Here, an overview is provided of all replies to the comments of the anonymous reviewers. Each concern is tackled separately. First the comment is listed, and our reply is pasted underneath in italics. Also, if we adapted the manuscript, this is added to our reply (underlined sentences represent the changes made to the draft.

Directly after the responses to all comments, we included a version of the manuscript marking all the performed changes.

Reply comments Reviewer #1

1. The authors used the Conditional Spectral Granger Causality framework to evaluate local biosphere – climate interactions at a global scale. This was done at three temporal scales (monthly, seasonally and yearly) and using vegetation dynamics (based on LAI) retrieved from both satellite observations and earth system model data. Overall, I think it is a very interesting and innovative approach. Although the method has a few restrictions, such as the inability to account for off-site effects of vegetation on climate, these are well acknowledged in the discussion.

Thank you for your insightful comments and support of the manuscript.

2. The authors could consider to change the title to multi-temporal scales instead of scales as the latter may also refer to spatial scale.

We acknowledge the possibility for confusion and have changed the title accordingly.

New title: Global biosphere–climate interaction: a multi-temporal scale appraisal of observations and models

3. Although not in the scope of this paper, could the approach be useful to evaluate how the interactions change over time?

Conditional Spectral Granger Causality can be used to address changes over time (see Dhamala et al., 2008). Currently, the wavelet spectrum is averaged over all time steps. This results in more robust statistical measures (i.e. higher statistical confidence), at the expense of a partial loss of time domain information. Resolving the time-frequency space requires more statistical power, which can only be achieved by averaging across large spatial extent. As the reviewer states, exploring the time dimension lies out of the scope of the current manuscript, but is definitely part of our future plans.

Dhamala, M., Rangarajan, G. & Ding, M. (2018). Estimating Granger causality from Fourier and wavelet transforms of time series data. Phys. Rev. Lett., 100, 018701.

4. There is likely an important anthropogenic effect on both vegetation and climate dynamics. Could this impact the obtained results?

Anthropogenic effects impacting climate on the long term, and resulting in multi-decadal trends, are not addressed in this study due to the limited data record. As the reviewer noticed, based on the three-decade record length available for the analyses, and considering unavoidable time series edge effects, we can only *resolve reliably time scales with periods smaller than 10 year. Conversely, vegetation disturbances directly driven by human activities, such as deforestation, agricultural practices, etc., can generate variability in the vegetation indices on a much broader range of scales, thus directly affecting our analyses. However, because this variability is not necessarily related to climate, it will be assimilated into residual noise in our approach. Granger causality assumes causal sufficiency and regions with unobservable causes (in this case those leading to e.g. deforestation) will be poorly resolved by the framework. This is now explicitly mentioned in the revised version.*

In text, Sect. 3.1: <u>Noteworthy is that anthropogenic effects, which are not addressed here, can also impact vegetation and climate at short temporal scales. For example, irrigation and deforestation can result in a decoupling between climate and vegetation (Lawrence et al., 2015; Chen et al., 2019). In the tropics, deforestation results in a warming effect due to reduced plant transpiration, which in turn may induce a decline in precipitation, creating a warmer and drier regime (Lawrence et al., 2015). Irrigation allows for growing crops in water-limited regions, consequently inducing energy constraints which are captured by the CSGC. Note that due to the limited data record, the effects of global warming trends and carbon dioxide fertilisation – and the consequent trends in vegetation greening and water use efficiency (Reichstein et al., 2013; Wu et al., 2015; Zhu et al., 2016) – are not directly addressed in this study.</u>

5. The inter-annual impact of climate on vegetation is very patch over Africa and North America in contrast to the modelled output (fig 2). Do the authors have an idea why this happens? Is this a methodological issue, data issue or are the drivers of long term trends more spatially heterogeneous (which is not catched by the models).

