co-determine the optimum LAI of the grass layer, which  
230 influences maximum daily NPP and the leaf phenology. When optimum LAI exceeds  
231 0 for ~~preceeding~~ ~~7~~ continuous days, ~~the~~ dormant phase of perennial vegetation layer  
232 changes into ~~the~~ growth phase ~~;~~ ~~w~~While when optimum LAI falls below 0 for  
233 ~~preceeding~~ ~~7~~ continuous days, ~~the~~ growth phase changes switches into to the dormant  
234 phase (Sato et al, 2007). SEIB-DGVM also explicitly simulates ~~the~~ light conditions  
235 and light competitions among different PFTs in the landscape based on its simulated  
236 its simulation of 3D canopy structure and radiative transfer scheme (Sato et al, 2007).

237

238 [insert Figure 3]

239

240 ~~The~~ SEIB-DGVM has been tested both globally (Sato et al., 2007) and regionally  
241 for various ecosystems (Sato et al., 2010; Sato, 2009; Sato and Ise, 2012), ~~which~~  
242 whose simulated results compared favorably with ground observations and satellite  
243 remote sensing measurements in terms of for ecosystem composition, structure and  
244 function. In particular, ~~the~~ SEIB-DGVM has been successfully validated and

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245 demonstrated its ability in simulating ecosystem structure and function in the African  
246 continent (Sato and Ise, 2012). Two plant function types (PFTs) of tropical woody  
247 species are simulated by SEIB-DGVM in Africa: tropical evergreen trees and tropical  
248 deciduous trees. The distribution of these two woody types in the simulation is largely  
249 determined by hydro-climatic environments. Tropical evergreen trees only develop in  
250 regions where water resources are sufficient all year around, so they can maintain  
251 leaves for all seasons; otherwise, tropical deciduous trees could survive and dominate  
252 the landscape as they can shed leaves if there is no sufficient water supply in its root  
253 zone during the dry season (Sato and Ise, 2012). For woody species, two plant  
254 function types (PFTs) of tropical woody species are modeled in Africa: tropical  
255 evergreen trees and tropical deciduous trees, which distinguish in their phenology,  
256 with the former having leaves all year around, and the latter shedding leaves during  
257 dry season, which is mostly controlled by root zone moisture status (Sato and Ise,  
258 2012).—Trees and grasses coexist in a cell, with the floor of a virtual forest  
259 monopolized by one of the two grass PFTs, C<sub>3</sub> or C<sub>4</sub> grass. T, the dominating grass  
260 type of which type is determined at the end of each year by air temperature,  
261 precipitation, and CO<sub>2</sub> partial pressure (Sato and Ise, 2012).

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262 ~~The SEIB model~~SEIB-DGVM was run at a ~~one degree~~1° ~~spatial resolution and~~  
263 at ~~a~~the daily ~~temporal resolution~~step. It was spun-up for 2000 years driven by the  
264 observed climate (1970-2000) repeatedly for the soil carbon pool to reach steady state,  
265 followed by 200 years simulation driven by the forcings based on the experiment  
266 design in Section 2.4. Because our purpose is to understand the direct impacts of  
267 intra-seasonal rainfall variability, we turned off the fire component of ~~the SEIB~~  
268 ~~model~~SEIB-DGVM to exclude fire-mediated feedbacks in the results. Though we are  
269 fully aware of the important role of fire in interacting with rainfall seasonality and  
270 ~~thus in their influence~~ing on African ecosystems ~~productivity and structures~~ (Bond et  
271 al., 2005; Lehmann et al., 2011; Staver et al., 2012), studying these interactions is  
272 beyond the scope of this work. For the similar reason, we fixed the atmospheric CO<sub>2</sub>  
273 concentration at 380 ppmv to exclude possible impacts of CO<sub>2</sub> fertilization effects.

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274

### 275 2.3 Synthetic weather generator

276 The synthetic weather generator used here ~~consists of~~has two major components: i) to  
277 stochastically generate daily rainfall based on a stochastic rainfall model, and ii) to  
278 conditionally sample all other environmental variables from historical records to  
279 preserve the covariance among climate ~~forcing~~forcing ~~foreing~~inputs~~variables~~.

280 The stochastic rainfall model can be ~~statistically~~ expressed as  $MAP = \alpha \lambda T_w / f_w$ ,  
281 and we set  $f_w$  to be 0.9, i.e. the period including 90% of total annual rainfall is defined  
282 as “~~wet~~wet season” (exchangeable with “~~rainy~~wet season” hereafter). In particular,  
283 we first use Markham (1970)’s approach to find the center of the rainy season, and  
284 then extend the same length to both sides of the center until the total rainfall amount  
285 in this temporal window (i.e. “rainy season”) is equal to 90% of the total annual  
286 rainfall. Rainy season and dry season have their own rainfall frequency and intensity.  
287 Two seasons are separately modeled based on the Market Poisson Process. Here we  
288 only focus on and manipulate rainy-season rainfall characteristics in our study, as  
289 rainy-season rainfall accounts for almost all the meaningful rainfall inputs for plant  
290 use. Thus in the following paper, whenever we mention  $\alpha$  or  $\lambda$ , we refer to those  
291 during the rainy season.

292 The “~~wet season~~” and “~~dry season~~” rainfall time series are ~~respectively modeled~~  
293 ~~using the Marked Poisson Process~~. In this rainfall model, any day can be either rainy  
294 or not, and a rainy day is counted as one rainy event; rainfall events occur as a  
295 Poisson Process, with the parameter  $1/\lambda$  (unit: days/event) being the mean intervals  
296 between rainfall events, and rainfall intensity  $\alpha$  for each rainfall event following an  
297 exponential distribution, with  $\alpha$  being the mean rainfall intensity per event  
298 (Rodríguez-Iturbe et al., 1999). The wet season length is modeled as a beta  
299 distribution bounded from 0 to 1, scaled by 365 days. All the necessary parameters to  
300 fit for the stochastic rainfall model ~~climatological values of these rainfall~~  
301 ~~characteristics~~ (including the mean and variance of rainfall frequency, intensity and  
302 length of wet and dry seasons) were derived from the satellite-gauge-merged rainfall  
303 measurement from TRMM 3b42V7 (Huffman et al., 2007) for the period of 1998 to  
304 2012, based on the above assumptions for the rainfall process. Specifically, we

305 ~~applied our definition of “rainy season” to each year of the TRMM rainfall data for~~  
306 ~~per pixel, and calculated the mean and variance of the “rainy season length”, using~~  
307 ~~which we fitted the beta distribution for  $T_w$ . For rainfall frequency and intensity, we~~  
308 ~~lumped all the wet or dry season rainfall record together to derive their parameters.~~  
309 ~~The ~~two~~ steps of the synthetic weather generator are described ~~as~~ below:~~

310 **Step 1:** Model the daily rainfall following the Marked Poisson process described  
311 above. In particular, for a specific year, we first stochastically generate the wet season  
312 length by sampling from the beta distribution, and the dry season length is determined  
313 accordingly. Then we generate the daily rainfall for wet and dry season respectively.

314 **Step 2:** Based on the simulated daily rainfall time series in Step 1, we conditionally  
315 sample temperature, wind, and humidity from the Global Meteorological Forcing  
316 Dataset (GMFD, Sheffield et al., 2006), as well as cloud fraction and soil temperature  
317 from the Climate Forecast System Reanalysis (CFSR) from National Centers for  
318 Environmental Prediction (NCEP) (Saha et al., 2010). ~~To sample for a specific day, all~~  
319 ~~the historical record within a 21-day time window centered at that specific day makes~~  
320 ~~up a sampling pool. For each day, a sample is randomly drawn from a pool that covers~~  
321 ~~all the historical record within a 21-day time window centered at the sampling day.~~  
322 From the sampling pool, we ~~find-choose~~ the day such that the historical rainfall  
323 amount of the chosen day is within (100-30)% to (100+30)% of the simulated daily  
324 rainfall amount. We then draw all ~~other-the~~ environmental variables ~~(except rainfall)~~  
325 on that sampled day to the new climate forcing. If we can find a sample from the pool  
326 ~~based on the above rule~~, this sampling is called “successful”. When there is more than  
327 one suitable sample, we randomly select one. When there is no suitable sample, we  
328 randomly select one day within the pool. The mean “successful” rate for all the  
329 ~~experiments and ensembles and all the experiments a~~cross Africa is 83%.

330 ~~The GMFD data (Sheffield et al., 2006) blends reanalysis data with observations~~  
331 ~~and disaggregates in time and space, and is available from 1948 to 2008, with~~  
332 ~~1.0 degree spatial resolution and daily temporal resolution. The CFSR data (Saha et~~  
333 ~~al., 2010) provides cloud fraction and simulated soil temperature from three soil~~  
334 ~~layers for the SEIB model. The CFSR version that we used is from 1979 to 2010, and~~

335 ~~the original 0.3 degree spatial resolution and 6 hourly temporal resolution are~~  
336 ~~aggregated to 1.0 degree and daily.~~

337 —To test the validity of the synthetic weather generator, we ran ~~the SEIB~~  
338 ~~model~~SEIB-DGVM using the historical climate record ( $S_{\text{climatology}}$ ) and the synthetic  
339 forcing ( $S_{\text{control}}$ ), with the latter generated using the weather generator based on the  
340 rainfall characteristics derived from the former. Figure S1 shows that the ~~SEIB~~  
341 ~~model~~SEIB-DGVM simulations driven by these two different forcings generate  
342 similar biome distributions with a Cohen's Kappa coefficient of 0.78 (Cohen, 1960),  
343 and similar GPP patterns in Africa, with the linear fits of annual GPP as:  
344  $GPP(S_{\text{control}}) = 1.03 \times GPP(S_{\text{climatology}}) + 0.215$  ( $R^2 = 0.89$ ,  $P < 0.0001$ ). Both biome and  
345 GPP patterns are consistent with observations (Sato and Ise, 2012). These results  
346 provide confidence in using the synthetic weather generator and SEIB-DGVM to  
347 conduct the further study.

348

#### 349 **2.4 Experiment design**

350 Three experiments are designed as follows, ~~and are shown in the conceptual diagram~~  
351 ~~(Figure 2)~~:

352 **Exp 1** (Perturbation of rainfall frequency and intensity, ~~and the experiment is~~ termed  
353 as  $S_{\lambda-\alpha}$  hereafter, ~~with S referring “Scenario”~~) Simulations forced by the synthetic  
354 forcings with varying  $\lambda$  and  $\alpha$  simultaneously for wet season (20% increases of  $\lambda$  and  
355 corresponding decreases of  $\alpha$  to make MAP unchanged; 20% decreases of  $\lambda$  and  
356 corresponding increases of  $\alpha$  to make MAP unchanged; no change for dry season  
357 rainfall characteristics), while fixing  $T_w$  at the current climatology;

358 **Exp 2** (Perturbation of rainfall frequency and rainy season length, termed as  $S_{T_w-\lambda}$ )  
359 Simulations forced by the synthetic forcing with varying  $T_w$  and  $\lambda$  simultaneously for  
360 wet season (20% increases of  $T_w$  and corresponding decreases of  $\lambda$  to make MAP  
361 unchanged; 20% decreases of  $T_w$  and corresponding increases of  $\lambda$  to make MAP  
362 unchanged; no change for dry season characteristics), while fixing  $\alpha$  at the current  
363 climatology;

364 **Exp 3** (Perturbation of rainy season length and intensity, termed as  $S_{T_w-\alpha}$ ) Simulations

365 forced by the synthetic forcing with varying  $T_w$  and  $\alpha$  simultaneously for wet season  
366 (20% increases of  $T_w$  and corresponding decreases of  $\alpha$  to make MAP unchanged;  
367 20% decreases of  $T_w$  and corresponding increases of  $\alpha$  to make MAP unchanged; no  
368 change for dry season characteristics), while fixing  $\lambda$  at the current climatology.

369 Because  $\lambda$  and  $T_w$  have bounded ranges ( $\lambda \sim [0, 1]$  and  $T_w \sim [0, 365]$ ), if the ~~se two~~  
370 ~~variables after perturbation~~ ~~updated value~~ exceeds the range, we would force the  
371 ~~new updated~~ ~~ir~~ value to be the lower or upper bound, and rearrange the other  
372 ~~corresponding variable~~ ~~rainfall characteristic~~ to ensure MAP unchanged. Each rainfall  
373 scenario has six ensemble realizations of synthetic climate forcings to account for the  
374 stochasticity of our synthetic weather generator.  
375 ~~For example in Exp 1, if after 10% increase the updated  $\lambda$  is larger than 1, we would~~  
376 ~~force the updated  $\lambda$  to be 1, and recalculate the changes in  $\alpha$  to keep MAP the same as~~  
377 ~~before. All the scenarios have six ensemble runs differentiated in their synthetic~~  
378 ~~forcings to account for the stochasticity of the synthetic weather generator.~~

379

### 380 **3. Results**

381 We present the differences in simulated biome distributions of the three experiments  
382 (i.e.  $S_{\lambda-\alpha}$ ,  $S_{T_w-\lambda}$ ,  $S_{T_w-\alpha}$ ) in ~~Figure 4~~ Figure 3, ~~(and Figure S2 and S3 for their spatial~~  
383 ~~patterns are shown in Figure S2 and S3).~~ ~~and the 4~~ Differences in simulated annually  
384 averaged soil moisture and GPP for each experiment are shown in Figure 5 Figure 4  
385 and 6. These differences ~~indicate~~ represent the simulated ecosystem sensitivity to the  
386 slight perturbation ~~away from the current climatology~~ of intra-seasonal rainfall  
387 characteristics deviating from the current climatology. ~~We present the differences~~  
388 ~~between +20% and -20% changes in each experiment. We also assessed shifts of +/-~~  
389 ~~10%, and found that these responses are similar with only smaller magnitudes and~~  
390 ~~thus not shown here. To further explore how MAP and these rainfall characteristics~~  
391 affect the simulated GPP, Figure 6 Figure 5 shows plots the difference ~~in of~~ simulated  
392 GPP as a function of mean annual precipitation MAP and the climatological value of a  
393 perturbed rainfall characteristic in the corresponding experiment. We term Figure 5 as  
394 “GPP sensitivity space”, and “positive GPP sensitivity” means that GPP changes at

395 the same direction with MAP or rainfall characteristics, and vice versa for “negative  
396 GPP response”. These “GPP sensitivity spaces” are generated based on the aggregated  
397 mean GPP in each bin of the rainfall properties. The bin size for MAP, rainfall  
398 frequency, rainfall intensity and rainy season length are 100 mm/year, 0.05 event/day,  
399 1 mm/event and 15 days respectively. We also provide the standard error (SE) of the  
400 “GPP sensitivity spaces” in each bin to assess their uncertainties, with higher SE  
401 meaning larger uncertainties. ~~paired with the standard error (SE) between~~  
402 ~~simulations to indicate the uncertainty of the result, as  $SE = \sigma / \sqrt{n}$ , where  $\sigma$  and n~~  
403 refer to the standard deviation of GPP values and the sample size in each bin  
404 respectively. ~~Thus changes in GPP and their associated standard errors are calculated~~  
405 ~~for each climatological bin; where the bin size for MAP, rainfall frequency, rainfall~~  
406 ~~intensity and rainy season length are 100 mm/year, 0.05 day<sup>-1</sup>, 1 mm and 15 days~~  
407 ~~respectively. We recognize that there are large heterogeneity in soil texture, altitude~~  
408 ~~and other factors which can influence simulation results at local scale, and using the~~  
409 ~~current approach essentially lumps these factors and highlights the impacts from our~~  
410 ~~interested variables (i.e. rainfall characteristics). A series of illustrations in Figure~~  
411 ~~7Figure 6 were generalized from the simulated time series, and will be~~ used to  
412 explain the underlying mechanisms.

413

414 [insert ~~Figure 4~~Figure 3; ~~Figure 5~~Figure 4; ~~Figure 6~~Figure 5]

415

### 416 3.1 Ecosystem sensitivity to rainfall frequency and intensity (Experiment $S_{\lambda-\alpha}$ )

417 Experiment  $S_{\lambda-\alpha}$  assesses ecosystem responses after increasing rainfall frequency  $\lambda$   
418 and decreasing rainfall intensity  $\alpha$  ( $\lambda \uparrow, \alpha \downarrow$ ) under a fixed total annual rainfall. The ~~The~~  
419 experiment  $S_{\lambda-\alpha}$  shows that the simulated biome distributions, after increasing rainfall  
420 frequency  $\lambda$  and decreasing its intensity  $\alpha$  ( $\lambda \uparrow, \alpha \downarrow$ ) under a fixed total annual rainfall,  
421 have small differences in the low rainfall regime (around 500 mm/year, Figure 4a),  
422 with show that a small portion of regions ~~converting are converted~~ from woodland to  
423 grassland at low rainfall regime (~500 mm/year), corresponding to a decrease of GPP

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424 ~~in these regions indicating a negative impact of increasing rainfall frequency when~~  
425 ~~total rainfall is very low.~~ In the high rainfall regime (around 1500 mm/year, ~~Figure~~  
426 ~~4~~~~Figure 3a~~), increasing rainfall frequency significantly converts tropical evergreen  
427 forests into woodlands. In the intermediate rainfall regime (600-1000 mm/year), there  
428 ~~are is~~ little changes in biome distributions. We further check the spatial patterns of  
429 differences in annual mean soil moisture and annual total GPP (~~Figure 5~~~~Figure 4a~~ and  
430 5b). We find that GPP increases with increasing rainfall frequency across most of the  
431 Africa continent, except in ~~the~~ very dry end (in the southern and eastern Africa) ~~as~~  
432 ~~well as and the~~ very wet regions (in central Africa and northeastern Madagascar). This  
433 GPP pattern mostly mirrors the soil moisture change ~~in woodlands and grasslands~~  
434 (~~Figure 5~~~~Figure 4b~~), except the wet tropics, where the changes of soil moisture and  
435 GPP are ~~in the reversed signs~~.

436 ~~Figure 6~~~~Figure 5a~~ shows the GPP sensitivity as a function of MAP and the  
437 climatological rainfall frequency, and we find three major patterns ~~stand out~~:

438 **Pattern 1.1:** Negative GPP sensitivity shows up in the very dry end of MAP regime  
439 (MAP < 400 mm/year) and with ~~very~~ ~~relatively~~ low rainfall frequency ( $\lambda < 0.3$   
440 ~~day<sup>-1</sup>event/day~~), i.e. GPP decreases with more frequent but less intense rainfall in this  
441 low rainfall ~~regime range, without changes in the total rainfall amount~~.

442 **Pattern 1.2:** Across most rainfall ~~range regimes~~ (MAP from 400 mm/year to 1600  
443 mm/year), increasing frequency of rainfall (and simultaneously decreasing rainfall  
444 intensity) lead to positive GPP sensitivity. This positive GPP sensitivity peaks at the  
445 low range of rainfall frequency ( $\sim 0.35$  ~~day<sup>-1</sup>event/day~~) and around the MAP of 1000  
446 mm/year.

447 **Pattern 1.3:** At the high range of MAP (>1800 mm/year) with low rainfall frequency  
448 ( $\sim 0.4$  ~~day<sup>-1</sup>event/day~~), GPP decreases with increased rainfall frequency.

449 ~~The relationship of GPP sensitivity to MAP and rainfall intensity (Fig. 6c) has no~~  
450 ~~clear patterns as previous ones, mostly because the GPP sensitivity space (Fig. A4c)~~  
451 ~~contains large uncertainties (Fig. A4d, shown as large variance in the data). Thus we~~  
452 ~~will not over-interpret the pattern in Fig. 6c. The GPP sensitivity with respect to MAP~~  
453 ~~and rainfall intensity (Figure 6c) contains more uncertainties and shows more~~

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454 ~~complex patterns, mostly because the space that most pixels cluster (Figure S4c) also~~  
455 ~~has large variance (Figure S4d). Thus we will not over interpret the pattern in Figure~~  
456 ~~6e.~~

457 ~~Illustrative time series in Figure 7a and 7b explain the above~~ Pattern 1.1 and  
458 Pattern 1.2 ~~can be explained by the illustrative time series in Figure 6a and 6b,~~  
459 respectively. ~~Figure 7~~Figure 6a shows that when rainfall events are small and very  
460 infrequent, increasing rainfall frequency while decreasing intensity would cause more  
461 frequent downcrossings of soil moisture at the wilting point  $S_w$ , which subsequently  
462 would reduce the effective time of carbon assimilation and plant growth (i.e. when  
463 soil moisture is below  $S_w$ , plants would be in the extreme water stress and slow down  
464 or stop physiological activity). ~~It is worth noting that t~~This case only happens where  
465 MAP is very low with low frequency, ~~where and~~ the biome is predominantly  
466 grasslands, which explains why negative changes in soil moisture and GPP in Figure  
467 4a and 4b are distributed in those regions. the spatial patterns of negative soil moisture  
468 and GPP sensitivity in Figure 5a and 5b. This result also corroborates the field  
469 findings of the negative impacts from increasing rainfall frequency in Heisler-White  
470 et al.(2009) and Thomey et al. (2011) at low rainfall regimes.

