Anonymous Referee's comments #1

We thank Anonymous Referee #1 for providing useful and constructive comments. We have carefully revised the manuscript and addressed all the points raised by the Referee.

General Comments:

This study investigates the vegetation response to drought by looking at the correlation between LAI and SPEI and compares the responses between the observed and modeled world. Overall, this study is very interesting, and the manuscript is well organized and reads relatively clearly.

Response:

Thank you for the feedback.

I do think the authors could explore deeper in discussing the differences of the observed and simulated vegetation response to drought and highlight the possible implications on model development in terms of better capturing the vegetation response to drought. Please see my specific comments below:

Response:

Thank you. We added a discussion of the possible reasons why models tend to overestimate vegetation response to drought and made suggestions on the future scope of model developments in a newly added Section 4.6, Lines 826 – 848, Page 30. This is copied below under specific comments number 10.

Specific comments:

1. Line 154-156: Is there a specific reason of choosing the period of 1982-2011 for this study? Why not extending to 2019?

Response:

The present study extends the timeframe for understanding drought impacts from 1982 to 2011 mainly because there were frequent droughts in the 2005 – 2011 window (Masih *et al.*, 2014). The timeframe was then extended back to cover a 30 year period to be long enough to cover impacts of climate change, which is particularly important considering that southern Africa experiences more frequent droughts with impacts exacerbated by climate change. This information is important for considering adaptation measures and understanding the role of climate change. Please see Lines 241 – 247, Page 7.

2. Line 84: please check the reference, it seems that the paper is published in 2010 instead of 2005. Besides, is it possible to update the reference to recent advance reflecting the statement of "southern Africa may lose about one-third of its current vegetation due to increasing exacerbation of drought in the region"?

Response:

Apologies for this, and thank you for the correction. The date has been updated in the revised manuscript.

The sentence "southern Africa may lose about one-third of its current vegetation due to increasing exacerbation of drought in the region" has been updated to a recent reference. The statement now reads *"It is reported that there has been significant loss of vegetation cover over the region over the last 30 years (Driver et al., 2012; DEA, 2015)"*. Please see Lines 81 – 82, Page 3.

3. Line 264-265: Do you also deseasonalize the simulated LAI before the correlation analysis?

Response:

Yes, we also deseasonalized the simulated LAI before correlation analysis. This was done to make appropriate comparisons. This has been clarified in the manuscript. Please see Line 304, Page 8.

4. Line 273-275: Is there a major difference between the CRU and CRUJRA datasets in terms of the precipitation and temperature fields? If so, what are the differences?

Response:

The major difference between CRU and CRUJRA is in terms of the spatial and temporal resolutions. CRU is gridded 'observed' data, although it is limited by the fact that temporal resolution is monthly. JRA is a reanalysis and has 6-hourly temporal resolution. JRA is reanalysis but the combined product uses the sub-monthly information from JRA and is constrained to the monthly CRU observations. With regards to the precipitation and temperature fields, the difference is negligible for southern Africa. Please see Figs. 5 for the spatial comparisons of the data. This text can be found under Section 4.2, Page 26 – 27, Lines 676 – 695.

For the study, we used CRUJRA because it is the data used to force the DGVMs, so the drought indices are being calculated based on the same data the models use for their simulations. It is useful to use data with shorter times because the study focuses on an evaluation of drought impact, which is sensitive to timescale. In drylands, for instance, the uncertainties associated with monthly data in drought monitoring are reduced when sub-monthly data are used (Mukherjee *et al*., 2017). Also see Section 4.2, Page 26 – 27, Lines 676 – 695.

5. Line 277-282: The description is a bit confusing. Do you calculate the correlation for each month separately using the 30 years data and then calculate the seasonal mean of the correlation? Please refine the description.

Response:

Apologies for the confusion.

Yes, we calculated correlation (twelve sequences in a year) of monthly LAI to monthly sequences of 1- to 24-months SPEI using the 30-years data. Seasonal mean of the correlation was then calculated. This has been added in the revised manuscript. Please see Lines 322 – 324, Page 8.