We thank the reviewer for this comment. We further explored these patterns after the referee's comment, and concluded that the shape parameter of the Morlet wavelet partly influences the results in this regard. This parameter provides a trade-off between spectral and temporal resolution. By increasing the time-resolution the conditional causality patterns at inter-annual scales can be better resolved. This improves the clarity in the figures, even if some heterogeneity remains. A further improvement followed one of the comments of Reviewer #2 (see comment #2), who requested an ensemble based on multiple datasets of LAI and climate variables, which would help resolve issues related data errors. Both the tuning of the shape parameter as well as the creation of the ensemble are adopted in the revised version and all figures are updated accordingly. We described the selection of the frequency parameter to balance the time and frequency resolution in the manuscript.

In text, Sect 2.2.2: …between predictors and target variable. <u>In order to perform the time-frequency decomposition, the Morlet wavelet is used and a balance between the time and frequency resolutions is obtained by setting the shape parameter to a value of 6, as in Torrence and Compo (1998), or Casagrande et al. (2015). Moreover,</u> to overcome the limitation…

6. Did the authors try to run the analysis over the same time period for the remote sensing and model data (page 4, line 17)? Do the results substantially differ?

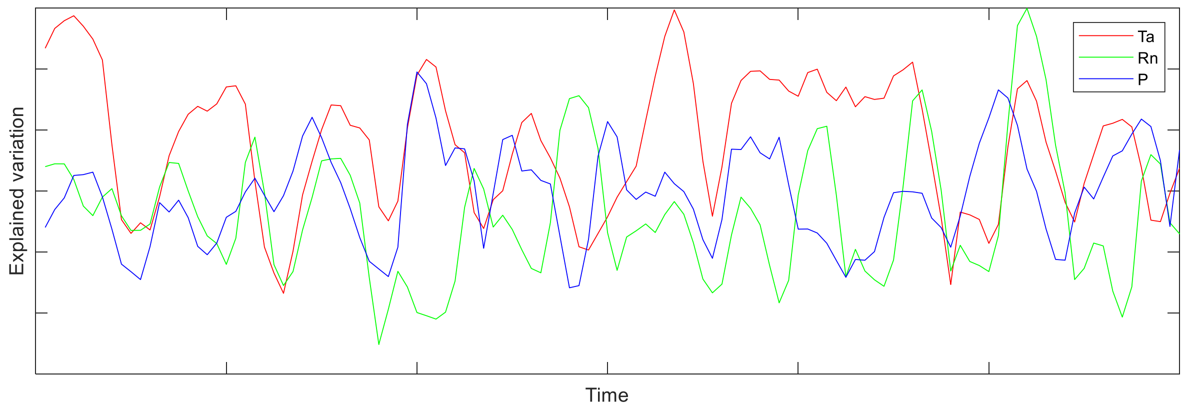
We thank the reviewer for this comment. We have already run the analysis over the same time period and found that almost no changes occurred. The results for inter-annual scales faint slightly, but the major patterns remain consistent. We have included the results to the supplementary and discussed them in the main text.

In text, Sect. 2.1.2: …under the assumption that sensitivities are stationary (see e.g. Green et al., 2017). <u>Sect. 3.2 addresses the validity of this assumption.</u> Nonetheless, we…

In text, Sect. 3.2: … (Fig 2e), and is also strongly overestimated in absolute terms at most latitudes, especially in the tropics. <u>Further analysis shows that the divergence in the considered period between observations and models (see Sect. 2.1) does not substantially impact results; repeating the analysis for the overlapping time range for observations and models (1982—2005) yields very similar findings (Fig. C1).</u>

7. The approach includes data outside the growing season to estimate the monthly interactions. Yet, variations in LAI might not be meaningful during this period. Could this potentially affect the results?