471 ~~Figure 7~~Figure 6b ~~explains~~ provides the hydrological mechanism for the positive  
472 sensitivity of soil moisture and GPP with increasing rainfall frequency over the most  
473 African continent (Pattern 1.2). Once individual rainfall event has enough intensity  
474 and rainfall ~~events are frequent~~ frequency is enough, downcrossings of  $S_w$  would not  
475 easily happen ~~;~~ instead, the accumulative rainy-season soil moisture becomes the  
476 dominant control of plant growth, and water stress (shaded areas between  $S_w$  and  $S^*$ ,  
477 Porporato et al., 2001) becomes the dominant source of growth stress for plants; and  
478 increasing rainfall frequency has can lead to a significant decrease in this type of plant  
479 water stress increase of soil moisture for plant water use (Figure 4a and 4b). This  
480 conclusion drawn from our numerical modeling is consistent with previous findings in  
481 Rodríguez-Iturbe and Porporato (2004) based on stochastic modeling. We also find  
482 that this positive impact GPP sensitivity reaches to its maximum in the intermediate  
483 total rainfall (~1000 mm/year) and relatively low rainfall frequency (~0.35

484 ~~day<sup>-1</sup>event/day~~), indicating that in these regimes increasing rainfall frequency could  
485 most effectively ~~decrease~~ increase plant water stress ~~soil moisture for plant water use~~  
486 and create marginal benefits of GPP to the increased rainfall frequency. Further  
487 increase in ~~Either too~~-large total annual rainfall ~~or too high or~~ rainfall frequency may  
488 uplift soil moisture status in general, which would reduce the sensitivity to water  
489 stress with fewer downcrossings of soil moisture critical point  $S^*$ ; and once the soil  
490 moisture is always ample (i.e. above  $S^*$ ), the changes in either MAP or rainfall  
491 frequency would not alter plant water stress.

492 Pattern 1.3 also shows a negative GPP sensitivity, but its mechanism is different  
493 from the previous case of Pattern 1.1. There is another negative GPP sensitivity  
494 shown in Pattern 1.3, but the mechanism is different from the previous negative GPP  
495 case. In regions with total rainfall usually more than 1800 mm/year, SEIB-simulated  
496 tropical forests exhibit radiation-limitation rather than water-limitation during wet  
497 season. Increase of rainfall frequency at daily scale would enhance cloud fraction and  
498 suppress plant productivity in these regions (Graham et al., 2003). Thus even though  
499 soil moisture still increases (~~Figure 5~~Figure 4a), GPP decreases with increased rainfall  
500 frequency. This mechanism also explains why tropical evergreen forests shrink its  
501 area with increased rainfall frequency (~~Figure 4~~Figure 3a).

502 It is worth noting that the magnitude of GPP changes due to rainfall frequency  
503 and intensity is relatively small in most of the woodlands, but can be relatively large  
504 for drylands with MAP below 600 mm/year (up to 10-20% of annual GPP). This  
505 pattern also explains why only modest changes in biome distribution ~~happen~~ for the  
506 transitional area between woodlands and grasslands in  $S_{\lambda-\alpha}$  (~~Figure 4~~Figure 3a).

507

508 [insert ~~Figure 7~~Figure 6]

509

### 510 **3.2 Ecosystem sensitivity to rainfall seasonality and frequency (Experiment $S_{TW-\lambda}$ )**

511 ~~The~~ experiment  $S_{TW-\lambda}$  assesses ecosystem responses after increasing rainy season  
512 length and decreasing rainfall frequency (i.e.  $T_w \uparrow, \lambda \downarrow$ ) under a fixed total annual  
513 rainfall. T ~~shows that~~ the simulated biome distribution, ~~after increasing rainy season~~

514 ~~length and decreasing rainfall frequency (i.e.  $T_w \uparrow$ ,  $\lambda \downarrow$ ) under a fixed total annual~~  
515 ~~rainfall, shows a gain of~~ ~~has an increase of~~ area in tropical evergreen forests, ~~which~~  
516 ~~are~~ converted from woodlands. ~~The northern Africa has~~, an area increase of  
517 woodlands converted from grasslands ~~in the northern Africa~~, and African Horn region  
518 ~~has~~ a small expansion of grasslands into woodlands ~~in the African Horn region~~  
519 ~~(Figure 4~~Figure 3b). ~~Figure 5~~Figure 4c and 4d show that increasing rainy season  
520 length  $T_w$  and decreasing frequency  $\lambda$  would significantly increase annual mean soil  
521 moisture and GPP (up to 30%) in most woodland area, ~~meanwhile decreased soil~~  
522 moisture and GPP are found in the southern and eastern Africa, ~~and~~ ~~tropical~~  
523 evergreen forests ~~show regions have~~ little response. We further explore the GPP  
524 sensitivity space in ~~Figure 6~~Figure 5e and 5g, and find the following interesting  
525 robust patterns (based on small standard errors shown in Figure 5f and 5h):  
526 ~~, which are mostly robust due to the small standard errors shown in Figure 6f and 6h:~~  
527 **Pattern 2.1:** The negative GPP sensitivity tends to happen where MAP is mostly  
528 below 1000 mm/year with long rainy season length ( $T_w > 150$  days) and low rainfall  
529 frequency ( $\lambda < 0.35$  ~~day<sup>-1</sup>event/day~~), ~~which is a unique rainfall regime that sporadically~~  
530 ~~spread rain events for a long rainy season.~~  
531 **Pattern 2.2:** When MAP and rainfall frequency are ~~both larger than certain~~  
532 ~~ranges~~large enough ( $MAP > 1000$  mm/year and  $\lambda > 0.4$  ~~day<sup>-1</sup>event/day~~), decreasing  $\lambda$   
533 while increasing~~trading the decrease of  $\lambda$  for the increase of~~  $T_w$  would significantly  
534 increase GPP. The maximum positive GPP sensitivity happens ~~in the rainfall regime~~  
535 ~~with the~~at the intermediate MAP range (1100-1500 mm/year) and the high rainfall  
536 frequency ( $\lambda \sim 0.7$  ~~day<sup>-1</sup>event/day~~).

537 **Pattern 2.3:** There exists an “optimal rainy season length” for relative changes in  
538 ecosystem productivity ~~at across large different~~ MAP ranges (the white area between  
539 the red and blue space in ~~Figure 6~~Figure 5e). For the same MAP, any deviation of  $T_w$   
540 from the “optimal rainy season length” would reduce GPP. longer than this length,  
541 rainy season lengthening would decrease GPP; while shorter than this length, rainy  
542 season lengthening would increase GPP. This “optimal rainy season length” follows  
543 an increasing trendes with MAP until 1400 mm/year.

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544 ~~Figure 7~~Figure 6c explains the hydrological mechanism for the negative GPP  
545 sensitivity in Pattern 2.1. In the situation with low MAP and infrequent rainfall events,  
546 decreasing rainfall frequency ~~to and~~ expanding rainy season length (i.e.  $T_w \uparrow$ ,  $\lambda \downarrow$ )  
547 would lead to longer ~~interval~~time b between rainfall events and possibly longer  
548 excursions below  $S_w$ , which would ~~restrain~~ disrupt continuous plant growth and have  
549 detrimental effects on ecosystem productivity. It is worth noting that long rainy season  
550 in dryland (~~Figure 6~~Figure 5e) is usually accompanied with low rainfall frequency  
551 (~~Figure 6~~Figure 5g). The southern African drygrasslands (south of 15°S) typically fall  
552 in this category, and these regions thus have negative GPP sensitivity (~~Figure 5~~Figure  
553 4c and 4d), accompanied by a small biome conversion from; ~~these regions also~~  
554 ~~correspond to the small biome conversion from~~ woodlands to grasslands in the low  
555 range of MAP (<300 mm/year) as shown in (~~Figure 4~~Figure 3b).

556 ~~Figure 7~~Figure 6d explains the hydrological mechanisms for the positive GPP  
557 sensitivity in Pattern 2.2, ~~which shows that~~ When rainfall is ample enough to  
558 maintain little or no water stress during rainy season, increasing the interval of rainfall  
559 events may introduce little additional water stress but can significantly extend the  
560 growing season. This situation mostly happens in woodlands, where limited water  
561 stress exists during ~~growing~~ rainy season, and dry season length is the major  
562 constraint for plant growth. Thus the increase of rainy season length extends the  
563 temporal niche for plant growth, and ~~significantly modifies the biome distribution,~~  
564 ~~which~~ leads to a significant woodland expansion~~large wood encroachment~~ to  
565 grasslands and as well as ~~also~~ an expansion of tropical evergreen forests ~~conversion~~  
566 ~~of woodlands to tropical evergreen forests, as shown into woodlands~~ (~~Figure 4~~Figure  
567 3b).

568 The little GPP sensitivity in tropical evergreen forest regions is mostly attributed  
569 to the long rainy season length ~~already existed~~ in this ~~type of~~ ecosystem. Thus further  
570 increasing  $T_w$  may reach to its saturation (365 days) and ~~has thus have~~ little impact to  
571 ecosystem productivity. This also explains why the magnitude of GPP sensitivity is  
572 much smaller at high MAP range than at the intermediate MAP range. Similar reason  
573 ~~also explains why the GPP sensitivity has the maximum response in the intermediate~~

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574 ~~MAP range rather than the high MAP range, at which GPP sensitivity has been~~  
575 ~~saturated.~~

576 The finding of “optimal rainy season length” across different rainfall regimes  
577 (~~Figure 6~~Figure 5e) is consistent with our previous empirical finding about the similar  
578 pattern of “optimal rainy season length” for tree fractional cover in Africa derived  
579 based on a satellite remote sensing product (Guan et al., 2014). The existence of  
580 “optimal rainy season length” ~~Two distinctive GPP sensitivities separated by the~~  
581 ~~“optimal rainy season length”, with this optimal length increasing with MAP,~~ fully  
582 demonstrates the importance to explicitly consider the non-linear impacts of rainy  
583 season length on ecosystem productivity under climate change, which has been  
584 largely overlooked before.

585

### 586 3.3 Ecosystem sensitivity to rainfall seasonality and intensity ( $S_{T_w-\alpha}$ )

587 ~~The results of the e~~Experiment  $S_{T_w-\alpha}$  have many similarities with those of  $S_{T_w-\lambda}$ ,  
588 including the similar changes in biome distributions (~~Figure 4~~Figure 3), soil moisture  
589 and GPP patterns (~~Figure 5~~Figure 4e and 4f). We further find that the GPP sensitivity  
590 space with MAP and rainy season length for  $S_{T_w-\alpha}$  (~~Figure 6~~Figure 5j) is also similar  
591 with that ~~of for~~  $S_{T_w-\lambda}$  (~~Figure 6~~Figure 5e). One new pattern-finding is that rainfall  
592 intensity has little impacts on ~~the GPP sensitivity~~, as the contour lines in ~~Figure~~  
593 ~~6~~Figure 5k are mostly parallel with y-axis (i.e. rainfall intensity); ~~in other words, the~~  
594 ~~trade-off between  $T_w$  and  $\alpha$  is mostly a function of MAP and  $T_w$ , but not  $\alpha$ , and the~~  
595 ~~largest marginal effects happen in the intermediate range of MAP, similar as in  $S_{T_w-\lambda}$ .~~

596 Figure 7Figure 6e and 6f explain the governing hydrological mechanisms for the  
597 patterns of  $S_{T_w-\alpha}$ , which also have many similarities with  $S_{T_w-\lambda}$ . For the negative case  
598 (~~Figure 7~~Figure 6e), decreasing rainfall intensity to extend and increasing rainy season  
599 length in the very low MAP regime may ~~possibly~~ lead to more downcrossings of  $S_w$   
600 and interrupt continuous plant growth. The positive case (~~Figure 7~~Figure 6e) is similar  
601 as that in ~~Figure 7~~Figure 6d, i.e. the repartitioning of excessive ~~rainy wet-season water~~  
602 rainfall to the dry season for an extended growing period would significantly benefit  
603 plant growth and possible increase tree fraction cover.

604

## 605 **4. Discussion**

606 In this paper we provide a new modeling approach to systematically ~~understand~~  
607 ~~interpret~~ the ecological impacts from changes in intra-seasonal rainfall characteristics  
608 (i.e. rainfall frequency, rainfall intensity and rainy season length) across biomes and  
609 climate gradients in the African continent.

610

### 611 **4.1 Limitation of the methodology**

612 Though ~~the-our~~ modeling framework ~~that-we-used~~ is able to characterize the diverse  
613 ecosystem responses to the shifts in different rainfall characteristics, it nevertheless  
614 has its limitations. The current rainfall model only deals with the case of single rainy  
615 season per year, and approximates the case of double rainy seasons per year to be ~~the~~  
616 single rainy season case. This assumption may induce unrealistic synthetic rainfall  
617 patterns in the equatorial dryland regions, in particular the Horn of Africa. ~~T~~, thus the  
618 ~~resulting-simulated~~ sensitivity of these regions may be less reliable. We also assume  
619 that rainfall frequency and intensity are homogenous throughout wet ~~and-dry~~ seasons  
620 ~~(or dry seasons)s~~, but in reality they ~~still~~ have seasonal variations. We only consider  
621 rainy season length for rainfall seasonality, and neglect the possible temporal phase  
622 change; ~~actually-in reality~~, rainfall seasonality change usually has length and phase  
623 shifts in concert. These rainfall-model-related limitations can be possibly overcome by  
624 simulating smaller intervals of rainfall processes (e.g. each month has their own  $\alpha$  and  
625  $\lambda$ ) rather than simulating the whole wet or dry season using one fixed set of  $\alpha$  and  $\lambda$ .  
626 Besides, only using one ecosystem model also means that the simulated ecosystem  
627 sensitivity can be model-specific. ~~Though magnitudes or thresholds for the~~  
628 ~~corresponding patterns may vary depending on different models, we argue that ;~~  
629 ~~though-we-believe~~ the qualitative results for the GPP sensitivity patterns (e.g. ~~Figure~~  
630 ~~5Figure 4~~ and ~~Figure-6Figure 5~~) should ~~mostly~~ hold as the necessary ecohydrological  
631 processes have been incorporated in ~~the SEIB-DGVM, magnitudes or thresholds in~~  
632 ~~these patterns may vary depending on different models. For example, GPP in tropical~~  
633 ~~evergreen forests (Figure 5b and Figure 6a) is less sensitive to radiation limitation as~~

634 ~~shown in satellite based observation than in the SEIB simulation in Africa (Guan et al.,~~  
635 ~~2013).~~ We also recognize that to exclude fire impacts in the current simulation may  
636 bring some ~~eaveats limitation in interpreting the results for this study,~~ as evidence  
637 shows that many savanna regions can be bistable due to fire effects (Staver et al 2011;  
638 Hirota et al 2011; Higgins and Scheiter 2012; also see for a possible rebuttal in Hanan  
639 et al, 2013). ~~and e~~ Changes in rainfall regimes ~~may~~ not only have direct effects on  
640 vegetation productivity, but can also indirectly ~~effects affect ecosystems~~ through  
641 ~~influeneing its interactions with~~ fire regimes, ~~and with~~ rapid biome shifts ~~may be being~~  
642 ~~a possible a~~ consequence. These feedbacks can be important in situations ~~where when~~  
643 ~~the changes in the~~ growing season length ~~changes, which~~ are related to fuel loads, fuel  
644 moisture dynamics and hence fire intensity (Lehmann et al., 2011). Quantifying these  
645 fire-rainfall feedbacks will be the important future direction to pursue.

646

#### 647 **4.2 Clarifying the impacts of rainfall frequency and intensity on ecosystem** 648 **productivity**

649 In this ~~modeling study, we provide a plausible answer to possibly resolve paper we~~  
650 ~~have resolved~~ the previous debate about whether increasing rainfall intensity (or  
651 equivalently decreasing rainfall frequency, i.e.  $\lambda \downarrow$ ,  $\alpha \uparrow$ ) has positive or negative  
652 impacts on above-ground primary productivity ~~with under~~ a fixed annual rainfall total.  
653 We identify that negative GPP sensitivity with increased rainfall frequency is possible  
654 at very low MAP range (~ 400 mm/year) with ~~very relatively~~ low rainfall frequency  
655 ( $< 0.35$  ~~day<sup>-1</sup> event/day~~) (Figure ~~6~~ Figure 5a), due to the increased downcrossings of  
656 soil moisture wilting point, which restricts plant growth (Figure ~~7~~ Figure 6a). ~~Our This~~  
657 derived MAP threshold (~400 mm/year) ~~to distinguish different GPP sensitivities with~~  
658 ~~rainfall frequency~~ is consistent with our meta-analysis based on the previous field  
659 studies (Table 1), which shows a threshold of MAP at 340 mm/year separates positive  
660 and negative impacts of more intense rainfall on ANPP ~~aboveground net primary~~  
661 production (ANPP). Our findings are also consistent with ~~another other~~ studies about  
662 increased tree encroachments with increased rainfall intensity in ~~very~~ low rainfall  
663 regime ( $< 544$  mm/year, Kulmatiski and Beard, 2013), which essentially follows the

664 same mechanism as identified in ~~Figure 7~~Figure 6a.

665 In addition, we thoroughly investigated the ecosystem responses across ~~all the a~~  
666 ~~wide ranges~~ of ~~annual~~ rainfall in Africa, ~~and w~~We find that beyond the very low  
667 rainfall range (below 400 mm/year), most grasslands and woodlands would benefit  
668 from increasing rainfall frequency, which also corroborate the previous large-scale  
669 findings about the positive effects of increased rainfall frequency (and decreased  
670 rainfall intensity) for tree fractions across the African continent (Good and Caylor,  
671 2011). The only exception happens at the very wet end of MAP (~1800mm/year)  
672 where cloud-induced radiation-limitation may suppress ecosystem productivity with  
673 increased rainfall frequency. We also find that changes in rainfall frequency and  
674 intensity mostly ~~af~~fect grassland-dominated savannas (changes of GPP up to 20%),  
675 and the corresponding effects are much smaller in woodlands and have little impact  
676 on woodland distribution. Though this work is only based on a single model, it  
677 provides a primary assessment for understanding of interactive changes between  $\lambda$  and  
678  $\alpha$  in ecosystem functioning, ~~which and~~ expands ~~the analysis to the full spectra of a~~  
679 ~~wide range of annual~~ rainfall ~~ranges conditions~~ compared with previous studies (e.g.  
680 Porporato et al., 2004).

681

### 682 4.3 Ecological importance of rainy season length

683 The results involving rainy season length (i.e.  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$ ) ~~have fully demonstrated~~  
684 ~~provide evidence for~~ the ecological importance of rainfall seasonality. The magnitudes  
685 of changes in soil moisture, GPP and biome distribution in  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$  are much  
686 larger than those of  $S_{\lambda-\alpha}$ , with almost one order of magnitude difference. These  
687 disproportional impacts ~~of of~~  $T_w$  indicate that slight changes in rainy season length  
688 could modify biome distribution and ecosystem function more dramatically compared  
689 with the same percentage changes in rainfall frequency and intensity. We also notice  
690 that  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$  have similar results, ~~which~~This ~~is~~ because that both  $\lambda$  and  $\alpha$   
691 describe rainfall characteristics within wet season, while  $T_w$  describes rainfall  
692 characteristics of both dry season and wet season. Cautions are required that our  
693 simplified treatment rainy season length may overestimate its importance, and we did

694 not consider the rainfall phase information here. –

695 Given the importance of rainy season length, its ecological impacts under climate  
696 change are largely understudied, though substantial shifts in rainfall seasonality have  
697 been projected in both Sahel and South Africa (Biasutti and Sobel, 2009; Shongwe et  
698 al., 2009; Seth et al., 2013). Here we only address the rainfall seasonality in terms of  
699 its length, and future changes in rainfall seasonality may modify their phase and  
700 magnitude in concert. The climate community has focused on the increase of extreme  
701 rainfall events (Field et al., 2012), which could be captured by the changes in  $\lambda$  or  $\alpha$   
702 towards heavier tails in their distribution. However, explicit and systematic  
703 assessments and projection on rainfall seasonality changes (including both phase and  
704 magnitude) are still limited even in the latest Intergovernmental Panel on Climate  
705 Change (IPCC) synthesis reports (Field et al., 2012; Stocker et al., 2013). More  
706 detailed studies related to these changes and their ecological implications are required  
707 for future hydroclimate-ecosystem research.

