Additional Editorial comments:

Additionally, it is still not clear how you are calculating correlation for wet and dry events in section 3.9. How is it possible to calculate correlation for a single year? Are you calculating correlation using sub-monthly data over each of those years? Please explain.

Response:

Thank you, Editor, for your feedback and comment.

In section 3.9, where we compared the impacts of extreme events (wet and dry years) at different time period, we considered just observation i.e. CRU (drought) and satellite-calculated LAI. Here, we calculated correlations using monthly data of both climate and vegetation variables over each of the years. The observed climate (CRU) data are not sub-monthly. Only the CRUJRA (reanalysis), which was used for model correlation, is sub-monthly. Model was not analysed in this section because our goal was simply to examine the observed impacts (or influence) of an extreme event.

Here, we define extreme events as wet years - i.e. the periods with precipitation higher than normal; and the dry years which include the periods of very high dry spells.

Our analyses involved, firstly, a spatiotemporal correlation between CRU and satellite-calculated LAI for the year (12-month period) of an extreme event occurrence. Thereafter, we computed correlation over a 30-year period (1982-2011). We calculated impacts/changes as anomaly (or difference) between an extreme wet or dry year and the 30-year mean. The anomaly is the magnitude of impacts added by the extreme event in a particular year. Our analyses follow Pan *et al*. (2015).

We have updated the analyses in the manuscript.

References:

Pan, S., S. R. S. Dangal, B. Tao, J. Yang, and H. Tian. 2015. Recent patterns of terrestrial net primary production in Africa influenced by multiple environmental changes. Ecosystem Health and Sustainability 1(5):18. http://dx.doi.org/10.1890/EHS14-0027.1

Editorial comments:

Thank you for submitting a revised version of the manuscript. Reviewer #1 has provided some important comments that need to be addressed before the manuscript can be suitable for publication. Mainly the reviewer would see further clarification on the part of evaluation of observed vs modeled LAI.

Response:

Thank you. We have addressed the comments given by reviewer #1 and have provided further clarification in the updated manuscript.

Please see our response to reviewer's comment below.

Anonymous Reviewer's comments #1

The authors have done a commendable job in addressing most of the questions in the revised submission and the overall quality of the presentation has improved. I have only two major comments below:

Response:

Thank you for feedback. We have addressed these two major comments.

1. Figure 3: I have trouble understanding what do the authors mean by spatiotemporal correlation? Does that mean the correlation coefficient for the shown scatter plot which includes monthly values across the time and space of the domain? If so, I don't think the values/pattern can inform much on the comparison.

Response:

Yes, in the previous manuscript, the mean correlation coefficient that was shown for spatiotemporal correlation includes monthly values across time and space of the domain.

However, based on your suggestion, we have removed the spatiotemporal correlation plot.

The same concerns for Figure 3 (Q) that the domain averaged annual LAI is not able to demonstrate whether the model is able to capture the interannual variability as compared to the observation. Besides, the ensemble spread is much larger than the variation of LAI time series, making the comparison less meaningful as well.

Response:

In the same vein, we have also removed the interannual variability that was shown in Figure 3 (Q) from the revised manuscript. We have moved it to Fig. S8 in supplemental.

I suggest the authors to calculate the correlation between GIMMS LAI and modelled LAI for both the original and deseasonalized time series for each grid point and show the correlation maps rather than a spatiotemporal correlation. Disucssion on 1) how model captures the LAI seasonal/interannual variations in terms of bioms and models and 2) how that may indicate the difference between observed and modeled system regarding vegetation response to drought are needed. Please refine Figure 3 and the corresponding text to address the issue.

Response:

Thank you for your suggestion.

Following your suggestion, we now show spatial maps of correlation between GIMMS LAI and modelled LAI for both the original and deseasonalized time series for each grid points. These are shown in Figure 3 as copied below. Please see Page 13, Section 3.2; Lines 399 – 405.