6. Section 3.1: How about the correlation between the simulated and observed monthly LAI time series? Figure 2 has indicated that the spatial pattern between the simulated and observed LAI matches relatively well, but I wonder how they compare to each other in terms

of seasonal and interannual variation? I guess this might be helpful when explaining the difference between the vegetation response to drought in the observed and modeled space?

Response:

Thank you for the suggestions. Figure 2 illustrates a spatiotemporal correlation, incorporating both the spatial and temporal patterns between observed and simulated LAI. We also have made comparison of the annual cycle of LAI for observation and models (TRENDY) across six biomes over southern Africa for the period 1982 – 2011 as shown in Figs. 3 (now Fig. 4) - Please see Lines 431 – 435, Page 14, and Fig. S5.

Based on your suggestion, we have now added a **new Fig. 3 (shown below)** to separate spatial and temporal patterns and highlight interannual variation. Figure 3 shows 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 their spatiotemporal correlations; and (Q) shows their inter-annual variability for the period 1982 – 2011 (as copied below). Please see Line 381 – 390; Page 12 of the revised manuscript for this information. The analyses were adopted after Luo *et al* (2013). A discussion on this has been added to the text.

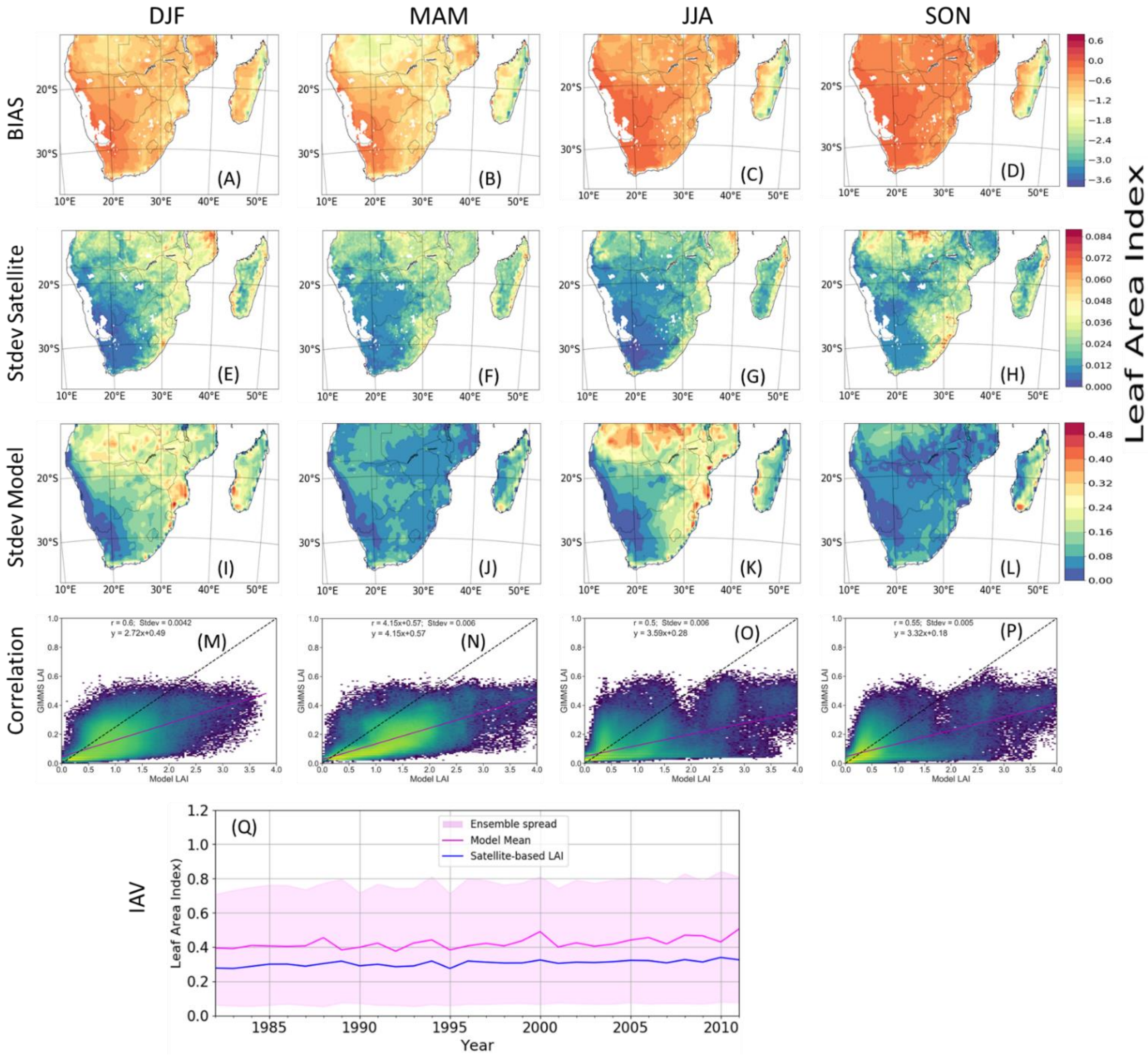

Figure 3. Spatial seasonal distribution and inter-annual variability (IAV) of satellite-calculated and modelled LAI (multi-model mean) over southern Africa. (A) – (D) show the difference (bias); (E) – (H) and (I) – (L) show their standard deviation (Stdev); (M) – (P) show their spatiotemporal correlations; and (Q) shows their inter-annual variability for the period 1982 – 2011.