708

#### 709 **4.4 Not all rainfall regimes are ecologically equivalent**

710 As Figure 1 gives a convincing example that the same total annual rainfall may arrive  
711 in a very different way, our results further demonstrate that ecosystems respond  
712 differently to the changes in these intra-seasonal rainfall variability. For example, with  
713 similar MAP, drylands in West Africa and Southwest Africa ~~can have~~ show reversed  
714 responses to the same changes in intra-seasonal rainfall variability. As shown in the  
715 experiments of  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$ , increasing  $T_w$  while decreasing  $\lambda$  or  $\alpha$  generates  
716 slightly positive soil moisture and GPP sensitivity in West Africa (~~Figure 5~~ Figure 4c  
717 and 4d), but would cause relatively large GPP decrease in Southwest Africa. The  
718 prior hydroclimate conditions of these two regions can explain these differences: West  
719 Africa has much shorter rainy season with more intense rainfall events; ~~which is~~  
720 ~~totally contrary to~~ in contrast, Southwest Africa, ~~which~~ has a long rainy season but  
721 many small and sporadic rainfall events. As a result, under a fixed annual rainfall total,  
722 slightly increasing rainy season and meanwhile decreasing rainfall intensity would  
723 benefit plant growth in West Africa, but the same change would lengthen dry spells in

724 Southwest Africa and bring negative effects to the ecosystem productivity. We further  
725 deduce that the rainfall use efficiency (RUE, defined as the ratio of plant net primary  
726 production ~~and to~~ total rainfall amount) in these two drylands could be different: West  
727 Africa may have lower RUE, and the intense rainfall could lead to more  
728 infiltration-excess runoff, and thus less water would be used by plants; while  
729 Southwest Africa can have higher RUE, because its sporadic and feeble rainfall events  
730 would favor grass to fully take the advantage of the ephemerally existed water  
731 resources. This conclusion is partly supported by Martiny et al. (2007) based on  
732 satellite remote sensing. We further hypothesize that landscape geomorphology in  
733 these two drylands may be different and therefore reflect distinctive rainfall  
734 characteristics. More bare soil may exist in West Africa grasslands due to  
735 intense-rainfall-induced erosion, while Southwest Africa may have more grass  
736 fraction and less bare soil fraction. Testing these interesting hypotheses is beyond the  
737 scope of this paper, but is worthy the further exploration.

738

739

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745

746

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Table 1. Summary of previous representative studies on assessing the impacts of rainfall characteristics (i.e. rainfall frequency, intensity and seasonality) on the structure and function of terrestrial ecosystem.

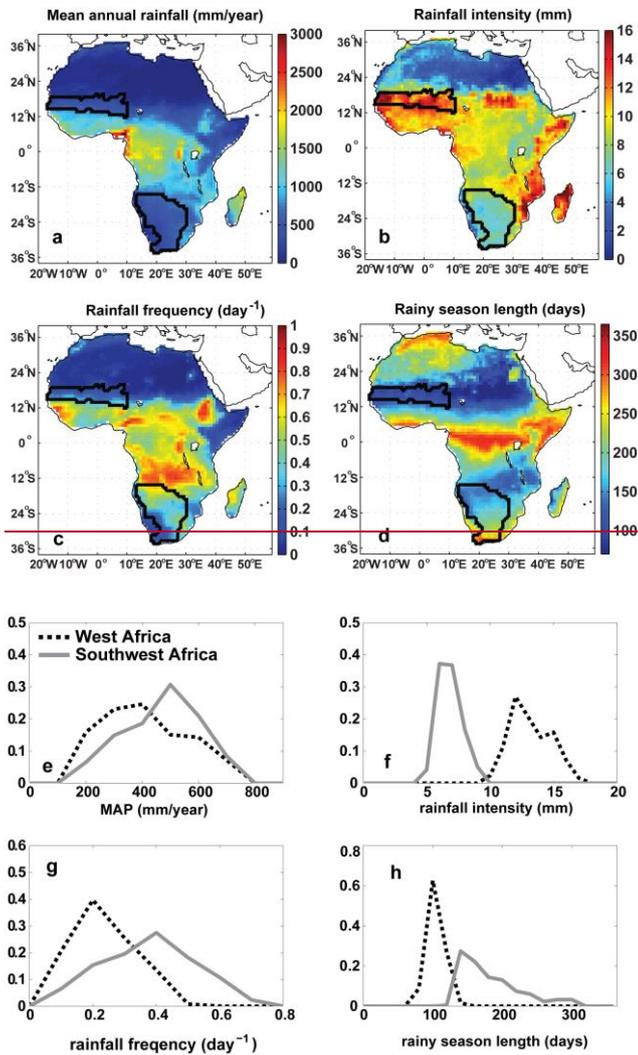
**Focus:** frequency (freq); intensity (int); seasonality (sea); variation (CV).

**Methods:** Field Experiments (Field); Remote Sensing (RS); Flux Tower (Flux).

**Major Conclusion:** increasing rainfall intensity (or decreasing frequency) has positive impacts (int+); increasing intensity (or decreasing frequency) has negative impacts (int-); increasing rainfall CV has positive impacts (CV+); increasing rainfall CV has negative impacts (CV-).

Focus	Methods	Spatial Scale	Time scale	MAP (mm/year)	Ecosystem type	Major Conclusion	Reference
freq; int	RS	Africa continent	intra-annual climatology	[0,3000]	Africa all	(int-) woody cover	Good and Caylor, 2011
freq; int	RS	US		[163,1227]	US	(int-) ANPP greatest in arid grassland (16%) and Mediterranean forest (20%) and less for mesic grassland and temperate forest (3%)	Zhang et al., 2013
freq; int	RS	Pan-tropics (35°N to 15°S)	inter-annual	[0,3000]	Tropical ecosystems	(CV+) wood cover in dry tropics; (CV-) wood cover in wet tropics	Holmgren et al., 2013
freq; int	RS	Northern China	intra-annual	[100,850]	temperate grassland and forests	(int-) NDVI for temperate grassland and broadleaf forests, not for coniferous forest	Fang et al., 2005
freq; int	Flux	Northern Hemisphere	intra-annual	[393±155,906±243]	shrubland and forest	(int-) GPP, RE and NEP	Ross et al., 2012
seas	RS	Africa continent	climatology	[0,3000]	Africa all	rainy season onset and offset controls vegetation growing season	Zhang et al., 2005
freq; int	Field	plot (Kansas, USA)	intra-annual	615	grassland	(int-) ANPP	Knapp et al., 2002

(fix MAP)							
freq; int	Field	plot (Kansas, USA)	intra-annual	835	grassland	(int-) ANPP	Fay et al., 2003
(fix MAP)							
increase seasonal rainfall	Field	plot(Texas, USA)	intra-annual	365	grassland	(int-) ANPP	Robertson et al., 2009
freq; int	Field	plot (Kansas, USA)	intra-annual	[320,830]	grassland	(int-)ANPP for MAP=830mm/yr; (int+)ANPP for MAP=320mm/yr	Heisler-White et al., 2009
freq; int	Field	plot( New Mexico, USA)	intra-annual	250	grassland	(int+) ANPP	Thomey et al., 2011
freq; int	Field	Plot(Kansas, USA)	intra-annual	834	grassland	(int-) soil CO2 flux	Harper et al., 2005
(fix MAP)							
freq; int	Field	plot(Kruger National Park, South Africa)	intra-annual	544	sub-tropical savanna	(int+) wood growth; (int-) grass growth	Kulmatiski and Beard, 2013
sea	Field	plot(Oregon, USA)	intra-annual	[140,530]	grassland	impact biomass and bare soil fraction	Bates et al., 2006; Svejcar et al., 2003
(fix MAP)							
sea	Field						
freq; int; MAP	Field	plot(South Africa)	intra-annual	[538,798]	grassland	(int-) ANPP	Swemmer et al., 2007
MAP; sea	Field	plot(Spain)	intra-/inter-an nual	242	grassland	Mediterranean dryland ecosystem has more resilience for intra- and inter-annual changes in rainfall	Miranda et al., 2008



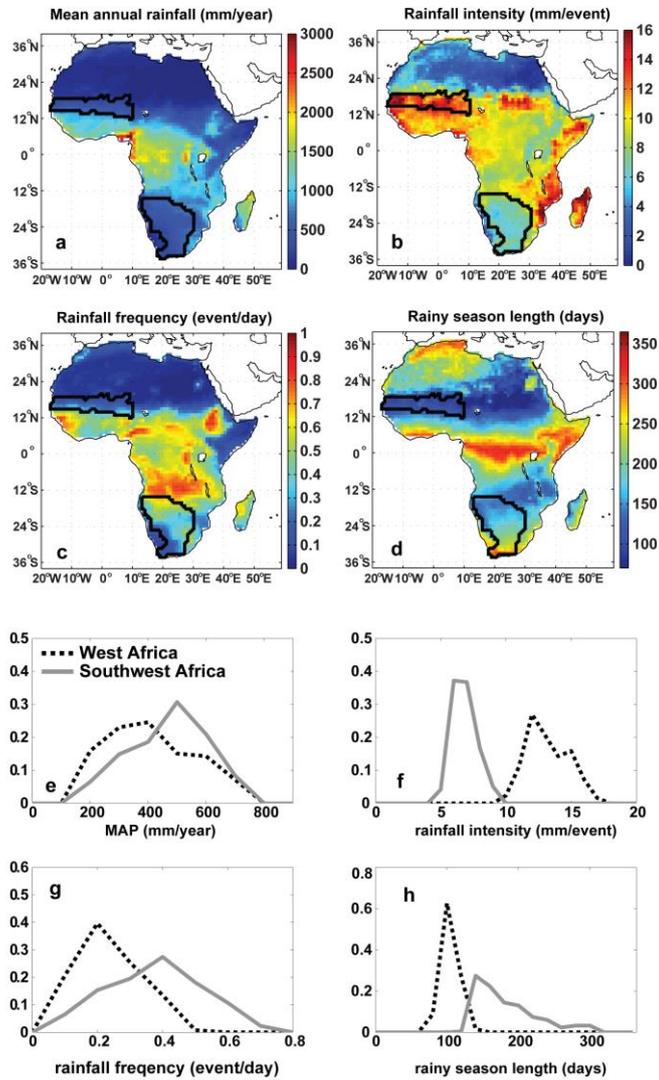


Figure 1. a-b: Spatial pattern of the rainfall characteristics in Africa: a-MAP; b-rainfall intensity; c-rainfall frequency; d-rainy season length. The black-line identified areas refer to two savanna regions in West and Southwest Africa. e-f: Normalized histograms of the rainfall characteristics in two savanna regions of West and Southwest Africa. e-MAP (bin width for the x-axis: 100 mm/year); f-rainfall intensity (bin width for the x-axis: 1 mm/event); g-rainfall frequency (bin width for the x-axis: 0.1 event/day); h-rainy season length (bin width for the x-axis: 20 days).--

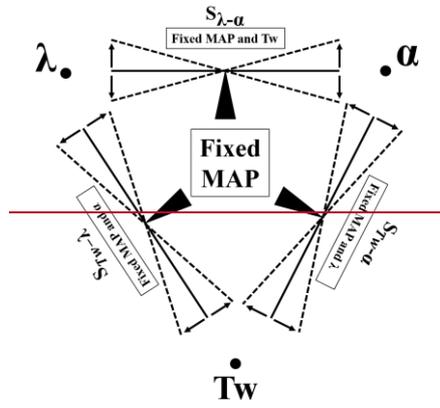


Figure 2. Conceptual diagram of the experiment designs for three experiments ( $S_{\lambda-\alpha}$ ,  $S_{Tw-\lambda}$ ,  $S_{Tw-\alpha}$ ).

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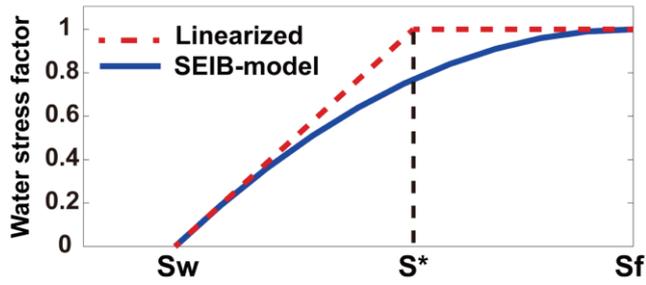


Figure 2. Schematic diagram of water stress factor ranging from 0 (most stressful) to 1 (no stress), which acts to reduce transpiration and carbon assimilation. The red dotted line is based on Porporato et al. (2001) with a reversed sign, and the SEIB-model SEIB-DGVM has a nonlinear implementation (blue solid line, Sato and Ise, 2012).

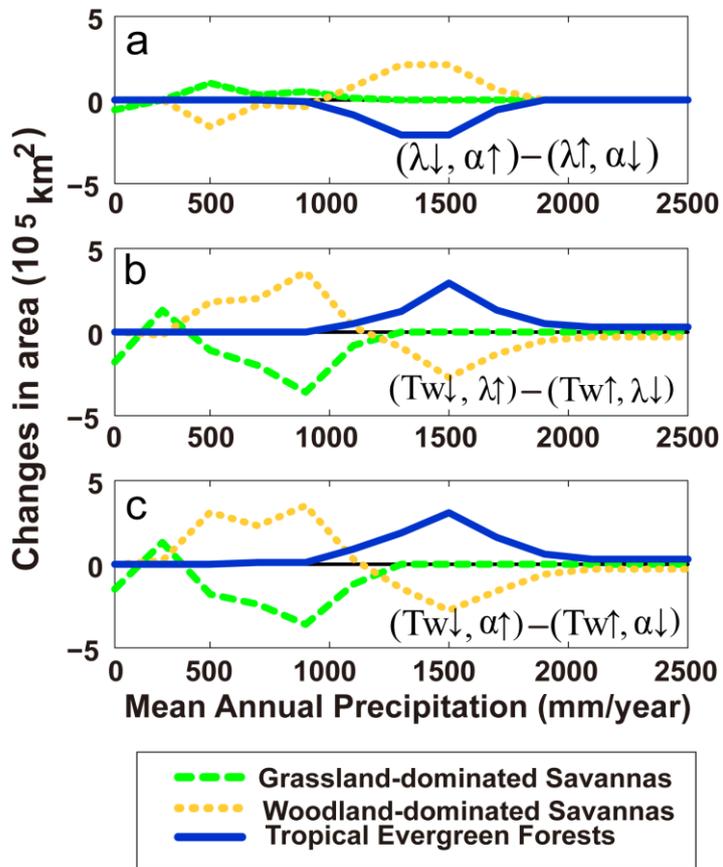
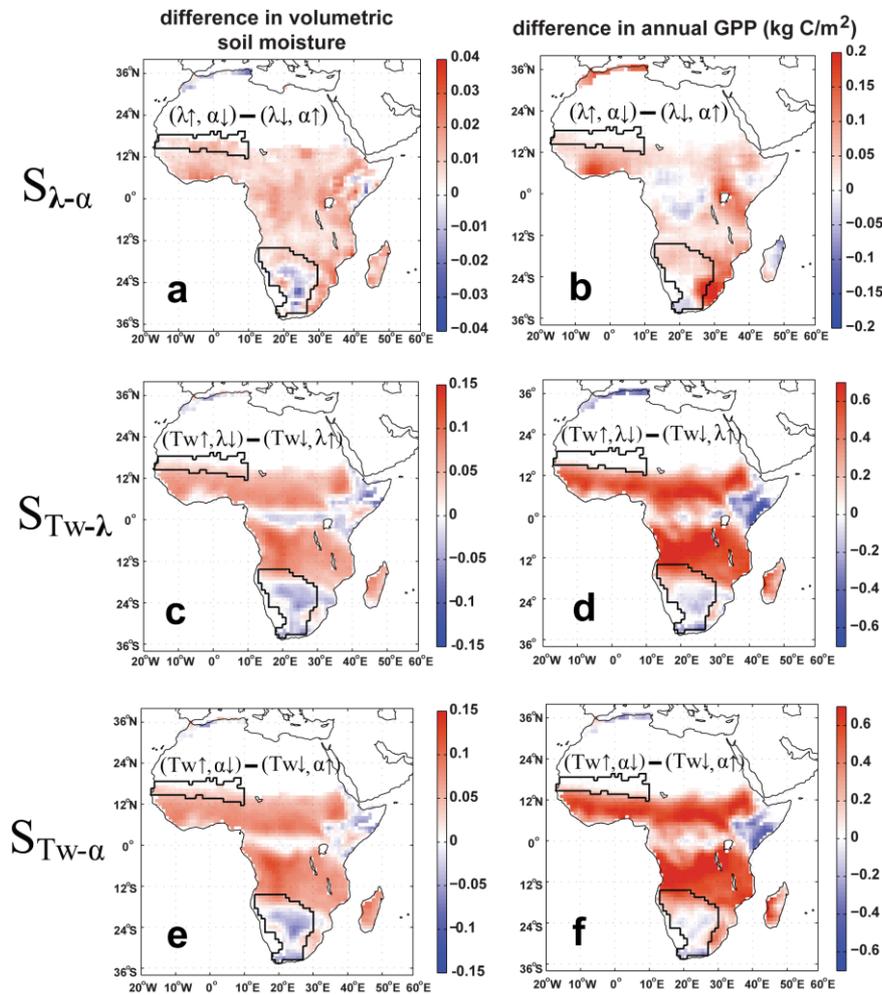
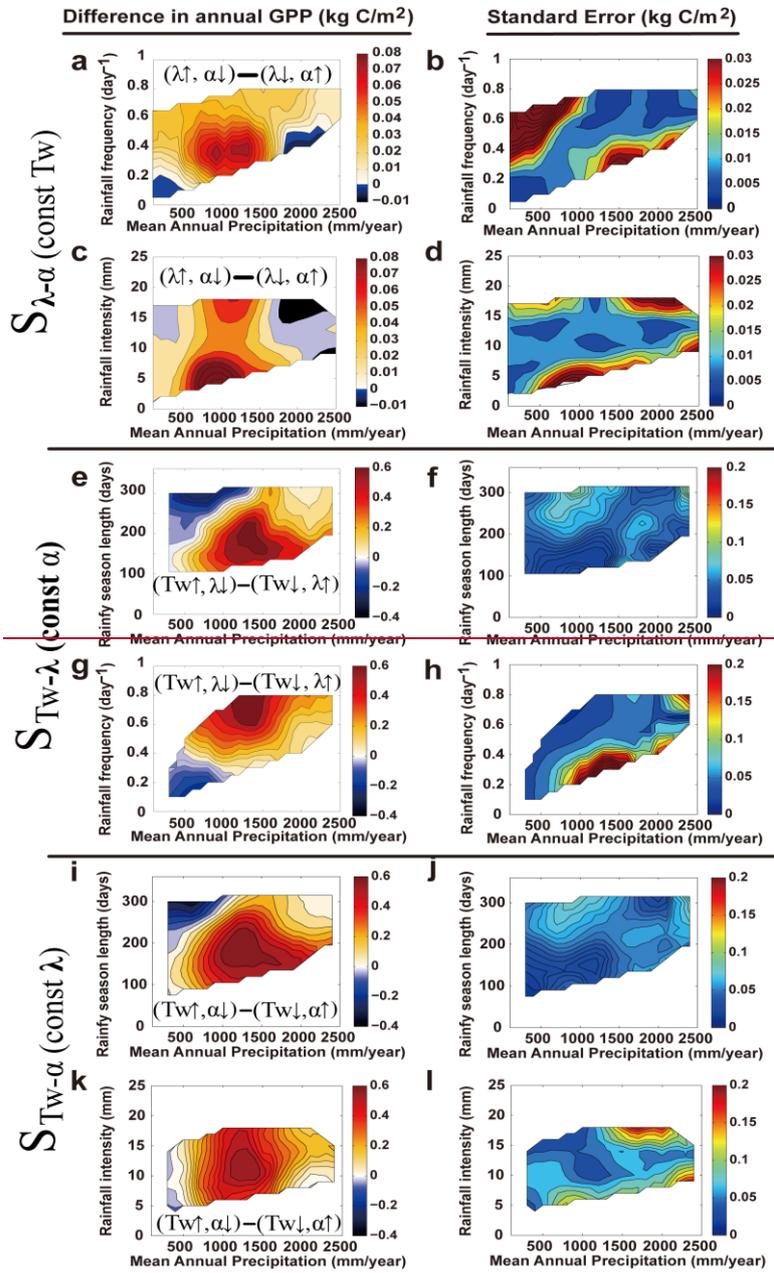
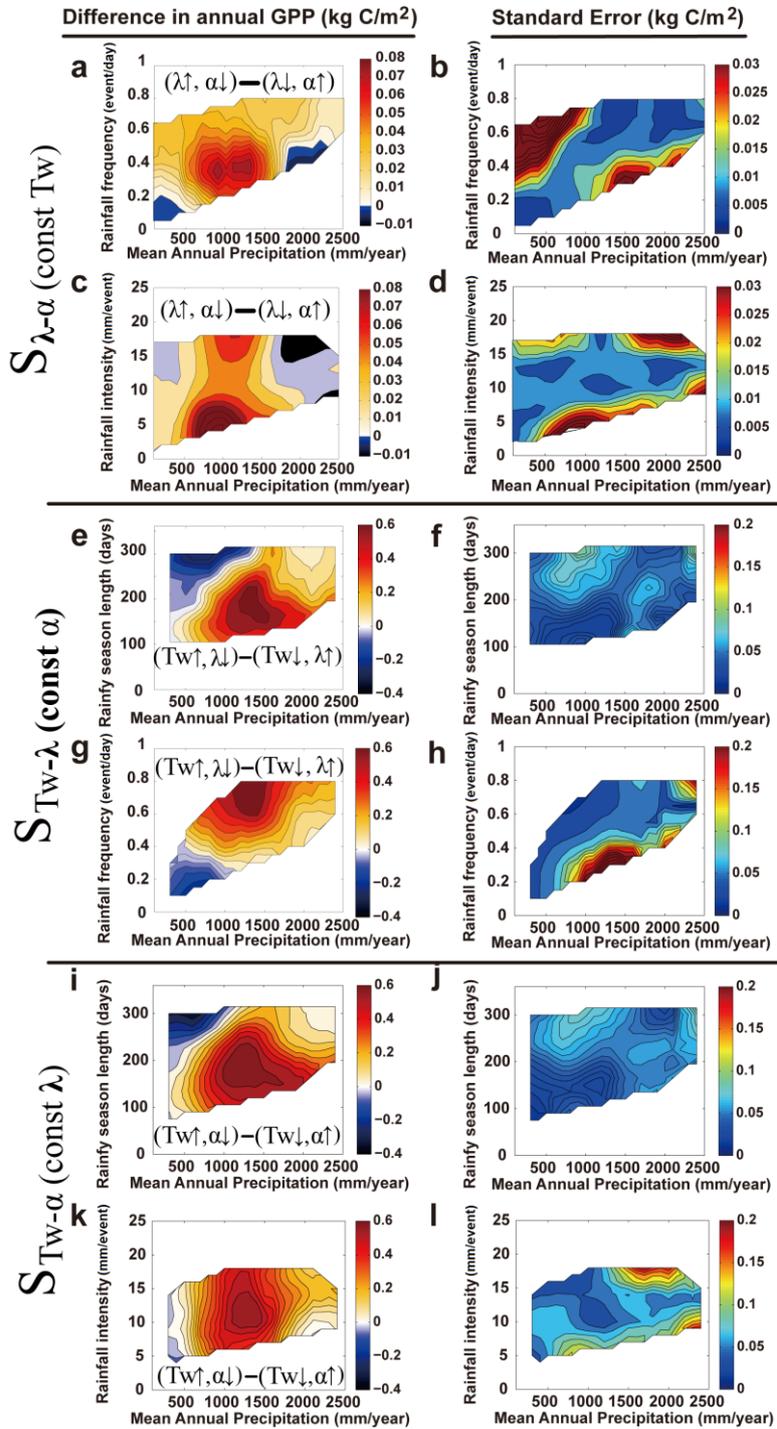