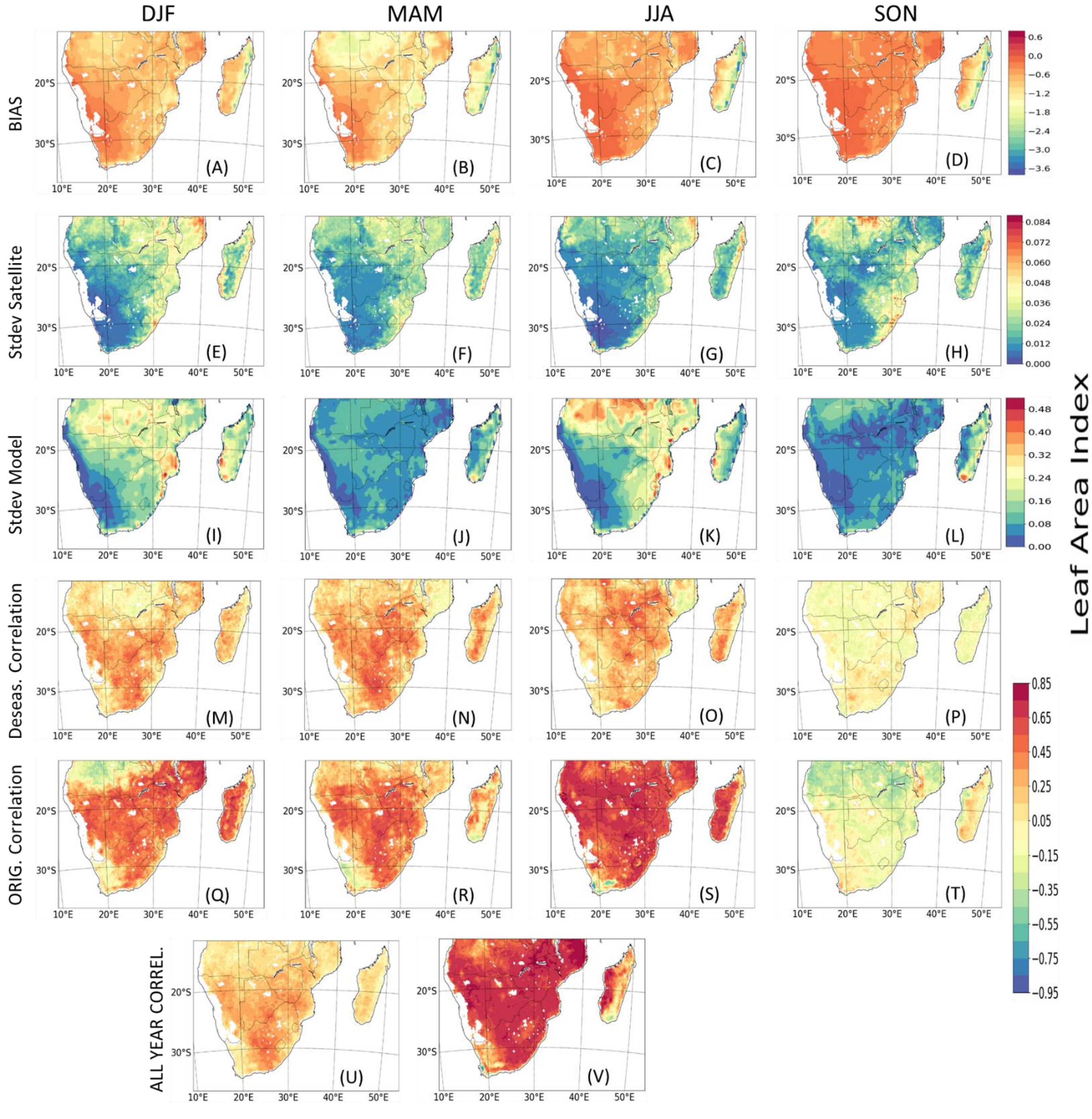

Figure 3. Spatial seasonal distribution and inter-annual variability (IAV) of satellite-calculated and modelled LAI (multi-model mean) over southern Africa. (A) – (D) show the difference (bias); (E) – (H) and (I) – (L) show their standard deviation (Stdev); (M) – (P) show the correlations between deseasonalized GIMMS LAI and modelled LAI; (Q) – (T) show their correlations for original GIMMS LAI and modelled LAI and (U) – (V) show correlations between GIMMS LAI and modelled LAI but for the period 1982 – 2011. The inter-annual variability for observed and modelled LAI for the period 1982 – 2011 is shown in Fig. S8.