7. Figure S5: It is interesting that for Mediterranean and Tropical forest, models almost fail to simulate the second peak around September. Any possible explanations?

Response:

Thank you for noting this. For Fig. S5, some of the models do not capture this peak around September over the Mediterranean and Tropical biomes. A possible explanation is that the models do not well reproduce the changes in the biomass and leaf area cover around that period (due to phenological responses to environmental variables). For instance, some models may simulate leaf-off for stress deciduous vegetation types prior to September.

For both biomes, spring rainfall contribute to vegetation growth in the region, which may not be well reproduced by the models. These have added to the text. Please see Section 4.3, Lines 710 – 714, Page 27.

8. Line 328: While the first sentence mentioned that “This section compares the seasonal cycle of observation (CRU) and reanalysis (CRUJRA) climate variables. . .”, I only see one set of climate variables in Figure 3. Are they from CRU or CRUJRA? And there is no discussion with respect to the comparison between the two. Please consider add on the corresponding figures/analyses.

Response:

Apologies and thank you for pointing our attention to it. The set of climate variables now include CRU and CRUJRA. We have made the necessary correction in line 394, Page 12.

We made spatial comparison of both CRU and CRUJRA in Fig. S6 (and Fig. 5). As you have suggested, we have added corresponding figures/analyses. This can found in in Lines 426 – 435, Page 14 of the revised manuscript. The discussion has been modified to reflect the changes. Please see the adjustment of the figure (now Fig.4) below:

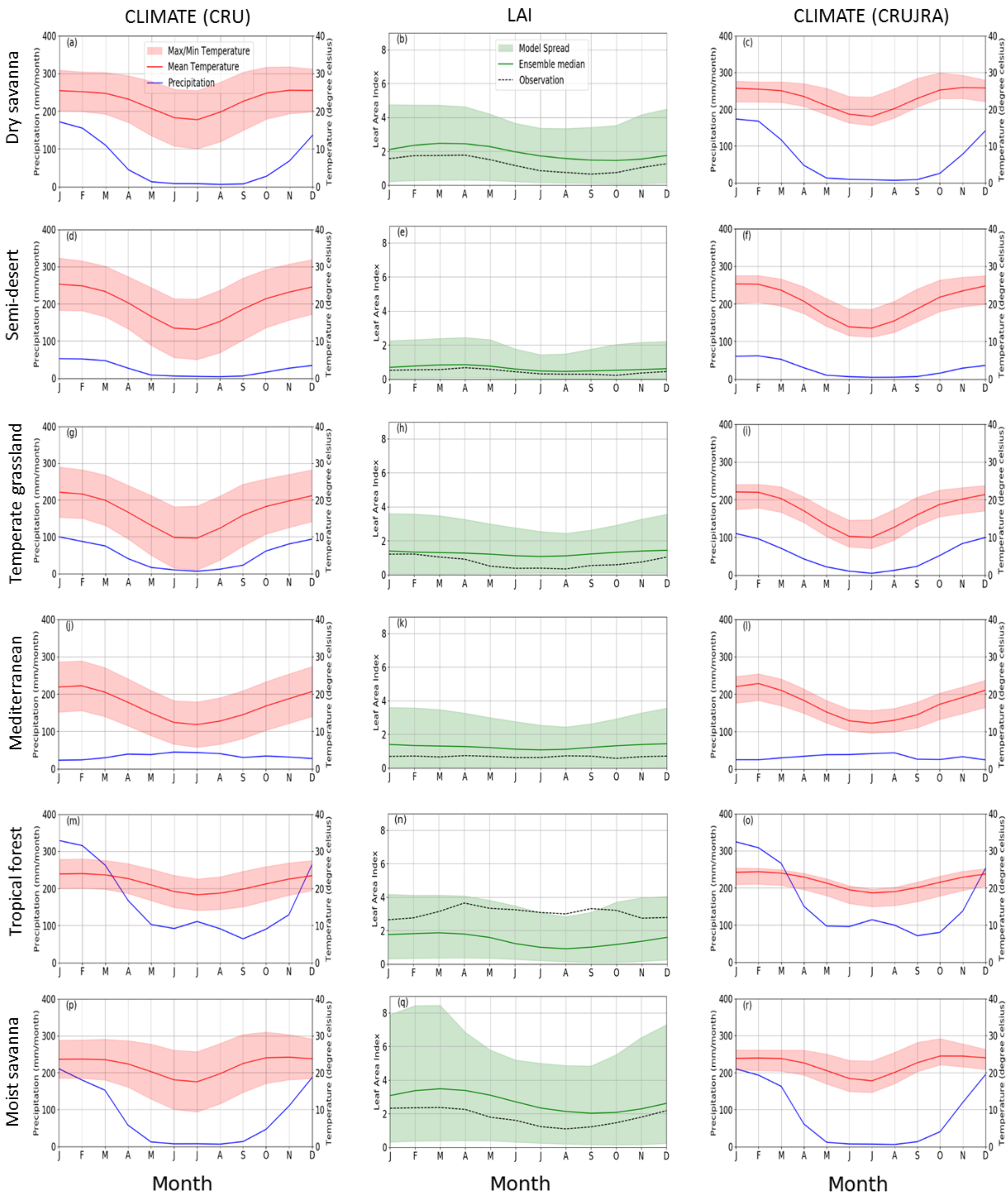

Figure 4. Annual cycle of observed climate variables (precipitation, mm/month; maximum, minimum and mean temperature, ºC) and LAI for observation and multi-model mean (TRENDY) across six southern African biomes over for the period 1982 – 2011. The annual cycle of the LAI for individual models are shown in Figure S5.

Furthermore, we should note, that a comparison of the spatial distribution of CRU and CRUJRA (formerly Fig. S6) has also been moved to revised manuscript, based on the suggestion of reviewer. This figure is now Fig. 5 and is shown in Lines 436 – 436, Page 15.

9. Line 375: "The severity of drought intensity is similar for all SPEI" – which character in Figure 4 do the authors refer to?

Response:

We were referring to the magnitude of the severity which is on the y-axis of 1-month to 24-month SPEI. This is now clarified in the text. Please see Line 455 Page 16.

10. Section 3.4 & 4.4: This finding is very interesting. I think it's worth to populate the discussion regarding possible reasons why models tend to overestimate the magnitude and time scale of vegetation response to drought and advice on future scopes of model developments.

Response:

Thank you. We added a discussion of the possible reasons why models tend to overestimate vegetation response to drought, and made suggestions on future scope of model developments in a newly added Section 4.6 Please Lines 826 – 848, Page 30. The text is copied below:

4.6 Variations in observed and simulated vegetation response to drought, and implications on model development

The biases shown by models could be attributed to the different limitations of individual DGVMs, and addressing these shortcomings would improve models' performances. For example, the sub-optimal performance of CLM may be partly due to the inability of the model to capture foliage production and root system of vegetation for transpiration. The model is also unable to produce savanna ecosystems, which it simulates by approximating vegetation of forest and grassland ecoregions (Dahlin et al., 2020). In addition, the ineffective simulation of deciduousness would have contributed to the model biases in response simulations. Therefore, targeting these limitations is important for improving model's performance in simulating morphology and physiological functioning of vegetation biomes. Furthermore, the DGVMs (e.g. JULES, DLEM) used in the study poorly replicate important ecological and physiological processes that are critical to capture the dynamics of savanna systems. Other DGVMs (e.g. JSBACH) poorly simulate significant environmental variables such as fire, which is very crucial for the vegetation growth cycle, particularly in the savanna biome (Thonicke et al., 2001; Romps et al., 2014; Kim et al., 2018; D'Onofrio et al., 2020). Also, over southern Africa, land use change (LUC) is a common and frequent occurrence, and is an important factor for vegetation turnover. However, most models do not well capture land management, which is an important driver of land cover change in the region. Thus, there is a need for future model development to account for rapid LUC over different regions. However, the disparity in observed and simulated response of vegetation to drought cannot be fully accounted for by the DGVMs alone. The reanalysis (CRUJRA) has also shown some limitations in the simulation of climate variables. Compared to observation-based CRU, CRUJRA has closer magnitudes of maximum and minimum temperature, and addressing this would improve simulated response.
Please see lines 829 – 850, Page 30.

11. Section 3.5: Why stratify the analyses based on latitude instead of the vegetation biome types?

Response:

We stratified the analyses based on latitude and investigate and identify the shift in response based on the vegetation types across the latitudinal belt. We have made clarifications on this in the revised manuscript. Please see Lines 506 – 508, Page 19.

We also classified our analyses based on vegetation types. Please see Figure 9 (formerly fig. 7).

In summary, we did both.

12. Figure 6: is the red line represent "ensemble median" or "ensemble mean"? I noticed that sometimes "ensemble mean" is used and sometimes "ensemble median" is used. Please check and clarify across the text/figures.

Response:

For Fig. 6 (now Fig. 8), the red line is ensemble mean. Ensemble median was used in Fig. 5 (now Fig. 7), where we calculated correlations. We have made further clarification across the text and figures. Also see Lines 509 – 524, Page 19 – 20.

13. Figure 7: While models overestimate the drought time scale for most of the vegetation biomes, it seems that they tend to underestimate the time scale for Dry savanna. Any ideas on what might be causing this difference?

Response:

A possible reason for the difference why the time scale for Dry savanna was underestimated may be because phenological triggers for dry savannah vegetation types respond differently to environmental variables, which the models do not capture. The African Dry savanna region is characterized by rapid vegetation changes due to fire, land-use among others, as well as senescence for prolonged dry periods (Rahimzadeh-Bajgiran *et al*., 2012; Zhu and Liu, 2015). Similarly, models all represent fire differently, and this could contribute to model responses. This has been added to the text. Please Lines 542 – 547, Page 21.

14. Table 1: It seems that CLM performs the worst among others. Could the authors explore a bit on why this is the case?

Response:

We plan to explore the reasons for this in future investigations. A possible reason for the weak performance of CLM may be its representation of the canopy construction of the PFTs and of its foliage clumping representation. In addition, CLM is limited in its simulations of vegetation with regards to transpiration, due to rooting among others (Dahlin *et al*., 2020). Furthermore, CLM does not well simulate savanna ecosystems, but instead uses a combination of grasses, shrubs, and trees. There are also some problems (such as an unusual green-up in dry season) identified with stress deciduous responses (Dahlin *et al*., 2015). Please see Lines 589-594, Page 23.

15. Section 3.8: Could the authors elaborate on how the impact of extreme events are evaluated and the rationale behind? For instance, how the correlation of a wet year of 2000 is calculated? I have trouble understand how the response for a single year is projected onto the response for a longer time span.

Response:

Apologies for the confusion. The objective was to investigate the impacts of extreme hot and dry years on LAI. In order to understand this, we selected very dry years and compared the response during these periods to wet years. We investigated the response in the individual years without projecting onto the response for a longer time span. Our method was adopted after Pan *et al* (2015). Clarifications have been made in the revised manuscript. Please Lines 599 – 609, Page 24.

Technical corrections:

16. Line 220: A period is missing after ". . .understanding drought impacts through 2011".

Response:

Thank you for the correction.

17. Line 244: Please correct for the typo – "Penman-Monteith".

Response:

Thank you.