Figure 3. Differences in simulated dominated biomes in the three experiments (i.e.  $S_{\lambda-\alpha}$ ,  $S_{Tw-\lambda}$ ,  $S_{Tw-\alpha}$ ).

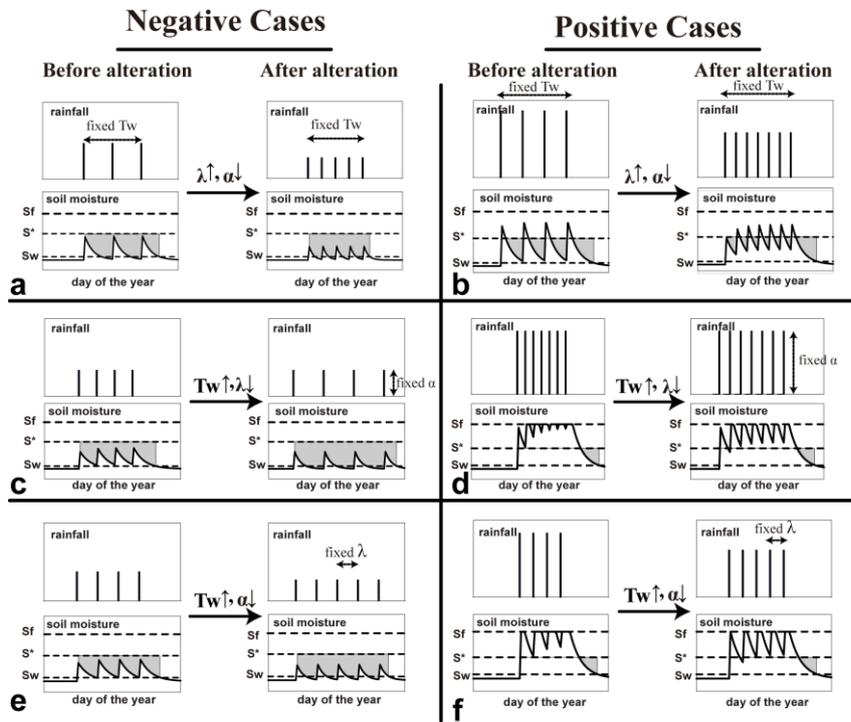


**Figure 4.** Simulated changes in annual mean soil moisture (0-500mm, first column) and annual mean GPP (second column) for different experiments. Please note that the scales of  $S_{\lambda-\alpha}$  is much smaller than those of  $S_{TW-\lambda}$  and  $S_{TW-\alpha}$ . The two areas with black boundaries in each panel are West African grassland and Southwest African grassland associated with Figure 1. The spatial patterns shown here are smoothed by 3\*3 smoothing window from the raw data.





~~Figure 6~~Figure 5. Differences in simulated annual GPP as a function of mean annual precipitation and one of the perturbed rainfall characteristics in all the three experiments (i.e.  $S_{\lambda-\alpha}$ ,  $S_{TW-\lambda}$ ,  $S_{TW-\alpha}$ ) in the left column. The right column shows the correspondent standard errors (SE, calculated as  $SE = \frac{\sigma}{\sqrt{n}}$ , where  $\sigma$  refers to the standard deviation within each bin,  $n$  is the sample size in each bin, and  $n$  and  $\sigma$  are shown in Figure S4), with larger values associated with more uncertainties and requires more caution in interpretation. The contours are based on the binned values, with for each 100 mm/year in MAP, each 0.05 ~~day~~<sup>event/day</sup> in rainfall frequency, each 1 ~~mm~~<sup>mm/event</sup> in rainfall intensity and each 15 day in rainy season length.



**Figure 6.** Illustrative time series for hydrological controls on plant root-zone soil moisture dynamics for all the experiments, and these illustrations are generalized based on the simulated time series from the experiments. Both negative and positive cases are shown, and cases with directly hydrological controls are shown (i.e. cloud-induced negative impacts in tropical forests are not shown). The cumulative shaded areas refer to “plant water stress” defined by Porporato et al. (2001).

Supplementary materials:

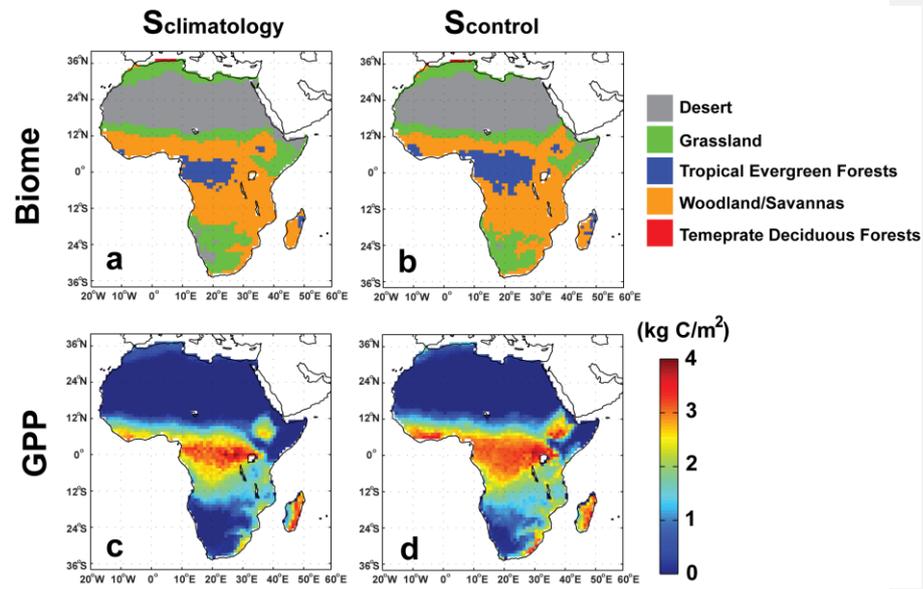


Figure S1. Comparison of biomes and annual GPP between  $S_{climatology}$  and  $S_{control}$  to test the validity of the synthetic weather generator. The biome definition follows Sato and Ise (2012).

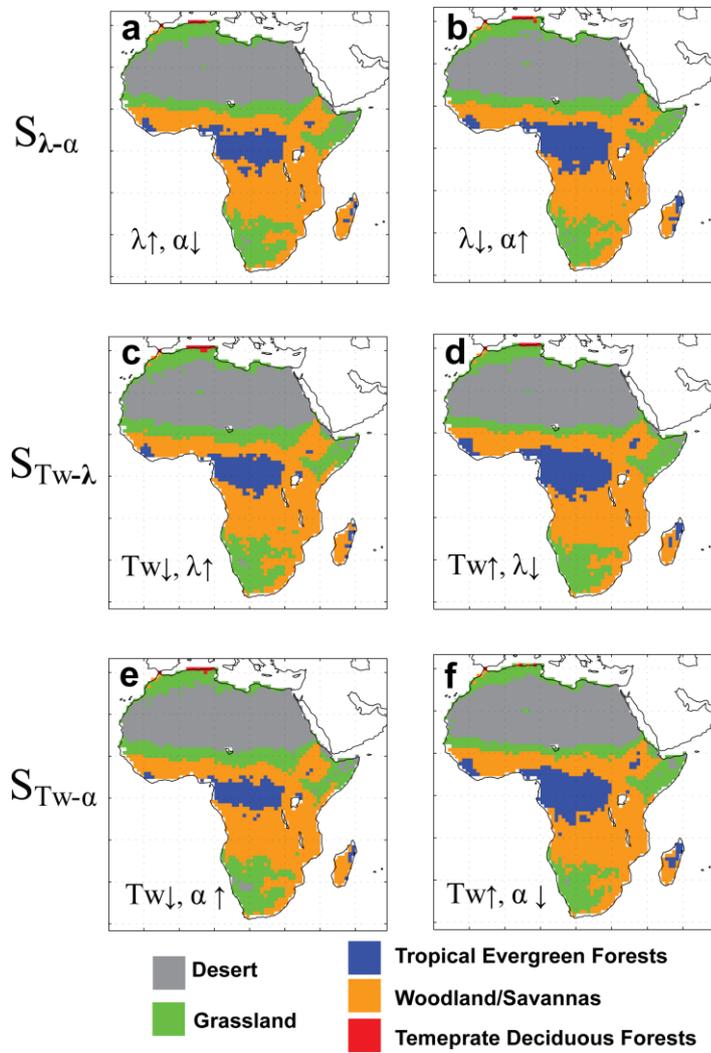


Figure S2. Simulated biomes for different experiments.

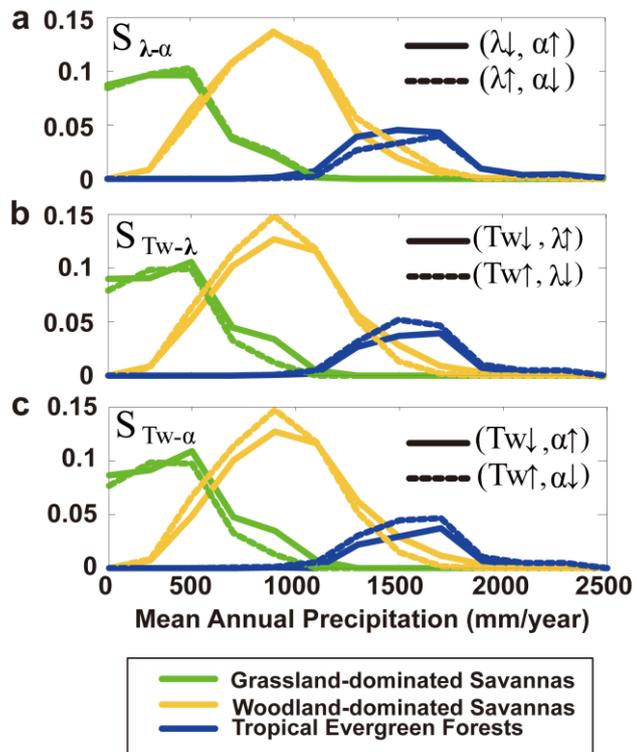
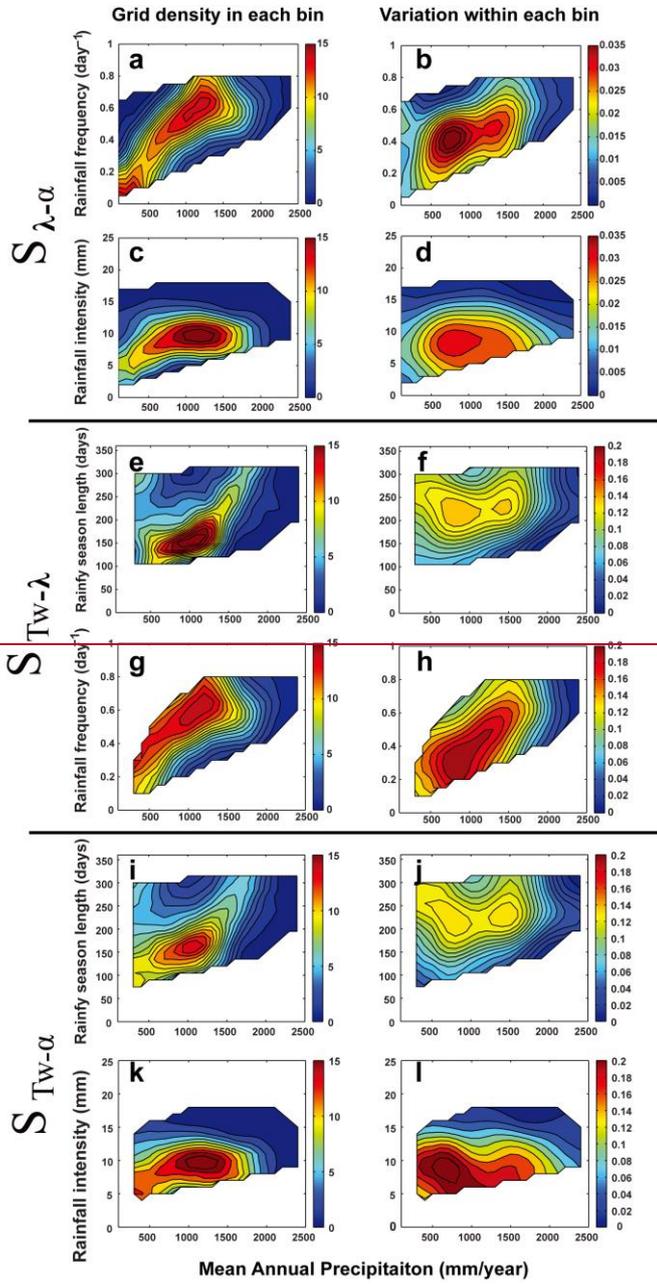


Figure S3. Normalized histograms of three simulated dominating biomes in the three experiments.



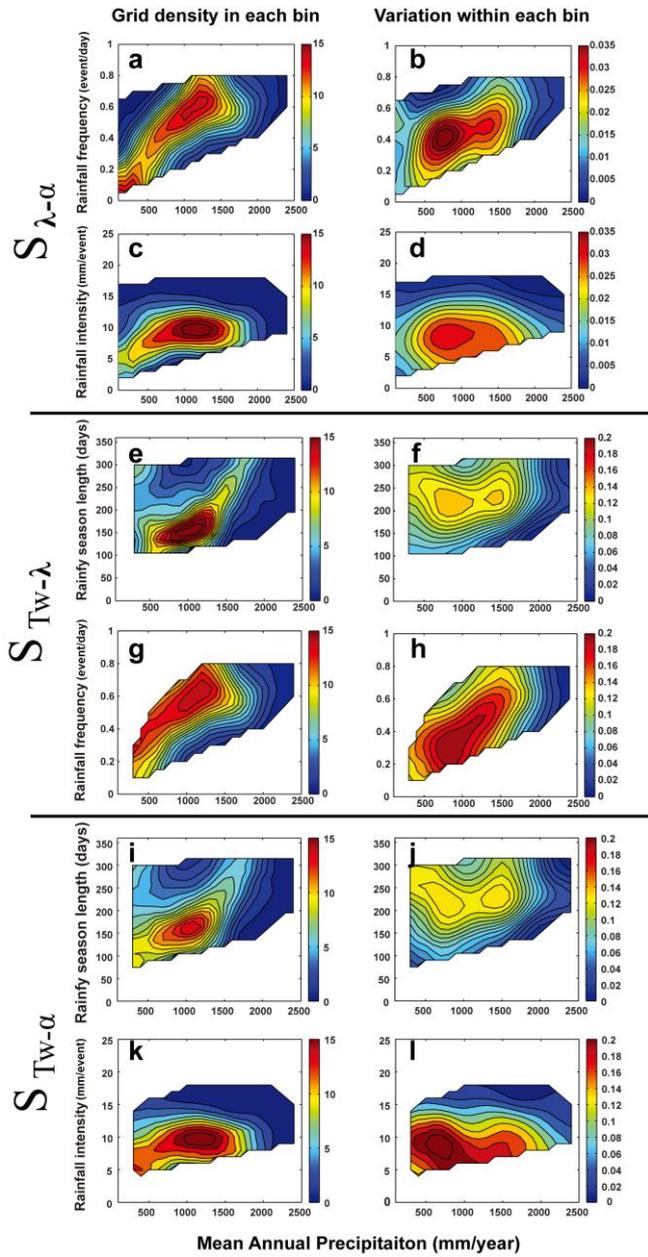


Figure S4. The sample size ( $n$ ) in each bin (left column) and standard deviation ( $\sigma$ ) in each bin (right column), corresponding to [Figure 6](#)[Figure 5](#). In [Figure 6](#)[Figure 5](#) right column, standard deviation (SE) is calculated as  $SE = \frac{\sigma}{\sqrt{n}}$ .

1       **Continental-scale impacts of intra-seasonal rainfall variability**  
2                               **on simulated ecosystem responses in Africa**

3  
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29 **Abstract:**

30 Climate change is expected to change intra-seasonal rainfall variability, arising from  
31 shifts in rainfall frequency, intensity and seasonality. These intra-seasonal changes are  
32 likely to have important ecological impacts on terrestrial ecosystems. Yet, quantifying  
33 these impacts across biomes and large climate gradients is largely missing. This gap  
34 hinders our ability to better predict ecosystem services and their responses to climate  
35 change, esp. for arid and semi-arid ecosystems. Here we use a synthetic weather  
36 generator and an independently validated vegetation dynamic model (SEIB-DGVM)  
37 to virtually conduct a series of “rainfall manipulation experiments” to study how  
38 changes in the intra-seasonal rainfall variability affect continent-scale ecosystem  
39 responses across Africa. We generated different rainfall scenarios with fixed total  
40 annual rainfall but shifts in: i) frequency vs. intensity, ii) rainy season length vs.  
41 frequency, iii) intensity vs. rainy season length. These scenarios were fed into  
42 SEIB-DGVM to investigate changes in biome distributions and ecosystem  
43 productivity. We find a loss of ecosystem productivity with increased rainfall  
44 frequency and decreased intensity at very low rainfall regimes (<400 mm/year) and  
45 low frequency (<0.3 event/day); beyond these very dry regimes, most ecosystems  
46 benefit from increasing frequency and decreasing intensity, except in the wet tropics  
47 (>1800 mm/year) where radiation limitation prevents further productivity gains. This  
48 result reconciles seemingly contradictory findings in previous field studies on rainfall  
49 frequency/intensity impacts on ecosystem productivity. We also find that changes in  
50 rainy season length can yield more dramatic ecosystem responses compared with  
51 similar percentage changes in rainfall frequency or intensity, with the largest impacts  
52 in semi-arid woodlands. This study demonstrates that not all rainfall regimes are  
53 ecologically equivalent, and that intra-seasonal rainfall characteristics play a  
54 significant role in influencing ecosystem function and structure through controls on  
55 ecohydrological processes. Our results also suggest that shifts in rainfall seasonality  
56 have potentially large impacts on terrestrial ecosystems, and these understudied  
57 impacts should be explicitly examined in future studies of climate impacts.