We have also provided discussion on how model captures the LAI seasonal/interannual variations of biomes and models, and how that may indicate the difference between observed and modelled system regarding vegetation response to drought. The texts are copied below.

Please see Section 3.2, Page 12, Lines 376 – 395; Section 4.5, Pg 30 - 31, Lines 806 - 834 and Section 4.6, Page 31, Lines 835 – 868.

3.2 Seasonal and interannual variations of observed and modelled LAI

The comparison of seasonal and interannual variation of observed and modelled LAI is given in Fig. 3. The model shows a stronger positive bias in JJA and SON in comparison to summer and winter months; and a negative bias over the tropical forest region of Madagascar (Figs. 3A – 3D). In addition, model mostly overestimate the seasonal patterns of LAI in some regions during DJF and JJA, and underestimate LAI in MAM and SON (Figs. 3E – 3L). Over most parts of the region, there is a strong correlation and good agreement between observed and modelled LAI in DJF, MAM and JJA although it is weaker in SON (Figs. 3M – 3T). The strong correlation is more prevalent in JJA than other seasons (Fig. 3S); while it is weakest in southern parts of the region. However, the correlation is largely negative over Angola in DJF and SON (Figs. 3Q, 3T). Furthermore, the correlations between model and observed LAI is weaker in deseasonalized data (hereafter, Deseas. Correlation; Figs. 3M– 3P) than in original data (hereafter, ORIG. Correlation; Figs. 3Q– 3T), thereby showing the effects of seasonal patterns on time-series data. With respect to the period, 1982 – 2011 (hereafter, ANNUAL), the correlation between modelled and observed LAI are different for deseasonalized and original data (Figs. 3U – 3V). For the former (Fig. 3U), there is gradient in the correlation across the region, with higher values in central and southern parts than in Angola and Madagascar. However, with the original LAI data (Fig. 3V), the correlation is very high (about 0.85) and more prevalent, except in eastern Madagascar and Western Cape Province of South Africa.

4.5 How well the seasonal and interannual variations of LAI are captured in DGVM simulations

The models exhibit biases in the simulation of seasonal and interannual variations of LAI over southern Africa. Two major factors may be given for performance of the models. First, the influence of precipitation forcing data largely affect the seasonal cycle of LAI as well as the interannual variability (see Figs. 3 & S8). Although the difference between the forcing data for observed and modelled LAI (i.e. CRU and CRUJRA respectively) is small, it still influences the simulations by the DGVMs. The precipitation uncertainty has larger influence in some regions and biomes than others. For instance, the overestimation of LAI by models in arid biome of Namibia and Mediterranean vegetation of South Africa may be due to the irregularity in precipitation, whereby the precipitation changes are too little to be identified (in CRUJRA), as well as due the large spatial variability (Fekete et al., 2004; Greve et al., 2014). On the other hand, over the savanna biome of Angola, the underestimation is likely because of the sparse distribution of precipitation data, which permeates to CRUJRA (Fekete et al., 2004). Secondly, the differences in observed and simulated LAI may be due to the impacts of land use and land cover change on the latter (LULCC) on simulation, through soil moisture as well as evapotranspiration (Piao et al., 2015). LULCC exerts strong influence on water consumption, nutrient cycling, and root depth (Piao et al., 2007; Mango et al., 2011), and the extent of the influence also varies across biomes. For example, in MAM, over temperate grassland biome of South Africa, where the model underestimates LAI, the bias is likely because the models fail *to simulate the frequency of evapotranspiration, which is about five times much less than the forest biome (Yang et al., 2015).*

However, over most parts of the region, the correlation between observed and modelled LAI is strong, except in JJA season. This means that the models generally simulate the pattern of LAI distribution in southern Africa. We also note that, the lower correlations between observed and modelled LAI when the data were deseasonalized, is due to the sensitivity of LAI to variability and seasonality. These differences between observed and modelled system have impacts on how vegetation response to drought is captured, which we discuss in Section 4.6.