18. Line 275: A period is missing in the end.

Response:

Noted. Thank you.

19. Line 419: Typo: "magnitude"

Response:

Thank you.

20. Line 589-590: Should be "Fig. S6"?

Response:

Thank you for the correction.

References

Dahlin, K. M. et al. 2015. Environmental drivers of drought deciduous phenology in the Community Land Model. – *Biogeosciences* 12: 5061– 5074.

Dahlin KM, Akanga D, Lombardozzi DL, Reed DE, Shirkey G, Lei C, Abraha M & J Chen. (2020) Challenging a global land surface model in a local socio-environmental system. Land. 9(398): 1- 21. DOI: 10.3390/land9100398

Department of Environmental Affairs (DEA). 2015. Climate Change Adaptation Plans for South African Biomes (ed. Kharika, J.R.M., Mkhize, N.C.S., Munyai, T., Khavhagali, V.P., Davis, C., Dziba, D., Scholes, R., van Garderen, E., von Maltitz, G., Le Maitre, D., Archibald, S., Lotter, D., van Deventer, H., Midgely, G. and Hoffman, T). Pretoria.

D'Onofrio, D., Baudena, M., Lasslop, G., Nieradzik, L. P., Wårlind, D., and von Hardenberg, J. (2020). Linking vegetation-climate-fire relationships in subsaharan africa to key ecological processes in two dynamic global vegetation models front. Environ. Sci. 8, 136. 10.3389/fenvs.2020.00136.

Driver A, Sink, KJ, Nel, JN, Holness, S, Van Niekerk, L, Daniels, F, Jonas, Z, Majiedt, PA, Harris, L and Maze, K 2012. National Biodiversity Assessment 2011: An assessment of South Africa's biodiversity and ecosystems. Synthesis Report. South African National Biodiversity Institute and Department of Environmental Affairs, Pretoria.

Kim, J.B., Kerns, B.K., Drapek, R.J., Pitts, G.S., Halofsky J.E. (2018). Simulating vegetation response to climate change in the Blue Mountains with MC2 dynamic global vegetation model Clim. Serv., 10 , pp. 20-32

Luo, L.; Tang, W.; Lin, Z.; Wood, E.F. Evaluation of summer temperature and precipitation predictions from NCEP CFSV2 retrospective forecast over China. *Clim. Dyn.* 2013, *41*, 2213–2230

Masih, I., Uhlenbrook, S., Maskey, S., and Smakhtin, V.: Stream-flow trends and climate linkages in the Zagros Mountain, Iran. Clim. Change, 104, 317–338, doi:10.1007/s10584-009-9793-x, 201, 2014.

Mukherjee, N., Zabala, A., Huge, J., Nyumba, T. O., Esmail, B. A., and Sutherland, W. J.: Comparison of techniques for eliciting views and judgements in decision-making. Methods in Ecology and Evolution, **9**, 54– 63, https://doi.org/10.1111/2041-210X.12940, 2017.

Pan, S., S. R. Dangal, B. Tao, J. Yang, and H. Tian (2015), Recent patterns of terrestrial net primary production in Africa influenced by multiple environmental changes, *Ecosyst. Health Sustainability*, **1**(5), 1–15.

Rahimzadeh-Bajgiran, P., Omasa, K., & Shimizu, Y. (2012). Comparative evaluation of the Vegetation Dryness Index (VDI), the Temperature Vegetation Dryness Index (TVDI) and the improved TVDI (iTVDI) for water stress detection in semi-arid regions of Iran. ISPRS Journal of Photogrammetry and Remote Sensing, 68, 1–12. doi:10.1016/j.isprsjprs.2011.10.009

Romps, D.M., Seeley, J.T., Vollaro, D., Molinari J. (2014). Projected increase in lightning strikes in the United States due to global warming Science, 346 (6211) , pp. 851-854

Thonicke, K., Venevsky, S., Sitch, S., and Cramer, W.: The role of fire disturbance for global vegetation dynamics: coupling fire into a Dynamic Global Vegetation Model, Global Ecol. Biogeogr., 10, 661–677, 2001.

Zhu, X., Liu, D., 2015. Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS J. Photogr. Rem. Sens. 102, 222–231.