58 **Keywords:** rainfall frequency, rainfall intensity, rainfall seasonality, biome

59 distribution, Gross Primary Production (GPP), Africa

60

## 61 **1. Introduction**

62 Due to increased water holding capacity in the atmosphere as a consequence of global  
63 warming (O’Gorman and Schneider, 2009), rainfall is projected to change in intensity  
64 and frequency across much of the world (Easterling et al., 2000; Trenberth et al., 2003;  
65 Chou et al., 2013), in conjunction with complex shifts in rainfall seasonality (Feng et  
66 al., 2013; Seth et al., 2013). These changes possibly indicate a large increase in the  
67 frequency of extreme events and variability in rainfall (Easterling et al., 2000; Allan  
68 and Soden, 2008), and many of these changes may be accompanied with little changes  
69 in total annual rainfall (Knapp et al., 2002; Franz et al., 2010). Meanwhile, regions  
70 sharing similar mean climate state may have very different intra-seasonal variabilities,  
71 and the ecological significance of intra-seasonal climate variabilities has been largely  
72 overlooked previously in terrestrial biogeography (Good and Caylor, 2011). For  
73 example, ecosystems in West Africa and Southwest Africa (Figure 1) share similar  
74 total annual rainfall, but West Africa has much more intense rainfall events within a  
75 much shorter rainy season, while Southwest Africa has a longer and less intense rainy  
76 season. The same amount of total rainfall can come in very different ways, which may  
77 cause distinctive ecosystem responses and structure. Understanding the impacts of  
78 these regional differences in intra-seasonal rainfall variability and their possible future  
79 changes on terrestrial ecosystems is critical for maintaining ecosystem services and  
80 planning adaptation and mitigation strategies for ecological and social benefits  
81 (Anderegg et al., 2013).

82

83 [insert Figure 1]

84

85 The changes in intra-seasonal rainfall characteristics, specifically frequency,  
86 intensity and seasonality, have critical significance to ecosystem productivity and  
87 structure (Porporato et al., 2001; Weltzin et al., 2003; Williams and Albertson, 2006;  
88 Good and Caylor, 2011; Guan et al., 2014), but previous studies on this topic

89 (summarized in Table 1) have their limitations in the following aspects. First, existing  
90 relevant field studies mostly focus on a single ecosystem, *i.e.* grasslands, and  
91 subsequently only low rainfall regimes have been examined to date (mostly below  
92 800mm/year, see Table 1). Grasslands have the largest sensitivity to hydrological  
93 variabilities among all natural ecosystems (Scanlon et al., 2005; Guan et al., 2012),  
94 however inferences drawn from a single ecosystem are limited in scope and difficult  
95 to apply to other ecosystems. Second, even within grasslands, different studies have  
96 seemingly contradictory findings (see Table 1), and there is a lack of a comprehensive  
97 framework to resolve these inconsistencies. Specifically, whether increased rainfall  
98 intensity with decreased rainfall frequency has positive (Knapp et al., 2002; Fay et al.,  
99 2003; Robertson et al., 2009; Heisler-White et al., 2009) or negative impacts  
100 (Heisler-White et al., 2009; Thomey et al., 2011) on grassland productivity is still  
101 under debate. Third, previous relevant studies mostly focus on the impacts of rainfall  
102 frequency and intensity (Table 1 and Rodríguez-Iturbe and Porporato, 2004), and  
103 largely overlook the possible changes in rainfall seasonality. Rainfall frequency and  
104 intensity mostly describe rainfall characteristics within the rainy season, but do not  
105 account for the impacts of interplay between rainy season length and dry season  
106 length (Guan et al., 2014). For ecosystems predominately controlled by water  
107 availability, rainy season length constrains the temporal niche for active plant  
108 physiological activities (van Schaik et al., 1993; Scholes and Archer, 1997), and large  
109 variations in rainfall seasonality can lead to significant shifts in biome distribution  
110 found from paleoclimate pollen records (e.g. Vincens et al., 2007). Given changes in  
111 rainfall seasonality have been found in various tropical regions (Feng et al., 2013) and  
112 have been projected in future climate (Biasutti and Sobel, 2009; Shongwe et al., 2009;  
113 Seth et al., 2013), studies investigating their impacts on terrestrial ecosystems are  
114 relatively rare, and very few field studies are designed to address this aspect (Table 1,  
115 Bates et al., 2006; Svejcar et al., 2003; Chou et al., 2008). Finally, there is an  
116 increasing trend of large-scale studies addressing rainfall variability and ecological  
117 responses using satellite remote sensing (Fang et al., 2005; Zhang et al., 2005; Good  
118 and Caylor, 2011; Zhang et al., 2013; Holmgren et al., 2013) and flux network data

119 (Ross et al., 2012). These large-scale studies are able to expand analyses to more  
120 types of ecosystems and different climate conditions, and provide valuable  
121 observation-based insights. However there are very few theoretical modeling works to  
122 corroborate this effort. All these above issues call for a comprehensive modeling study  
123 to investigate different aspects of intra-seasonal rainfall variability on terrestrial  
124 ecosystems spanning large environmental gradients and various biomes.

125 In this paper, we aim to study ecological impacts of intra-seasonal rainfall  
126 variability on terrestrial ecosystems. In particular, we design virtual “rainfall  
127 manipulation experiments” to concurrently shift intra-seasonal rainfall characteristics  
128 without changing total annual rainfall. We focus on the impacts of these different  
129 rainfall scenarios on ecosystem productivity (e.g. Gross Primary Production, GPP)  
130 and biome distributions in the African continent, simulated by an independently  
131 validated dynamic vegetation model SEIB-DGVM (Sato and Ise, 2012). Previous  
132 modeling approaches in this topic (Gerten et al., 2008; Hély et al., 2006) designed  
133 various rainfall scenarios by rearranging (halving, doubling or shifting) the rainfall  
134 amount based on the existing rainfall observations. In contrast to these approaches, we  
135 design a weather generator based on a stochastic rainfall model (Rodríguez-Iturbe et  
136 al., 1999), which allows us to implement a series of experiments by synthetically  
137 varying two of the three rainfall characteristics (rainfall intensity, rainfall frequency,  
138 and rainy season length) while fixing total annual rainfall at the current climatology.  
139 We choose Africa as our test-bed mostly because the following two reasons: (1) the  
140 rainfall regimes and biomes have large gradients varying from extremely dry  
141 grasslands to highly humid tropical evergreen forests; (2) Africa is a continent usually  
142 assumed to have few temperature constraints (Nemani et al., 2003), which will help to  
143 isolate the impacts of precipitation from temperature, as one challenge in attributing  
144 climatic controls on temperate ecosystems or Mediterranean ecosystems is the  
145 superimposed influences from both temperature and precipitation. The overarching  
146 science question we will address is: **How do African ecosystems respond to possible**  
147 **changes in intra-seasonal rainfall variability (i.e. rainfall frequency, intensity and**  
148 **rainy season length)?**

149

150 [insert Table 1]

151

## 152 **2. Materials and Methods**

### 153 **2.1 Methodology overview**

154 Table 1 summarizes previous field-based rainfall manipulation experiments, such as  
155 the one that Knapp et al. (2002) did in a grassland that concurrently increasing rainfall  
156 frequency and decreasing rainfall intensity while fixing total rainfall. The central idea  
157 of our study is to design similar rainfall manipulation experiments but test them  
158 virtually in the model domain across large environment gradients. We manipulate  
159 rainfall changes through a weather generator based on a parsimonious stochastic  
160 rainfall model (Rodriguez-Iturbe et al., 1984). We model the total amount of rainfall  
161 during rainy season as a product of the three intra-seasonal rainfall characteristics for  
162 the rainy season, rainfall frequency ( $\lambda$ , event/day), rainfall intensity ( $\alpha$ , mm/event),  
163 and rainy season length ( $T_w$ , days) (More details in section 2.3). Thus it is possible to  
164 simultaneously perturb two of the rainfall characteristics away from their  
165 climatological values while preserving the mean annual precipitation (MAP)  
166 unchanged. We then feed these different rainfall scenarios into a well-validated  
167 dynamic vegetation model (SEIB-DGVM, section 2.2) to study simulated ecosystem  
168 responses. Detailed experiments design is described in section 2.5.

169

### 170 **2.2 SEIB-DGVM model and its performances in Africa**

171 We use a well-validated vegetation dynamic model SEIB-DGVM (Sato et al., 2007)  
172 as the tool to study ecosystem responses to different rainfall variabilities. This model  
173 follows the traditional “gap model” concept (Shugart, 1998) to explicitly simulate the  
174 dynamics of ecosystem structure and function for individual plants at a set of virtual  
175 vegetation patches, and uses results at these virtual patches as a surrogate to represent  
176 large-scale ecosystem states. Thus individual trees are simulated from establishment,  
177 competition with other plants, to death, which creates “gaps” for other plants to  
178 occupy and develop. SEIB-DGVM includes mechanical-based and empirical-based

179 algorithms for land physical processes, plant physiological processes, and plant  
180 dynamic processes. SEIB-DGVM contains algorithms that explicitly involve the  
181 mechanisms of plant-related water stress (Figure 2; Sato and Ise, 2012). With similar  
182 concepts to previous studies (e.g. Milly, 1992; Porporato et al., 2001), the current  
183 SEIB-DGVM implements a continuous “water stress factor” (Equation 2) based on  
184 the soil moisture status (Equation 1), scaling from 0 (most stressful) to 1 (with no  
185 stress), which then acts to scale the stomatal conductance for plant transpiration and  
186 carbon assimilation.

$$187 \quad stat_{water} = (S - S_w) / (S_f - S_w) \quad (\text{Equation 1})$$

$$188 \quad \text{Water stress factor} = 2 * stat_{water} - stat_{water}^2 \quad (\text{Equation 2})$$

189 where  $S$ ,  $S_w$  and  $S_f$  refer to the fraction of volumetric soil water content within the  
190 rooting depth, at the wilting point, and at field capacity, respectively. Figure 2  
191 provides a schematic diagram of “water stress factor” from the SEIB-DGVM, and we  
192 also include an approximated linear model that has been widely adopted elsewhere  
193 (e.g. Milly, 1992; Porporato et al., 2001). The linear model uses an extra variable  $S^*$ ,  
194 so called “critical point” of soil moisture: when  $S > S^*$ , there is no water stress (water  
195 stress factor = 1); and when  $S < S^*$ , water stress factor linearly decreases with the  
196 decrease of  $S$ . Though SEIB-DGVM adopts a quadratic form for “water stress factor”,  
197 it essentially functions similarly as the linear model, such that  $S^*$  distinguishes two  
198 soil moisture regimes that below which there is a large sensitivity of water stress to  
199 soil moisture status, and above which there is little water stress. Understanding how  
200 this “water stress factor” functions is the key to explain the following results.

201

202 [insert Figure 2]

203

204 SEIB-DGVM allows development of annual and perennial grasses as well as multiple  
205 life cycles of grass at one year based on environmental conditions. Multiple life cycles  
206 of tree growth per year are possible in theory but rarely happen in simulations (Sato  
207 and Ise, 2012). Soil moisture status is the predominant factor to determine LAI of the  
208 vegetation layer, which influences maximum daily productivity and leaf phenology.

209 When LAI exceeds 0 for 7 continuous days, dormant phase of perennial vegetation  
210 layer changes into growth phase. While when LAI falls below 0 for 7 continuous days,  
211 growth phase switches to dormant phase (Sato et al, 2007). SEIB-DGVM also  
212 explicitly simulates light conditions and light competition among different PFTs in the  
213 landscape based on its simulated 3D canopy structure and radiative transfer scheme  
214 (Sato et al, 2007).

215 SEIB-DGVM has been tested both globally (Sato et al., 2007) and regionally for  
216 various ecosystems (Sato et al., 2010; Sato, 2009; Sato and Ise, 2012), whose  
217 simulated results compare favorably with ground observations and satellite remote  
218 sensing measures for ecosystem composition, structure and function. In particular,  
219 SEIB-DGVM has been successfully validated and demonstrated its ability in  
220 simulating ecosystem structure and function in the African continent (Sato and Ise,  
221 2012). Two plant function types (PFTs) of tropical woody species are simulated by  
222 SEIB-DGVM in Africa: tropical evergreen trees and tropical deciduous trees. The  
223 distribution of these two woody types in the simulation is largely determined by  
224 hydro-climatic environments. Tropical evergreen trees only develop in regions where  
225 water resources are sufficient all year around, so they can maintain leaves for all  
226 seasons; otherwise, tropical deciduous trees could survive and dominate the landscape  
227 as they can shed leaves if there is no sufficient water supply in its root zone during the  
228 dry season (Sato and Ise, 2012). Trees and grasses coexist in a cell, with the floor of a  
229 virtual forest monopolized by one of the two grass PFTs, C<sub>3</sub> or C<sub>4</sub> grass. The  
230 dominating grass type is determined at the end of each year by air temperature,  
231 precipitation, and CO<sub>2</sub> partial pressure (Sato and Ise, 2012).

232 SEIB-DGVM was run at 1 ° spatial resolution and at the daily step. It was spun-up  
233 for 2000 years driven by the observed climate (1970-2000) repeatedly for the soil  
234 carbon pool to reach steady state, followed by 200 years simulation driven by the  
235 forcings based on the experiment design in Section 2.4. Because our purpose is to  
236 understand the direct impacts of intra-seasonal rainfall variability, we turned off the  
237 fire component of SEIB-DGVM to exclude fire-mediated feedbacks in the results.  
238 Though we are fully aware of the important role of fire in interacting with rainfall

239 seasonality and their influence on African ecosystems (Bond et al., 2005; Lehmann et  
240 al., 2011; Staver et al., 2012), studying these interactions is beyond the scope of this  
241 work. For the similar reason, we fixed the atmospheric CO<sub>2</sub> concentration at 380  
242 ppmv to exclude possible impacts of CO<sub>2</sub> fertilization effects.

243

### 244 **2.3 Synthetic weather generator**

245 The synthetic weather generator used here has two major components: i) to  
246 stochastically generate daily rainfall based on a stochastic rainfall model, and ii) to  
247 conditionally sample all other environmental variables from historical records to  
248 preserve the covariance among climate forcing variables.

249 The stochastic rainfall model can be expressed as  $MAP = \alpha \lambda T_w / f_w$ , and we set  $f_w$   
250 to be 0.9, i.e. the period including 90% of total annual rainfall is defined as “rainy  
251 season” (exchangeable with “wet season” hereafter). In particular, we first use  
252 Markham (1970)’s approach to find the center of the rainy season, and then extend the  
253 same length to both sides of the center until the total rainfall amount in this temporal  
254 window (i.e. “rainy season”) is equal to 90% of the total annual rainfall. Rainy season  
255 and dry season have their own rainfall frequency and intensity. Two seasons are  
256 separately modeled based on the Market Poisson Process. Here we only focus on and  
257 manipulate rainy-season rainfall characteristics in our study, as rainy-season rainfall  
258 accounts for almost all the meaningful rainfall inputs for plant use. Thus in the  
259 following paper, whenever we mention  $\alpha$  or  $\lambda$ , we refer to those during the rainy  
260 season.

261 In this rainfall model, any day can be either rainy or not, and a rainy day is  
262 counted as one rainy event; rainfall events occur as a Poisson Process, with the  
263 parameter  $1/\lambda$  (unit: days/event) being the mean intervals between rainfall events, and  
264 rainfall intensity  $\alpha$  for each rainfall event following an exponential distribution, with  $\alpha$   
265 being the mean rainfall intensity per event (Rodríguez-Iturbe et al., 1999). The wet  
266 season length is modeled as a beta distribution bounded from 0 to 1, scaled by 365  
267 days. All the necessary parameters to fit for the stochastic rainfall model (including  
268 the mean and variance of rainfall frequency, intensity and length of wet and dry

269 seasons) were derived from the satellite-gauge-merged rainfall measurement from  
270 TRMM 3b42V7 (Huffman et al., 2007) for the period of 1998 to 2012, based on the  
271 above assumptions for the rainfall process. Specifically, we applied our definition of  
272 “rainy season” to each year of the TRMM rainfall data for per pixel, and calculated  
273 the mean and variance of the “rainy season length”, using which we fitted the beta  
274 distribution for  $T_w$ . For rainfall frequency and intensity, we lumped all the wet or dry  
275 season rainfall record together to derive their parameters. The two steps of the  
276 synthetic weather generator are described below:

277 **Step 1:** Model the daily rainfall following the Marked Poisson process described  
278 above. In particular, for a specific year, we first stochastically generate the wet season  
279 length by sampling from the beta distribution, and the dry season length is determined  
280 accordingly. Then we generate the daily rainfall for wet and dry season respectively.

281 **Step 2:** Based on the simulated daily rainfall time series in Step 1, we conditionally  
282 sample temperature, wind, and humidity from the Global Meteorological Forcing  
283 Dataset (GMFD, Sheffield et al., 2006), as well as cloud fraction and soil temperature  
284 from the Climate Forecast System Reanalysis (CFSR) from National Centers for  
285 Environmental Prediction (NCEP) (Saha et al., 2010). To sample for a specific day, all  
286 the historical record within a 21-day time window centered at that specific day makes  
287 up a sampling pool. From the sampling pool, we choose the day such that the  
288 historical rainfall amount of the chosen day is within  $(100-30)\%$  to  $(100+30)\%$  of the  
289 simulated daily rainfall amount. We then draw all the environmental variables (except  
290 rainfall) on that sampled day to the new climate forcing. If we can find a sample from  
291 the pool based on the above rule, this sampling is called “successful”. When there is  
292 more than one suitable sample, we randomly select one. When there is no suitable  
293 sample, we randomly select one day within the pool. The mean “successful” rate for  
294 all the experiments and ensembles across Africa is 83%.

295 To test the validity of the synthetic weather generator, we ran SEIB-DGVM using  
296 the historical climate record ( $S_{\text{climatology}}$ ) and the synthetic forcing ( $S_{\text{control}}$ ), with the  
297 latter generated using the weather generator based on the rainfall characteristics  
298 derived from the former. Figure S1 shows that the SEIB-DGVM simulations driven

299 by these two different forcings generate similar biome distributions with a Cohen's  
300 Kappa coefficient of 0.78 (Cohen, 1960), and similar GPP patterns in Africa, with the  
301 linear fit of annual GPP as:  $GPP(S_{\text{control}}) = 1.03 \times GPP(S_{\text{climatology}}) + 0.215$  ( $R^2=0.89$ ,  
302  $P<0.0001$ ). Both biome and GPP patterns are consistent with observations (Sato and  
303 Ise, 2012). These results provide confidence in using the synthetic weather generator  
304 and SEIB-DGVM to conduct the further study.

305

## 306 **2.4 Experiment design**

307 Three experiments are designed as follows:

308 **Exp 1** (Perturbation of rainfall frequency and intensity, termed as  $S_{\lambda-\alpha}$  hereafter)  
309 Simulations forced by the synthetic forcings with varying  $\lambda$  and  $\alpha$  simultaneously for  
310 wet season (20% increases of  $\lambda$  and corresponding decreases of  $\alpha$  to make MAP  
311 unchanged; 20% decreases of  $\lambda$  and corresponding increases of  $\alpha$  to make MAP  
312 unchanged; no change for dry season rainfall characteristics), while fixing  $T_w$  at the  
313 current climatology;

314 **Exp 2** (Perturbation of rainfall frequency and rainy season length, termed as  $S_{T_w-\lambda}$ )  
315 Simulations forced by the synthetic forcing with varying  $T_w$  and  $\lambda$  simultaneously for  
316 wet season (20% increases of  $T_w$  and corresponding decreases of  $\lambda$  to make MAP  
317 unchanged; 20% decreases of  $T_w$  and corresponding increases of  $\lambda$  to make MAP  
318 unchanged; no change for dry season characteristics), while fixing  $\alpha$  at the current  
319 climatology;

320 **Exp 3** (Perturbation of rainy season length and intensity, termed as  $S_{T_w-\alpha}$ ) Simulations  
321 forced by the synthetic forcing with varying  $T_w$  and  $\alpha$  simultaneously for wet season  
322 (20% increases of  $T_w$  and corresponding decreases of  $\alpha$  to make MAP unchanged;  
323 20% decreases of  $T_w$  and corresponding increases of  $\alpha$  to make MAP unchanged; no  
324 change for dry season characteristics), while fixing  $\lambda$  at the current climatology.