4.6 How well drought and LAI response is represented in DGVM simulations

The observed LAI is simulated within the models and calculated by GIMMS based on Mao and Yan, 2019. Lu et al., 2011 found that DGVMs perform better against observations than Earth system models (ESM) because they use observational-derived climate and can include more complex representations of vegetation processes. The ESM is a coupled model simulating its own climate, while the individual DGVMS models used in the present study are standalone, i.e. are applied with observational based meteorological forcing, and thus we remove one uncertainty. Since offline studies target the DGVM itself, removing one possible issue (incorrect climate drivers), it became imperative to use DGVM to study drought impacts.

DGVMs simulate the vegetation characteristics and impacts of climate on them. The validation of DGVM simulations of variables such as LAI is quite difficult. This is because of the unavailability of data on large spatiotemporal scale for the different vegetation classes (Potter and Klooster, 1998). Studies (e.g. Potter and Klooster, 1998) have also shown that errors present in the prediction of plant functional types (PFTs) tend to spread to biomass prediction in the model, thus possibly biasing estimates of carbon stored in terrestrial ecosystems. Nevertheless, the DGVMs used in this study simulate the spatial patterns of vegetation distribution though with a magnitude bias as shown in Fig. S2 in the supplementary material.

TRENDY models mostly simulate the temporal patterns of global and regional distributions of LAI response to drought. The biases shown by the models have been attributed to the fact that the models do not factor land use changes (Ahlstrom et al., 2015). This is evident in the simulation of LAI (please see Fig. S2).

The models' weaker simullations might also be because some of the DGVMs do not well reproduce the LAI magnitude. The negligible difference in the spatial distributions of SPEI of the models could be due to fact that the model PET does not play a strong role in drought occurent in the southern Africa and that precipitation is the main driver of drought in the region. The variations in the characterization of hydrological processes in the models are also a source of uncertainty because they reinforce the bifurcation in runoff outputs which has cascading effects on biospheric changes and evapotranspiration (Murray et al., 2011; Stewart et al., 2004). Also see Fig. S4 for correlations of the model ensemble median at different timescales. Another reason for the biases in the simulations may be to the design of the DGVM experimental set-up, which include the flux deviation between simulations without and with (Murray et al., 2011).

2. Figure 10/Section 3.8. Thanks to the authors for explaining the section. However, I think it is still unclear in terms of how the correlation is calculated and how the correlation difference can be made for each dry/wet years shown in Figure 10. Is the map showing the correlation difference or LAI difference? Please clarify.

Response:

The objective was to discuss the impacts of extreme drought events, and compound influences of drought on LAI during extreme hot and dry years. Here, extreme events are the wet years - i.e. the periods with precipitation higher than normal; and the dry years which include the periods of very high dry spells. To achieve this, we computed the correlation between LAI and corresponding dry/wet years at the different time periods. We considered just observation i.e. CRU (drought) and satellite-calculated LAI. Here, we calculated correlations using monthly data of both climate and vegetation variables over each of the years. The observed climate (CRU) data are not sub-monthly. Only the CRUJRA (reanalysis), which was used for model correlation, is sub-monthly. Model was not analyzed in this section because our goal was simply to examine the observed impacts (or influence) of an extreme event. Our analyses involved, firstly, a spatiotemporal correlation between CRU and satellite-calculated LAI for the year (12-month period) of an extreme event occurrence. Thereafter, we computed correlation over a 30-year period (1982-2011). We calculated the impacts/changes as anomaly (or difference) between an extreme wet or dry year and the 30-year mean. The anomaly is the magnitude of impacts added by the extreme event in a particular year. The maps of this correlation are then plotted. Our analyses follow Pan *et al*. (2015).

The maps show the correlation for the corresponding extreme events at different years. We have provided further clarification on the method in the revised manuscript. Please see Section 3.9, Lines 613 – 641, Page 25-26.

References:

Pan, S., S. R. S. Dangal, B. Tao, J. Yang, and H. Tian. 2015. Recent patterns of terrestrial net primary production in Africa influenced by multiple environmental changes. Ecosystem Health and Sustainability 1(5):18. http://dx.doi.org/10.1890/EHS14-0027.1