Yes, we agree with the reviewer that it would be more meaningful from a biological point of view to include only data from the growing season. We are currently working to resolve the time domain to the Conditional Spectral Granger Causality formulation (see comment #3), which would allow us to tackle this issue explicitly in the future. Below you can find a preliminary figure that shows the percentage of explained variation by climate at a monthly scale over a 10-year period for a pixel located in central Russia calculated using CSGC to address changes over time. We can clearly see that during wintertime, air temperature (and radiation) generally seem to inhibit vegetation growth, while during summer, when the temperature is high enough for plants to grow, water limitation spikes. This figure shows how we can disentangle drivers from in- and outside the growing season as they do differ. However, as stated in comment #3, this is out of the scope of this paper.



Also, we are confident that the adoption of an ensemble approach (see Reviewer #2 comment #2) will dampen the sensitivity of our method to the errors in the individual data sources, thus removing product-specific biases in wintertime.

8. What is the policy of the authors concerning sharing data/scripts? Are the authors planning to make these available via a repository/upon reasonable request/…?

We are open for sharing the scripts using GitHub after publication at https://github.com/lhwm. All datasets used in this study are freely available, for which links will be provided in the README.md file of the GitHub-page.

Reply comments Reviewer #2

1. The manuscript explores the biosphere-climate interactions at global scale. The method, based on a Granger Causality framework, quantifies the climate impact on vegetation and the vegetation feedback on climate using satellite observations. The same approach is then applied to four ESMs and differences between data and model results are discussed. The study is well written and potentially interesting as – to my knowledge – is the first work aimed to isolate the climate-vegetation interactions analytically using observations and can help the modelling community to improve ESMs. However, I have some major concerns that need to be carefully addressed before publication.

We thank the reviewer for the insightful comments and we hope that we have addressed all major and minor concerns adequately.

General comments

2. The study is based on a limited set of observational datasets: only one product per variable. In particular, LAI and precipitation data show large discrepancies and inconsistencies across products (Jiang et al., 2017). Results, based on such a limited set of products, may be largely affected by specific product uncertainties. The analysis should be replicated by using an ensemble of different products for LAI, P and possibly T and Rn. Results based on an ensemble of combinations would be much more robust. Comparison of results obtained from different combinations of products would also enable you to assess the validity of your approach and the consistency of your results. (Jiang, C. et al. Inconsistencies of inter-annual variability and trends in longterm satellite leaf area index products. Glob. Change Biol. 23, 4133–4146 (2017).)

We thank the reviewer for this comment. We agree that by creating an ensemble of LAI, P, T and Rn, we can significantly improve the robustness of the results. We have added three more LAI products, corresponding to those used in Jiang et al. (2017). Furthermore, for climate we added air temperature and net radiation from ECMWF's most recent reanalysis product ERA5, and two more precipitation products, namely ERA5 and GPCC. We added more products for LAI and precipitation as for air temperature or net radiation due to the larger inter-product variability. A brief description of all included products was added to the data section, and figures were updated after repeating the analysis for all ensemble members. Results for all model ensembles generally agree well (see comment 3).

In text, Sect. 2.1.1: <u>To avoid product-specific biases and artefacts, an ensemble of multiple observation-based products for each variable is created, consisting of: (a) four LAI, (b) two air temperature, (c) two net radiation, and (d) three precipitation data sets. The larger ensemble of data sets here adopted to characterise LAI and precipitation is motivated by the larger disparity among the different products of these variables (Jiang et al., 2017; Sun et al., 2018). Tab. 1 provides an overview of the available datasets.</u> Finally, the International Geosphere-Biosphere Program (IGBP) land cover classification (Loveland and Belward, 1997) is used to determine biome-specific behaviours…

Table 1. Summary of global data sets used for vegetation, i.e. LAI, and climate, i.e. air temperature (Ta), net radiation (Rn), and precipitation (P).