325 Because  $\lambda$  and  $T_w$  have bounded ranges ( $\lambda \sim [0, 1]$  and  $T_w \sim [0, 365]$ ), if these two  
326 variables after perturbation exceeds the range, we would force their value to be the  
327 lower or upper bound, and rearrange the other corresponding rainfall characteristic to  
328 ensure MAP unchanged. Each rainfall scenario has six ensemble realizations of

329 synthetic climate forcings to account for the stochasticity of our synthetic weather  
330 generator.

331

### 332 **3. Results**

333 We present the differences in simulated biome distributions of the three experiments  
334 (i.e.  $S_{\lambda-\alpha}$ ,  $S_{TW-\lambda}$ ,  $S_{TW-\alpha}$ ) in Figure 3, and their spatial patterns are shown in Figure S2  
335 and S3. Differences in simulated annually averaged soil moisture and GPP for each  
336 experiment are shown in Figure 4 and 6. These differences represent the simulated  
337 ecosystem sensitivity to the slight perturbation of intra-seasonal rainfall characteristics  
338 deviating from the current climatology. To further explore how MAP and these  
339 rainfall characteristics affect the simulated GPP, Figure 5 shows the difference of  
340 simulated GPP as a function of MAP and a perturbed rainfall characteristic in the  
341 corresponding experiment. We term Figure 5 as “GPP sensitivity space”, and “positive  
342 GPP sensitivity” means that GPP changes at the same direction with MAP or rainfall  
343 characteristics, and vice versa for “negative GPP response”. These “GPP sensitivity  
344 spaces” are generated based on the aggregated mean GPP in each bin of the rainfall  
345 properties. The bin size for MAP, rainfall frequency, rainfall intensity and rainy  
346 season length are 100 mm/year, 0.05 event/day, 1 mm/event and 15 days respectively.  
347 We also provide the standard error (SE) of the “GPP sensitivity spaces” in each bin to  
348 assess their uncertainties, with higher SE meaning larger uncertainties.  $SE = \frac{\sigma}{\sqrt{n}}$ ,  
349 where  $\sigma$  and n refer to the standard deviation of GPP values and the sample size in  
350 each bin respectively. A series of illustrations in Figure 6 were generalized from the  
351 simulated time series, and are used to explain the underlying mechanisms.

352

353 [insert Figure 3; Figure 4; Figure 5]

354

#### 355 **3.1 Ecosystem sensitivity to rainfall frequency and intensity (Experiment $S_{\lambda-\alpha}$ )**

356 Experiment  $S_{\lambda-\alpha}$  assesses ecosystem responses after increasing rainfall frequency  $\lambda$   
357 and decreasing rainfall intensity  $\alpha$  ( $\lambda\uparrow$ ,  $\alpha\downarrow$ ) under a fixed total annual rainfall. The

358 simulated biome distributions show that a small portion of regions are converted from  
359 woodland to grassland at low rainfall regime (~500 mm/year), corresponding to a  
360 decrease of GPP in these regions. In the high rainfall regime (around 1500 mm/year,  
361 Figure 3a), increasing rainfall frequency significantly converts tropical evergreen  
362 forests into woodlands. In the intermediate rainfall regime (600-1000 mm/year), there  
363 is little change in biome distributions. We further check the spatial patterns of  
364 differences in annual mean soil moisture and annual total GPP (Figure 4a and 5b). We  
365 find that GPP increases with increasing rainfall frequency across most of the Africa  
366 continent, except in the very dry end (in the southern and eastern Africa) and the very  
367 wet regions (in central Africa and northeastern Madagascar). This GPP pattern mostly  
368 mirrors the soil moisture change in woodlands and grasslands (Figure 4b), except the  
369 wet tropics, where the changes of soil moisture and GPP are reversed.

370 Figure 5a shows the GPP sensitivity as a function of MAP and the climatological  
371 rainfall frequency, and we find three major patterns:

372 **Pattern 1.1:** Negative GPP sensitivity shows up in the very dry end of MAP regime  
373 (MAP<400 mm/year) and with relatively low rainfall frequency ( $\lambda < 0.3$  event/day), i.e.  
374 GPP decreases with more frequent but less intense rainfall in this low rainfall range.

375 **Pattern 1.2:** Across most rainfall ranges (MAP from 400 mm/year to 1600 mm/year),  
376 increasing frequency of rainfall (and simultaneously decreasing rainfall intensity) lead  
377 to positive GPP sensitivity. This positive GPP sensitivity peaks at the low range of  
378 rainfall frequency (~0.35 event/day) and around the MAP of 1000 mm/year.

379 **Pattern 1.3:** At the high range of MAP (>1800 mm/year) with low rainfall frequency  
380 (~0.4 event/day), GPP decreases with increased rainfall frequency.

381 The relationship of GPP sensitivity to MAP and rainfall intensity (Fig. 6c) has no  
382 clear patterns as previous ones, mostly because the GPP sensitivity space (Fig. A4c)  
383 contains large uncertainties (Fig. A4d, shown as large variance in the data). Thus we  
384 will not over-interpret the pattern in Fig. 6c.

385 Pattern 1.1 and Pattern 1.2 can be explained by the illustrative time series in  
386 Figure 6a and 6b, respectively. Figure 6a shows that when rainfall events are small  
387 and very infrequent, increasing rainfall frequency while decreasing intensity would

388 cause more frequent downcrossings of soil moisture at the wilting point  $S_w$ , which  
389 subsequently would reduce the effective time of carbon assimilation and plant growth  
390 (i.e. when soil moisture is below  $S_w$ , plants would be in the extreme water stress and  
391 slow down or stop physiological activity). This case only happens where MAP is very  
392 low with low frequency and the biome is predominantly grasslands, which explains  
393 why negative changes in soil moisture and GPP in Figure 4a and 4b are distributed in  
394 those regions. This result also corroborates the field findings of the negative impacts  
395 from increasing rainfall frequency in Heisler-White et al.(2009) and Thomey et al.  
396 (2011) at low rainfall regimes.

397 Figure 6b provides the hydrological mechanism for the positive sensitivity of soil  
398 moisture and GPP with increasing rainfall frequency over the most African continent  
399 (Pattern 1.2). Once individual rainfall event has enough intensity and rainfall  
400 frequency is enough, downcrossings of  $S_w$  would not easily happen. Instead, the  
401 accumulative rainy-season soil moisture becomes the dominant control of plant  
402 growth, and increasing rainfall frequency has led to a significant increase of soil  
403 moisture for plant water use (Figure 4a and 4b). This conclusion drawn from our  
404 numerical modeling is consistent with previous findings in Rodríguez-Iturbe and  
405 Porporato (2004) based on stochastic modeling. We also find that this positive GPP  
406 sensitivity reaches to its maximum in the intermediate total rainfall (~1000 mm/year)  
407 and relatively low rainfall frequency (~0.35 event/day), indicating that in these  
408 regimes increasing rainfall frequency could most effectively increase soil moisture for  
409 plant water use and create marginal benefits of GPP to the increased rainfall frequency.  
410 Further increase in large total annual rainfall or rainfall frequency would reduce the  
411 sensitivity to water stress with fewer downcrossings of soil moisture critical point  $S^*$ ;  
412 and once the soil moisture is always ample (i.e. above  $S^*$ ), the changes in either MAP  
413 or rainfall frequency would not alter plant water stress.

414 Pattern 1.3 also shows a negative GPP sensitivity, but its mechanism is different  
415 from the previous case of Pattern 1.1. In regions with total rainfall usually more than  
416 1800 mm/year, SEIB-simulated tropical forests exhibit radiation-limitation rather than  
417 water-limitation during wet season. Increase of rainfall frequency at daily scale would

418 enhance cloud fraction and suppress plant productivity in these regions (Graham et al.,  
419 2003). Thus even though soil moisture still increases (Figure 4a), GPP decreases with  
420 increased rainfall frequency. This mechanism also explains why tropical evergreen  
421 forests shrink its area with increased rainfall frequency (Figure 3a).

422 It is worth noting that the magnitude of GPP changes due to rainfall frequency  
423 and intensity is relatively small in most of the woodlands, but can be relatively large  
424 for drylands with MAP below 600 mm/year (up to 10-20% of annual GPP). This  
425 pattern also explains why only modest changes in biome distribution happen between  
426 woodlands and grasslands in  $S_{\lambda-\alpha}$  (Figure 3a).

427

428 [insert Figure 6]

429

### 430 **3.2 Ecosystem sensitivity to rainfall seasonality and frequency (Experiment $S_{T_w-\lambda}$ )**

431 Experiment  $S_{T_w-\lambda}$  assesses ecosystem responses after increasing rainy season length  
432 and decreasing rainfall frequency (i.e.  $T_w \uparrow$ ,  $\lambda \downarrow$ ) under a fixed total annual rainfall. The  
433 simulated biome distribution shows a gain of area in tropical evergreen forests  
434 converted from woodlands. The northern Africa has an area increase of woodlands  
435 converted from grasslands, and African Horn region has a small expansion of  
436 grasslands into woodlands (Figure 3b). Figure 4c and 4d show that increasing rainy  
437 season length  $T_w$  and decreasing frequency  $\lambda$  would significantly increase annual  
438 mean soil moisture and GPP (up to 30%) in most woodland area. Meanwhile  
439 decreased soil moisture and GPP are found in the southern and eastern Africa.  
440 Tropical evergreen forests show little response. We further explore the GPP sensitivity  
441 space in Figure 5e and 5g, and find the following robust patterns (based on small  
442 standard errors shown in Figure 5f and 5h):

443 **Pattern 2.1:** The negative GPP sensitivity tends to happen where MAP is mostly  
444 below 1000 mm/year with long rainy season length ( $T_w > 150$  days) and low rainfall  
445 frequency ( $\lambda < 0.35$  event/day).

446 **Pattern 2.2:** When MAP and rainfall frequency are large enough (MAP > 1000  
447 mm/year and  $\lambda > 0.4$  event/day), decreasing  $\lambda$  while increasing  $T_w$  would significantly

448 increase GPP. The maximum positive GPP sensitivity happens at the intermediate  
449 MAP range (1100-1500 mm/year) and the high rainfall frequency ( $\lambda \sim 0.7$  event/day).

450 **Pattern 2.3:** There exists an “optimal rainy season length” for relative changes in  
451 ecosystem productivity across large MAP ranges (the white area between the red and  
452 blue space in Figure 5e). For the same MAP, any deviation of  $T_w$  from the “optimal  
453 rainy season length” would reduce GPP. This “optimal rainy season length” follows  
454 an increasing trend with MAP until 1400 mm/year.

455 Figure 6c explains the hydrological mechanism for the negative GPP sensitivity  
456 in Pattern 2.1. In the situation with low MAP and infrequent rainfall events,  
457 decreasing rainfall frequency and expanding rainy season length (i.e.  $T_w \uparrow$ ,  $\lambda \downarrow$ ) would  
458 lead to longer intervals between rainfall events and possibly longer excursions below  
459  $S_w$ , which would disrupt continuous plant growth and have detrimental effects on  
460 ecosystem productivity. It is worth noting that long rainy season in dryland (Figure 5e)  
461 is usually accompanied with low rainfall frequency (Figure 5g). The southern African  
462 drylands (south of 15 °S) typically fall in this category, and these regions thus have  
463 negative GPP sensitivity (Figure 4c and 4d), accompanied by a small biome  
464 conversion from woodlands to grasslands (Figure 3b).

465 Figure 6d explains the hydrological mechanisms for the positive GPP sensitivity  
466 in Pattern 2.2. When rainfall is ample enough to maintain little or no water stress  
467 during rainy season, increasing the interval of rainfall events may introduce little  
468 additional water stress but can significantly extend the growing season. This situation  
469 mostly happens in woodlands, where limited water stress exists during rainy season,  
470 and dry season length is the major constraint for plant growth. Thus the increase of  
471 rainy season length extends the temporal niche for plant growth, and leads to a  
472 significant woodland expansion to grasslands as well as an expansion of tropical  
473 evergreen forests to woodlands (Figure 3b).

474 The little GPP sensitivity in tropical evergreen forest regions is mostly attributed  
475 to the long rainy season length in this ecosystem. Thus further increasing  $T_w$  may  
476 reach to its saturation (365 days) and has little impact to ecosystem productivity. This  
477 also explains why the magnitude of GPP sensitivity is much smaller at high MAP

478 range than at the intermediate MAP range.

479 The finding of “optimal rainy season length” across different rainfall regimes  
480 (Figure 5e) is consistent with our previous empirical finding about the similar pattern  
481 of “optimal rainy season length” for tree fractional cover in Africa derived based on a  
482 satellite remote sensing product (Guan et al., 2014). The existence of “optimal rainy  
483 season length” fully demonstrates the importance to explicitly consider the non-linear  
484 impacts of rainy season length on ecosystem productivity under climate change,  
485 which has been largely overlooked before.

486

### 487 **3.3 Ecosystem sensitivity to rainfall seasonality and intensity ( $S_{TW-\alpha}$ )**

488 Results of Experiment  $S_{TW-\alpha}$  have many similarities with those of  $S_{TW-\lambda}$ , including the  
489 similar changes in biome distributions (Figure 3), soil moisture and GPP patterns  
490 (Figure 4e and 4f). We further find that the GPP sensitivity space with MAP and rainy  
491 season length for  $S_{TW-\alpha}$  (Figure 5i) is also similar with that for  $S_{TW-\lambda}$  (Figure 5e). One  
492 new finding is that rainfall intensity has little impact on GPP, as the contour lines in  
493 Figure 5k are mostly parallel with y-axis (i.e. rainfall intensity).

494 Figure 6e and 6f explain the governing hydrological mechanisms for the patterns  
495 of  $S_{TW-\alpha}$ , which also have many similarities with  $S_{TW-\lambda}$ . For the negative case (Figure  
496 6e), decreasing rainfall intensity and increasing rainy season length in the very low  
497 MAP regime may lead to more downcrossings of  $S_w$  and interrupt continuous plant  
498 growth. The positive case (Figure 6e) is similar as that in Figure 6d, i.e. the  
499 repartitioning of excessive wet-season rainfall to the dry season for an extended  
500 growing period would significantly benefit plant growth and possible increase tree  
501 fraction cover.

502

## 503 **4. Discussion**

504 In this paper we provide a new modeling approach to systematically interpret the  
505 ecological impacts from changes in intra-seasonal rainfall characteristics (i.e. rainfall  
506 frequency, rainfall intensity and rainy season length) across biomes and climate  
507 gradients in the African continent.

508

#### 509 **4.1 Limitation of the methodology**

510 Though our modeling framework is able to characterize the diverse ecosystem  
511 responses to the shifts in different rainfall characteristics, it nevertheless has its  
512 limitations. The current rainfall model only deals with the case of single rainy season  
513 per year, and approximates the case of double rainy seasons per year to be the single  
514 rainy season case. This assumption may induce unrealistic synthetic rainfall patterns  
515 in the equatorial dryland regions, in particular the Horn of Africa. Thus the simulated  
516 sensitivity of these regions may be less reliable. We also assume that rainfall  
517 frequency and intensity are homogenous throughout wet seasons (or dry seasons), but  
518 in reality they have seasonal variations. We only consider rainy season length for  
519 rainfall seasonality, and neglect the possible temporal phase change; in reality, rainfall  
520 seasonality change usually has length and phase shifts in concert. These  
521 rainfall-model-related limitations can be possibly overcome by simulating smaller  
522 intervals of rainfall processes (e.g. each month has their own  $\alpha$  and  $\lambda$ ) rather than  
523 simulating the whole wet or dry season using one fixed set of  $\alpha$  and  $\lambda$ . Besides, only  
524 using one ecosystem model also means that the simulated ecosystem sensitivity can  
525 be model-specific. Though magnitudes or thresholds for the corresponding patterns  
526 may vary depending on different models, we argue that the qualitative results for the  
527 GPP sensitivity patterns (e.g. Figure 4 and Figure 5) should hold as the necessary  
528 ecohydrological processes have been incorporated in SEIB-DGVM. We also  
529 recognize that to exclude fire impacts in the current simulation may bring some  
530 limitation for this study, as evidence shows that many savanna regions can be bistable  
531 due to fire effects (Staver et al 2011; Hirota et al 2011; Higgins and Scheiter 2012;  
532 also see for a possible rebuttal in Hanan et al, 2013). Changes in rainfall regimes not  
533 only have direct effects on vegetation productivity, but can also indirectly affect  
534 ecosystems through its interactions with fire, with rapid biome shifts being a possible  
535 consequence. These feedbacks can be important in situations when the changes in  
536 growing season length are related to fuel loads, fuel moisture dynamics and hence fire  
537 intensity (Lehmann et al., 2011). Quantifying these fire-rainfall feedbacks will be the

538 important future direction to pursue.

539

## 540 **4.2 Clarifying the impacts of rainfall frequency and intensity on ecosystem** 541 **productivity**

542 In this modeling study, we provide a plausible answer to possibly resolve the previous  
543 debate about whether increasing rainfall intensity (or equivalently decreasing rainfall  
544 frequency, i.e.  $\lambda \downarrow$ ,  $\alpha \uparrow$ ) has positive or negative impacts on above-ground primary  
545 productivity under a fixed annual rainfall total. We identify that negative GPP  
546 sensitivity with increased rainfall frequency is possible at very low MAP range (~ 400  
547 mm/year) with relatively low rainfall frequency (<0.35 event/day) (Figure 5a), due to  
548 the increased downcrossings of soil moisture wilting point, which restricts plant  
549 growth (Figure 6a). This derived MAP threshold (~400 mm/year) is consistent with  
550 our meta-analysis based on the previous field studies (Table 1), which shows a  
551 threshold of MAP at 340 mm/year separates positive and negative impacts of more  
552 intense rainfall on aboveground net primary production (ANPP). Our findings are also  
553 consistent with another study about increased tree encroachments with increased  
554 rainfall intensity in low rainfall regime (<544mm/year, Kulmatiski and Beard, 2013),  
555 which essentially follows the same mechanism as identified in Figure 6a.

556 In addition, we thoroughly investigated the ecosystem responses across a wide  
557 range of annual rainfall in Africa. We find that beyond the very low rainfall range  
558 (below 400 mm/year), most grasslands and woodlands would benefit from increasing  
559 rainfall frequency, which also corroborate the previous large-scale findings about the  
560 positive effects of increased rainfall frequency (and decreased rainfall intensity) for  
561 tree fractions across the African continent (Good and Caylor, 2011). The only  
562 exception happens at the very wet end of MAP (~1800mm/year) where cloud-induced  
563 radiation-limitation may suppress ecosystem productivity with increased rainfall  
564 frequency. We also find that changes in rainfall frequency and intensity mostly affect  
565 grassland-dominated savannas (changes of GPP up to 20%), and the corresponding  
566 effects are much smaller in woodlands and have little impact on woodland distribution.  
567 Though this work is only based on a single model, it provides a primary assessment

568 for understanding of interactive changes between  $\lambda$  and  $\alpha$  in ecosystem functioning,  
569 and expands the analysis to a wide range of annual rainfall conditions compared with  
570 previous studies (e.g. Porporato et al., 2004).

571

### 572 **4.3 Ecological importance of rainy season length**

573 The results involving rainy season length (i.e.  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$ ) provide evidence for  
574 the ecological importance of rainfall seasonality. The magnitudes of changes in soil  
575 moisture, GPP and biome distribution in  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$  are much larger than those of  
576  $S_{\lambda-\alpha}$ , with almost one order of magnitude difference. These disproportional impacts of  
577  $T_w$  indicate that slight changes in rainy season length could modify biome distribution  
578 and ecosystem function more dramatically compared with the same percentage  
579 changes in rainfall frequency and intensity. We also notice that  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$  have  
580 similar results. This is because that both  $\lambda$  and  $\alpha$  describe rainfall characteristics  
581 within wet season, while  $T_w$  describes rainfall characteristics of both dry season and  
582 wet season. Cautions are required that our simplified treatment rainy season length  
583 may overestimate its importance, and we did not consider the rainfall phase  
584 information here.

585 Given the importance of rainy season length, its ecological impacts under climate  
586 change are largely understudied, though substantial shifts in rainfall seasonality have  
587 been projected in both Sahel and South Africa (Biasutti and Sobel, 2009; Shongwe et  
588 al., 2009; Seth et al., 2013). Here we only address the rainfall seasonality in terms of  
589 its length, and future changes in rainfall seasonality may modify their phase and  
590 magnitude in concert. The climate community has focused on the increase of extreme  
591 rainfall events (Field et al., 2012), which could be captured by the changes in  $\lambda$  or  $\alpha$   
592 towards heavier tails in their distribution. However, explicit and systematic  
593 assessments and projection on rainfall seasonality changes (including both phase and  
594 magnitude) are still limited even in the latest Intergovernmental Panel on Climate  
595 Change (IPCC) synthesis reports (Field et al., 2012; Stocker et al., 2013). More  
596 detailed studies related to these changes and their ecological implications are required  
597 for future hydroclimate-ecosystem research.

598

#### 599 **4.4 Not all rainfall regimes are ecologically equivalent**

600 As Figure 1 gives a convincing example that the same total annual rainfall may arrive  
601 in a very different way, our results further demonstrate that ecosystems respond  
602 differently to the changes in these intra-seasonal rainfall variability. For example, with  
603 similar MAP, drylands in West Africa and Southwest Africa show reversed responses  
604 to the same changes in intra-seasonal rainfall variability. As shown in the experiments  
605 of  $S_{T_w-\lambda}$  and  $S_{T_w-\alpha}$ , increasing  $T_w$  while decreasing  $\lambda$  or  $\alpha$  generates slightly positive  
606 soil moisture and GPP sensitivity in West Africa (Figure 4c and 4d), but would cause  
607 relatively large GPP decrease in Southwest Africa. The prior hydroclimate conditions  
608 of these two regions can explain these differences: West Africa has much shorter rainy  
609 season with more intense rainfall events; in contrast, Southwest Africa has a long  
610 rainy season but many small and sporadic rainfall events. As a result, under a fixed  
611 annual rainfall total, slightly increasing rainy season and meanwhile decreasing  
612 rainfall intensity would benefit plant growth in West Africa, but the same change  
613 would lengthen dry spells in Southwest Africa and bring negative effects to the  
614 ecosystem productivity. We further deduce that the rainfall use efficiency (RUE,  
615 defined as the ratio of plant net primary production to total rainfall amount) in these  
616 two drylands could be different: West Africa may have lower RUE, and the intense  
617 rainfall could lead to more infiltration-excess runoff, and thus less water would be  
618 used by plants; while Southwest Africa can have higher RUE, because its sporadic  
619 and feeble rainfall events would favor grass to fully take the advantage of the  
620 ephemerally existed water resources. This conclusion is partly supported by Martiny  
621 et al. (2007) based on satellite remote sensing. We further hypothesize that landscape  
622 geomorphology in these two drylands may be different and therefore reflect  
623 distinctive rainfall characteristics. More bare soil may exist in West Africa grasslands  
624 due to intense-rainfall-induced erosion, while Southwest Africa may have more grass  
625 fraction and less bare soil fraction. Testing these interesting hypotheses is beyond the  
626 scope of this paper, but is worthy the further exploration.

627

628

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Table 1. Summary of previous representative studies on assessing the impacts of rainfall characteristics (i.e. rainfall frequency, intensity and seasonality) on the structure and function of terrestrial ecosystem.

**Focus:** frequency (freq); intensity (int); seasonality (sea); variation (CV).

**Methods:** Field Experiments (Field); Remote Sensing (RS); Flux Tower (Flux).

**Major Conclusion:** increasing rainfall intensity (or decreasing frequency) has positive impacts (int+); increasing intensity (or decreasing frequency) has negative impacts (int-); increasing rainfall CV has positive impacts (CV+); increasing rainfall CV has negative impacts (CV-).

Focus	Methods	Spatial Scale	Time scale	MAP (mm/year)	Ecosystem type	Major Conclusion	Reference
freq; int	RS	Africa continent	intra-annual climatology	[0,3000]	Africa all	(int-) woody cover	Good and Caylor, 2011
freq; int	RS	US		[163,1227]	US	(int-) ANPP greatest in arid grassland (16%) and Mediterranean forest (20%) and less for mesic grassland and temperate forest (3%)	Zhang et al., 2013
freq; int	RS	Pan-tropics (35°N to 15°S)	inter-annual	[0,3000]	Tropical ecosystems	(CV+) wood cover in dry tropics; (CV-) wood cover in wet tropics	Holmgren et al., 2013
freq; int	RS	Northern China	intra-annual	[100,850]	temperate grassland and forests	(int-) NDVI for temperate grassland and broadleaf forests, not for coniferous forest	Fang et al., 2005
freq; int	Flux	Northern Hemisphere	intra-annual	[393±155,906±243 ]	shrubland and forest	(int-) GPP, RE and NEP	Ross et al., 2012
seas	RS	Africa continent	climatology	[0,3000]	Africa all	rainy season onset and offset controls vegetation growing season	Zhang et al., 2005
freq; int	Field	plot (Kansas, USA)	intra-annual	615	grassland	(int-) ANPP	Knapp et al., 2002

(fix MAP)							
freq; int (fix MAP)	Field	plot (Kansas, USA)	intra-annual	835	grassland	(int-) ANPP	Fay et al., 2003
increase seasonal rainfall	Field	plot(Texas, USA)	intra-annual	365	grassland	(int-) ANPP	Robertson et al., 2009
freq; int	Field	plot (Kansas, USA)	intra-annual	[320,830]	grassland	(int-)ANPP for MAP=830mm/yr; (int+)ANPP for MAP=320mm/yr	Heisler-White et al., 2009
freq; int	Field	plot( New Mexico, USA)	intra-annual	250	grassland	(int+) ANPP	Thomey et al., 2011
freq; int (fix MAP)	Field	Plot(Kansas, USA)	intra-annual	834	grassland	(int-) soil CO2 flux	Harper et al., 2005
freq; int (fix MAP)	Field	plot(Kruger National Park, South Africa)	intra-annual	544	sub-tropical savanna	(int+) wood growth; (int-) grass growth	Kulmatiski and Beard, 2013
sea (fix MAP)	Field	plot(Oregon, USA)	intra-annual	[140,530]	grassland	impact biomass and bare soil fraction	Bates et al., 2006; Svejcar et al., 2003
sea	Field						
freq; int; MAP	Field	plot(South Africa)	intra-annual	[538,798]	grassland	(int-) ANPP	Swemmer et al., 2007
MAP; sea	Field	plot(Spain)	intra-/inter-an nual	242	grassland	Mediterranean dryland ecosystem has more resilience for intra- and inter-annual changes in rainfall	Miranda et al., 2008

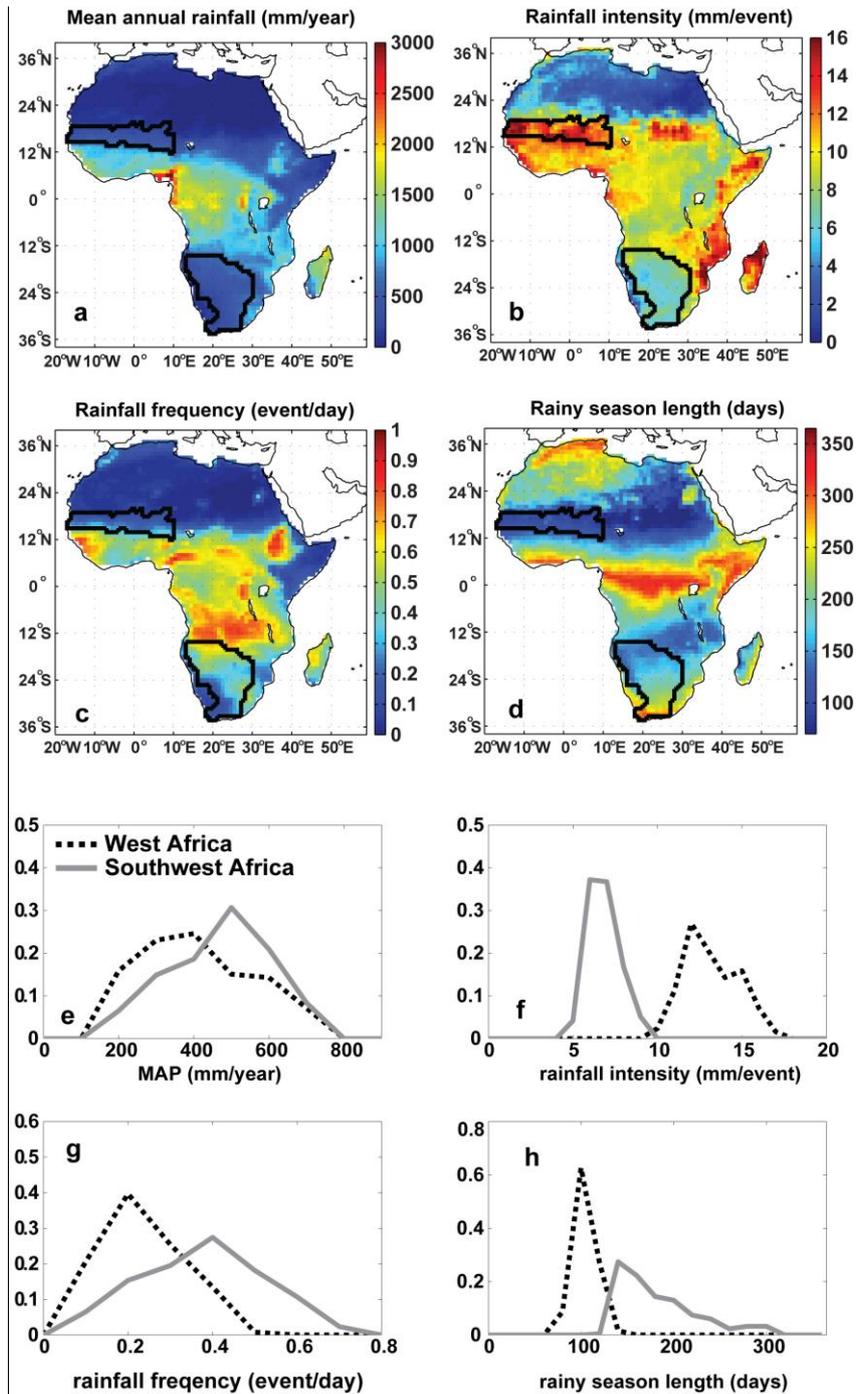


Figure 1. a-b: Spatial pattern of the rainfall characteristics in Africa: a-MAP; b-rainfall intensity; c-rainfall frequency; d-rainy season length. The black-line identified areas refer to two savanna regions in West and Southwest Africa. e-f: Normalized histograms of the rainfall characteristics in two savanna regions of West and Southwest Africa. e-MAP (bin width for the x-axis: 100 mm/year); f-rainfall intensity (bin width for the x-axis: 1 mm/event); g-rainfall frequency (bin width for the x-axis: 0.1 event/day); h-rainy season length (bin width for the x-axis: 20 days).

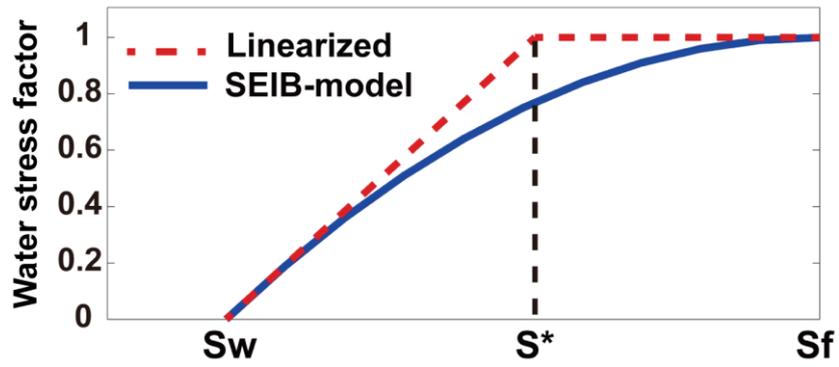


Figure 2. Schematic diagram of water stress factor ranging from 0 (most stressful) to 1 (no stress), which acts to reduce transpiration and carbon assimilation. The red dotted line is based on Porporato et al. (2001) with a reversed sign, and SEIB-DGVM has a nonlinear implementation (blue solid line, Sato and Ise, 2012).

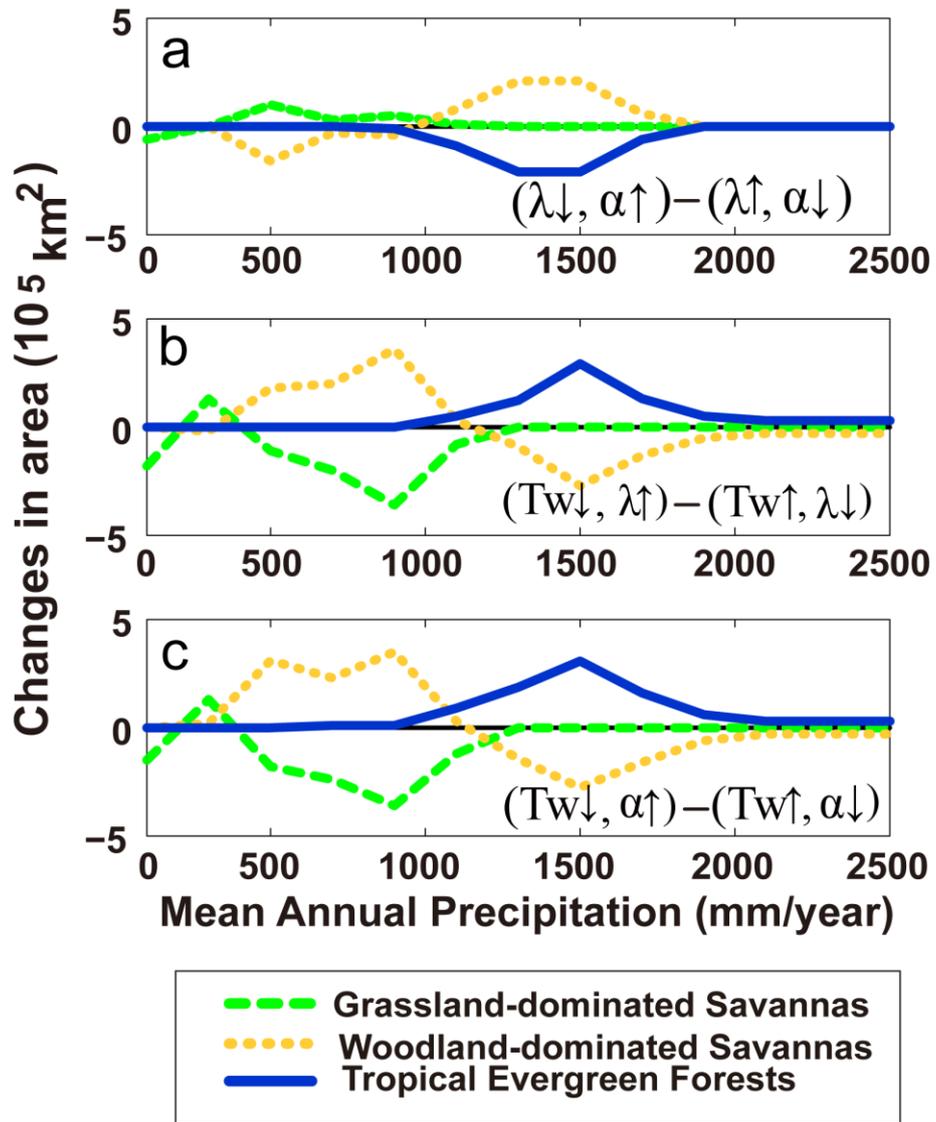


Figure 3. Differences in simulated dominated biomes in the three experiments (i.e.  $S_{\lambda-\alpha}$ ,  $S_{Tw-\lambda}$ ,  $S_{Tw-\alpha}$ ).

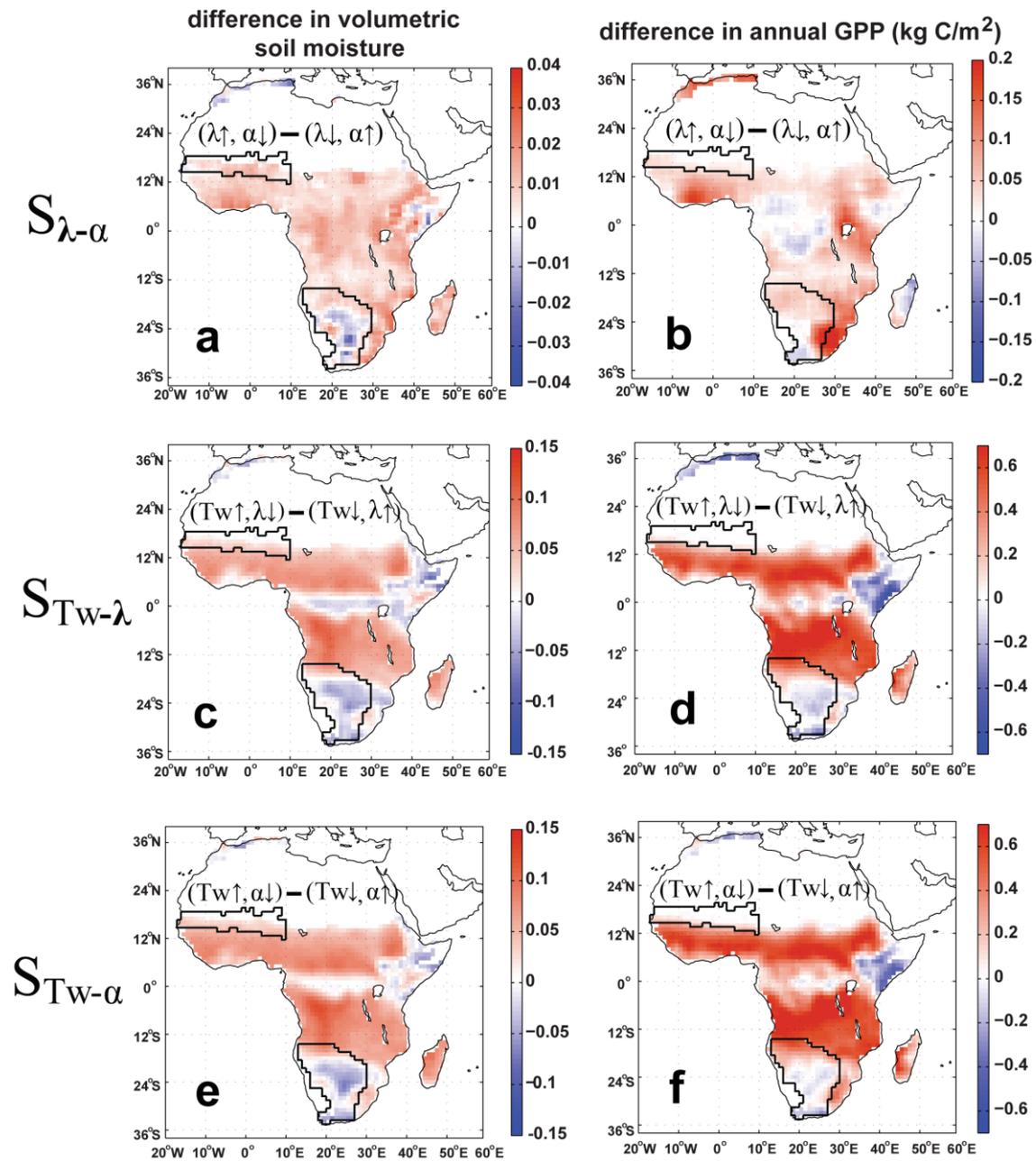


Figure 4. Simulated changes in annual mean soil moisture (0-500mm, first column) and annual mean GPP (second column) for different experiments. Please note that the scales of  $S_{\lambda-\alpha}$  is much smaller than those of  $S_{TW-\lambda}$  and  $S_{TW-\alpha}$ . The two areas with black boundaries in each panel are West African grassland and Southwest African grassland associated with Figure 1. The spatial patterns shown here are smoothed by 3\*3 smoothing window from the raw data.

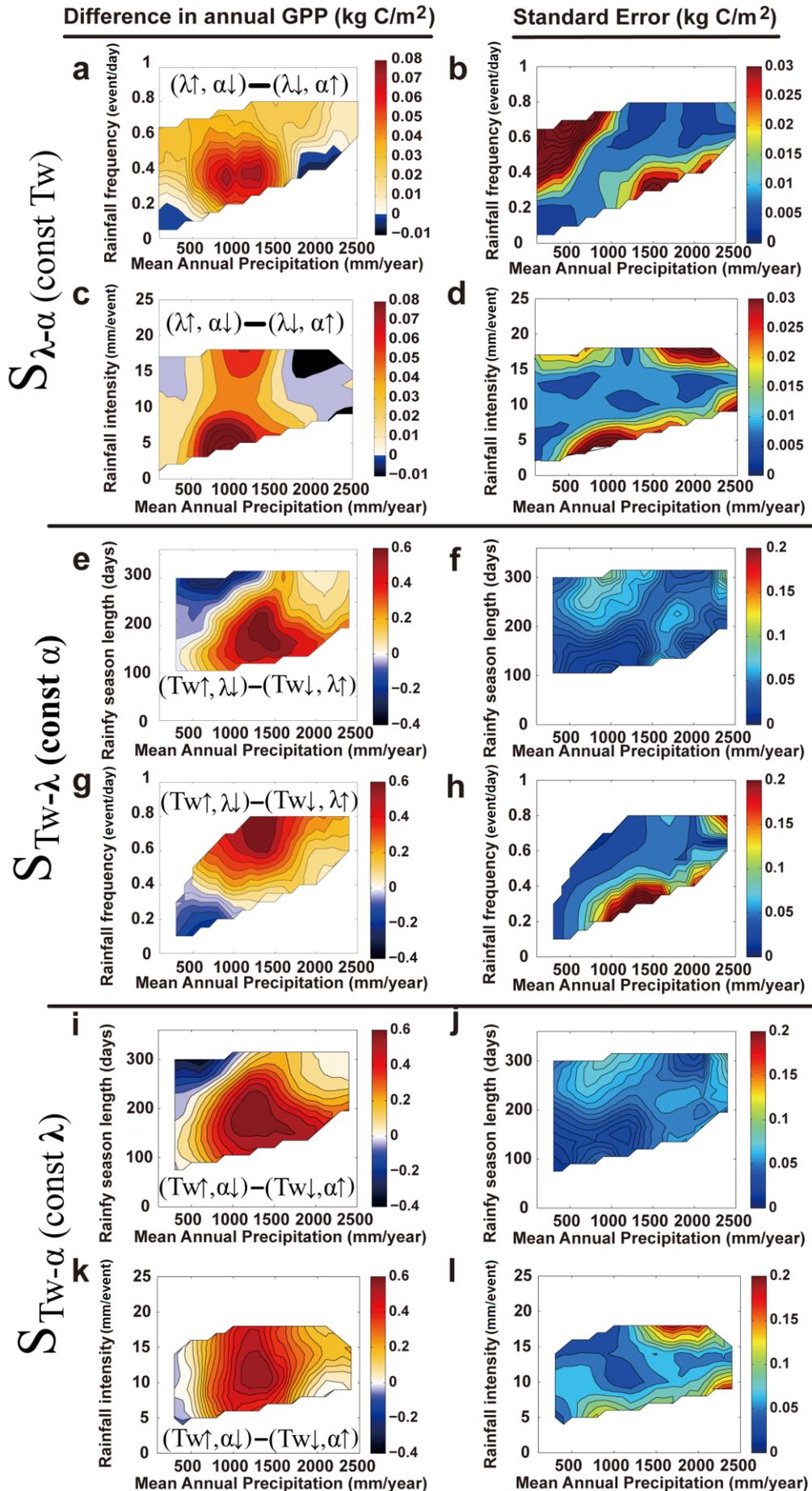


Figure 5. Differences in simulated annual GPP as a function of mean annual precipitation and one of the perturbed rainfall characteristics in all the three experiments (i.e.  $S_{\lambda-a}$ ,  $S_{TW-\lambda}$ ,  $S_{TW-a}$ ) in the left column. The right column shows the correspondent standard errors (SE, calculated as  $SE = \frac{\sigma}{\sqrt{n}}$ , where  $\sigma$  refers to the standard deviation within each bin,  $n$  is the sample size in each bin, and  $n$  and  $\sigma$  are shown in Figure S4), with larger values associated with more uncertainties and requires more caution in interpretation. The contours are based on the binned values, with for each 100 mm/year in MAP, each 0.05 event/day in rainfall frequency, each 1 mm/event in rainfall intensity and each 15 day in rainy season length.

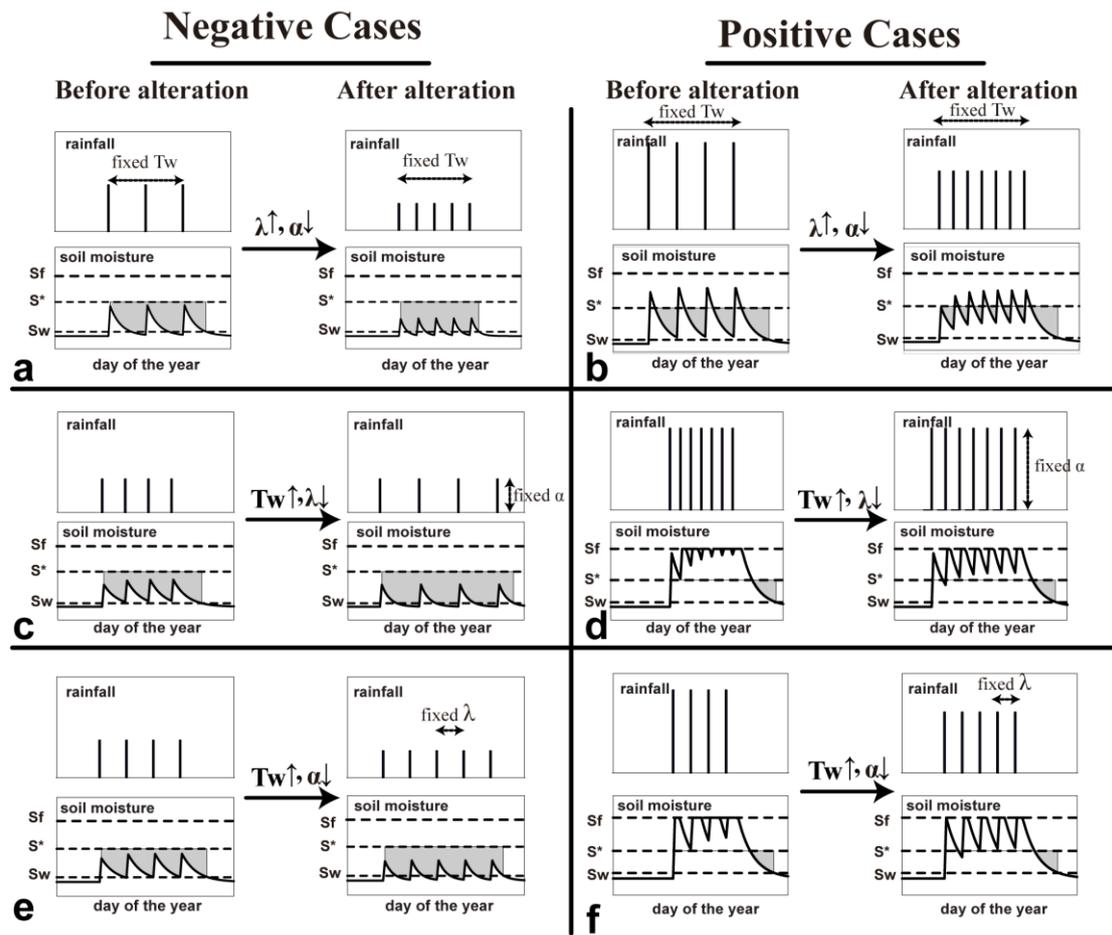


Figure 6. Illustrative time series for hydrological controls on plant root-zone soil moisture dynamics for all the experiments, and these illustrations are generalized based on the simulated time series from the experiments. Both negative and positive cases are shown, and cases with directly hydrological controls are shown (i.e. cloud-induced negative impacts in tropical forests are not shown). The cumulative shaded areas refer to “plant water stress” defined by Porporato et al. (2001).

Supplementary materials:

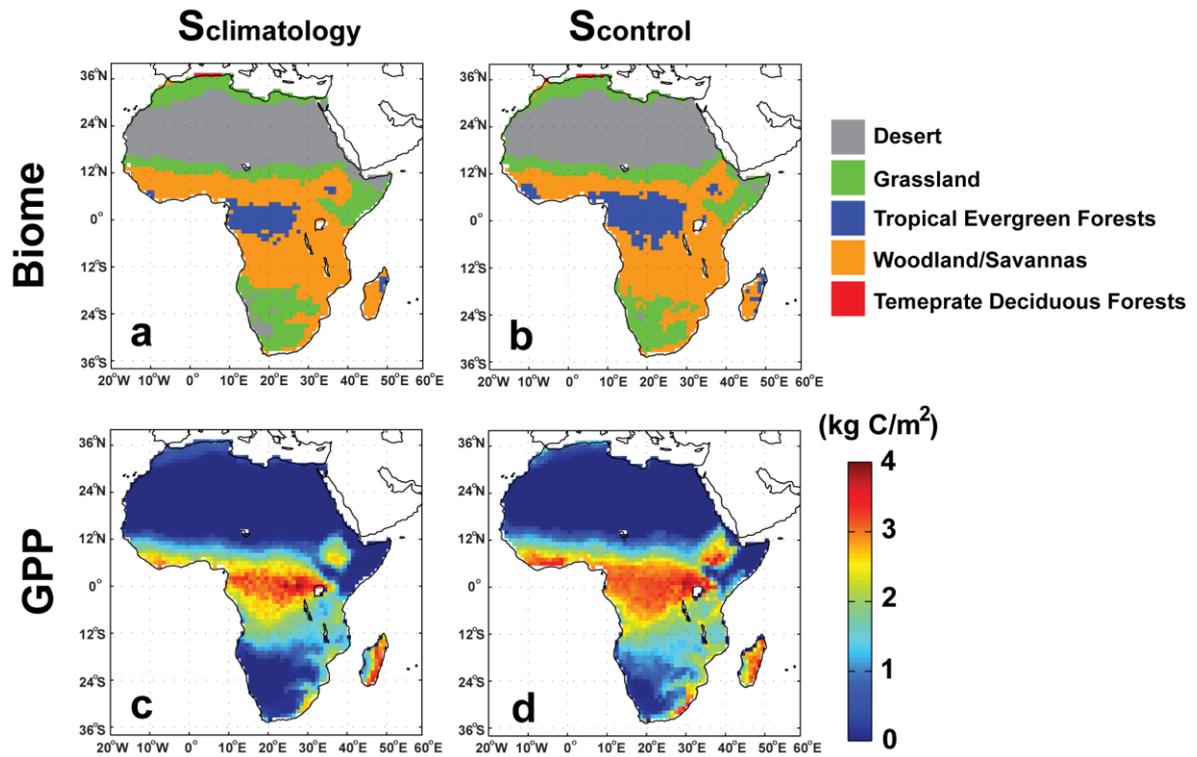


Figure S1. Comparison of biomes and annual GPP between  $S_{climatology}$  and  $S_{control}$  to test the validity of the synthetic weather generator. The biome definition follows Sato and Ise (2012).

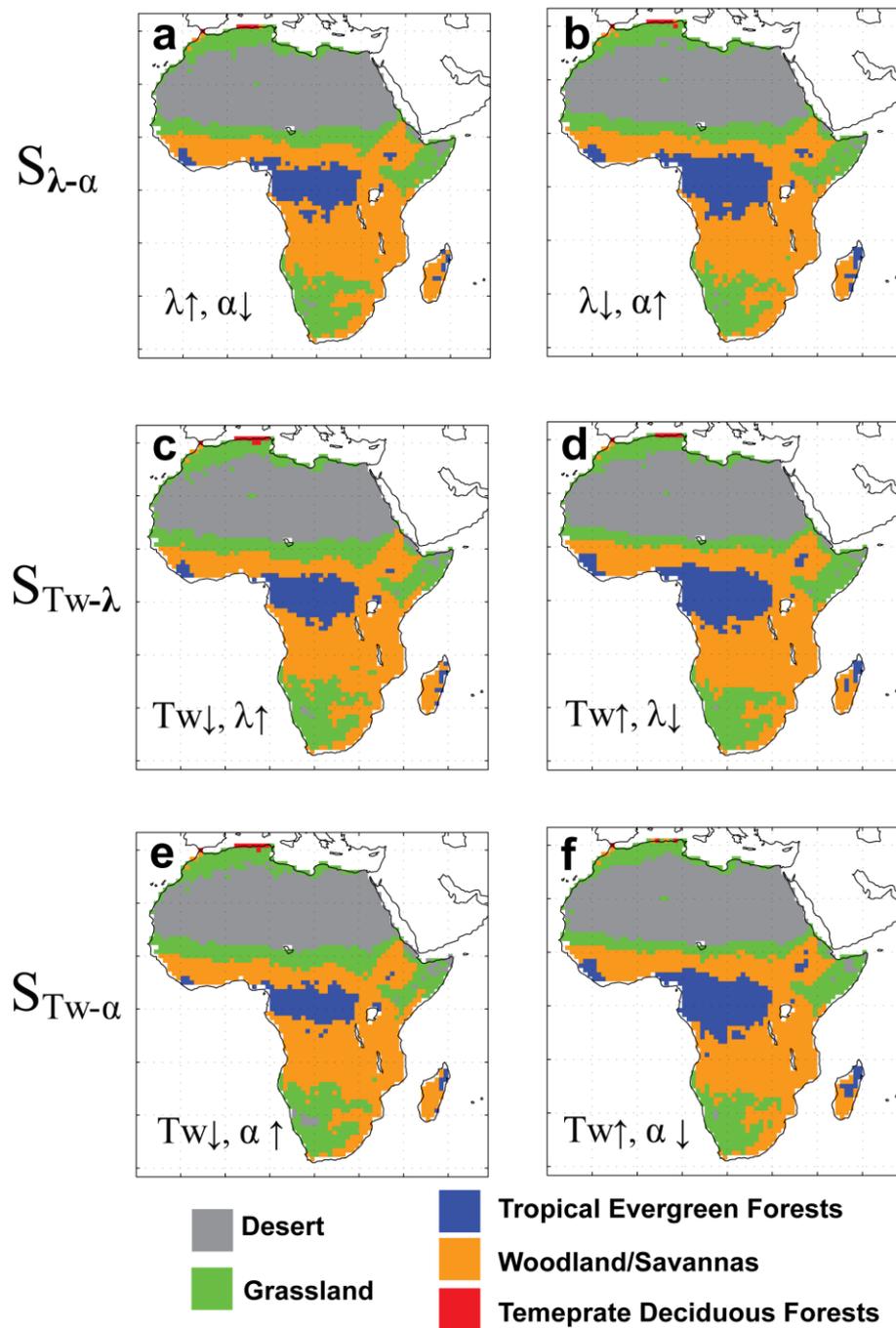


Figure S2. Simulated biomes for different experiments.

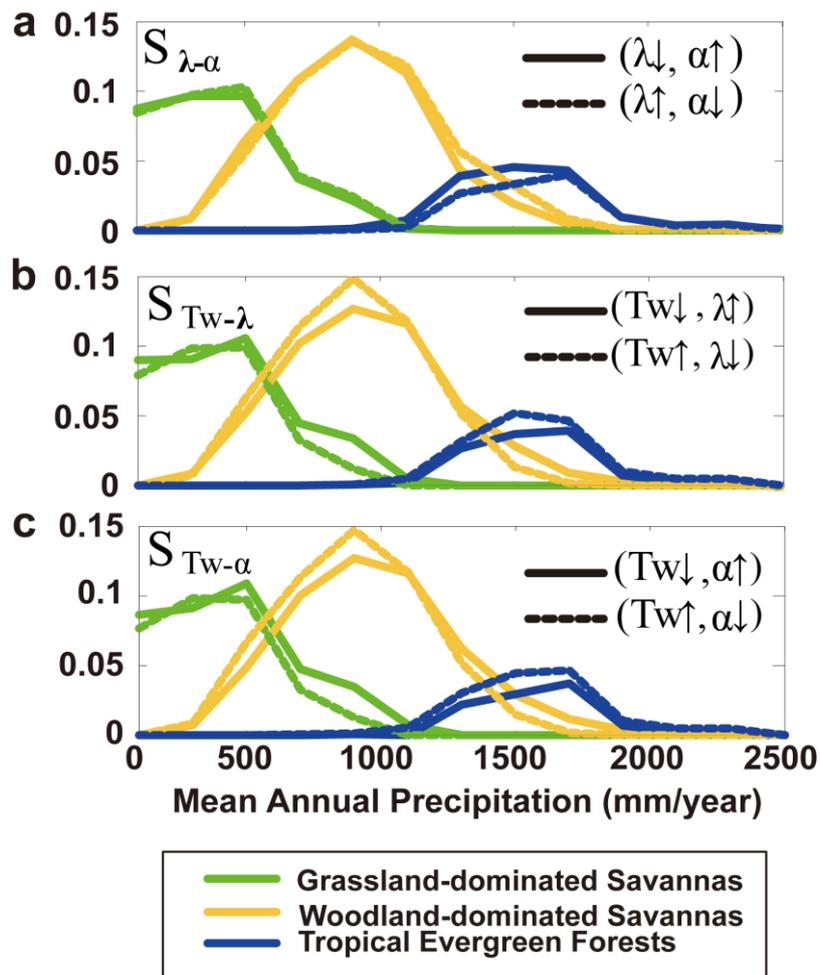


Figure S3. Normalized histograms of three simulated dominating biomes in the three experiments.

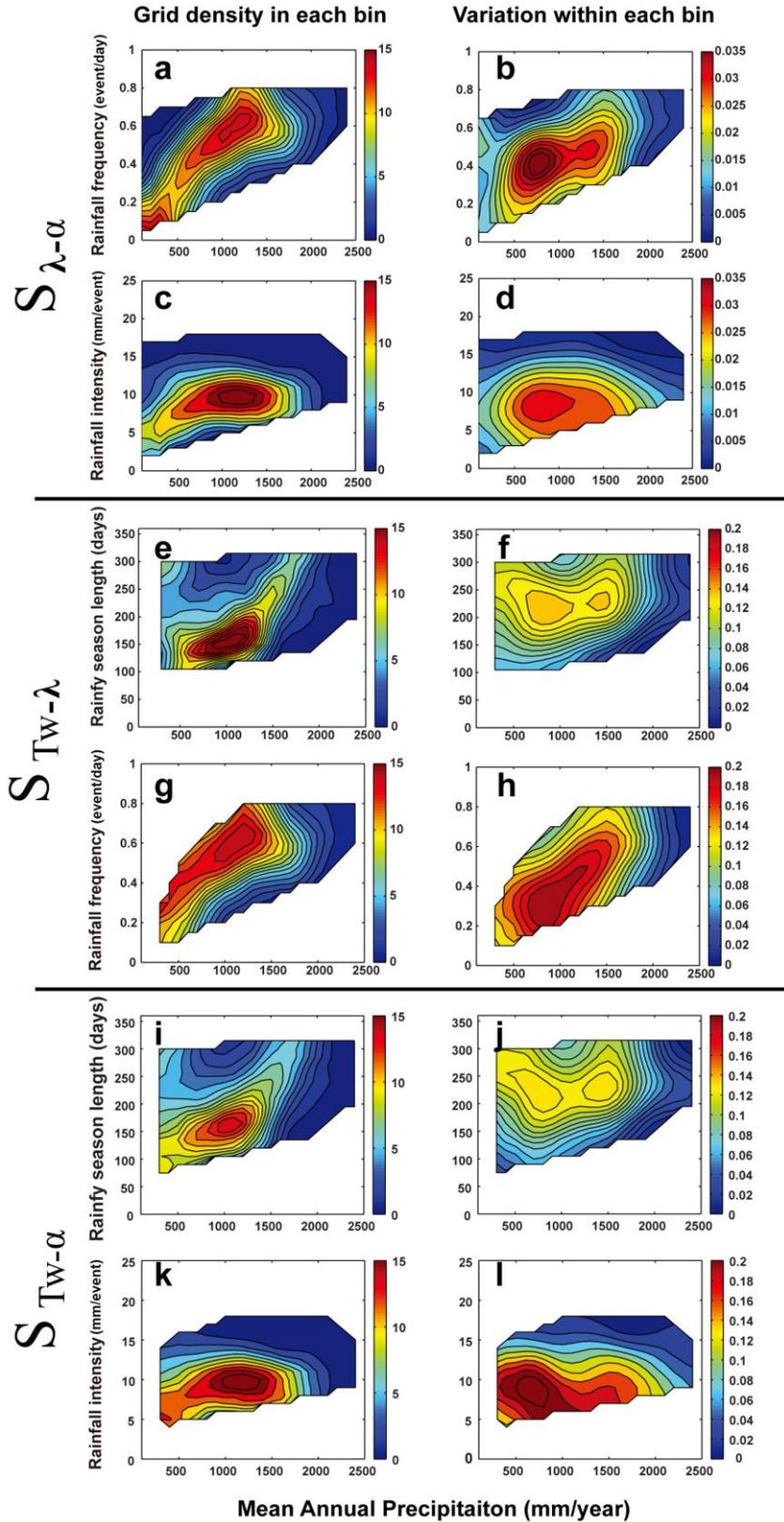


Figure S4. The sample size ( $n$ ) in each bin (left column) and standard deviation ( $\sigma$ ) in each bin (right column), corresponding to Figure 5. In Figure 5 right column, standard deviation (SE) is calculated as  $SE = \frac{\sigma}{\sqrt{n}}$ .