Product	***Minimum resolution***		***Variable***	***Reference***
	Spatial	***Temporal***		
Global Inventory Modelling and Mapping Studies 3rd generation (GIMMS3g)	*1/12°*	*1982-2015; bimonthly*	*LAI*	*Zhu et al. (2013)*
NOAA/AVHRR Thematic Climate Data Record (TCDR) Reflectance	*0.05°*	*1982-2018; daily*	*LAI*	*Claverie et al. (2016)*
GIMMS3g + Terra/MODIS C5 reflectance (GLOBMAP)	*1/13.75°*	*1982-2017; 28-day*	*LAI*	*Liu et al. (2012)*
NOAA/AVHRR LTDR + Terra/MODIS C5 reflectance (GLASS)	*0.05°*	*1982-2015; 8-day*	*LAI*	*Xiao et al. (2016)*
ECMWF ERA5	*32km*	*1979-…; hourly*	*Ta, Rn and P*	*Hersbach and Dee (2016)*
Climate Research Unit – National Centers for Environmental Prediction (CRU-NCEP) version 7	*0.05°*	*1901-2016; 6-hour*	*Ta, Rn and P*	*Viovy (2018)*
Global Precipitation Climatology Centre (GPCC)	*0.5°*	*1891-2016; daily*	*P*	*Schneider et al. (2011)*

3. Spatial patterns shown in figures (e.g., figs. 2, 3 and appendices) are very jeopardized and – a part of the radiation control patterns – are not very credible. There is a huge spatial heterogeneity even in regions characterized by the same environmental conditions. I'm wondering, if such spatial variability reflects some problems of stability in the algorithm or noise in the modelled signal. These strange patterns emerge particularly at longer time scales (seasonal, inter-annual) maybe because the sample size is more limited? I really find difficult to believe in such patterns and authors should make an extra effort to improve or at least understand such spatial variability. In my opinion, such spatial variability could originate from the native time series (possible uncertainties in the signal) and the processing of the signal, as I do not see any patterns that can be easily related to physical conditions. Maybe, the use of ensemble of different observational products (see previous comment) may help to retrieve a more robust signal.

We are aware of the heterogeneity at longer timescales, and also reviewer #1 (see comment #5) pointed to this issue. The problem is partly due to the parametrization of the frequency parameter of the wavelet, which provides a trade-off between temporal and spectral resolution. As mentioned in the response to reviewer #1 (see comment #5), fine-tuning the parameter to increase temporal resolution can improve the inter-annual patterns. However, the noisy patterns can also occur due to noise in the input data, as mentioned in comment #2, and the length of the available sample. By creating an ensemble of datasets and changing the frequency parameter, the noise related to errors in the data is greatly reduced, resulting in more homogeneous patterns, even at inter-annual scales. All figures are updated, and the result section is updated accordingly (only minor changes). We described the selection of the frequency parameter to balance the time and frequency resolution (see Reviewer #1 comment #5).

4. The benchmark of ESMs is very useful and interesting. However, the authors should try to identify potential areas of model improvements. This exercise should aim to clearly understand what are the strengths and deficiencies of each single model with respect to the data-model comparison performed. A table to synthesize areas of improvements could help to convey the key information to modelers.

Although we agree this might be of interest to the modelling community, we aimed not to single out individual models in this manuscript due to length restrictions. Moreover, we believe that by focusing on model *differences, or even specific model parameterisations, we might dilute the main findings that relate to the whole range of models. Therefore, we believe a model-specific interpretation is outside the scope of this study, and hope the reviewer may agree with this rationale.*

5. Remote sensing LAI data in winter season are affected by snow cover conditions. I'm wondering how you have addressed this issue. If you did not account for this, I think your results may be strongly affected by this bias.

We acknowledge that snow cover might affect the LAI in the high northern latitudes, especially at the seasonal and monthly scales. At the moment, we do not address this issue. As pointed in the response to reviewer #1 (see comment #7), we are currently working on adapting the CSGC algorithm to explicitly resolve different time steps/periods, which would, in the future, allow to resolve the causal relationships in time and mask out periods of poor data quality. This however requires an in-depth adaptation of the method. In the response to reviewer #1 (see comment #7), we added a preliminary figure showing the temporal variation in explained variance by three drivers over a 10-year period. This clearly shows that, in the future, we can tackle this issue. Furthermore, we are also confident that the adoption of an ensemble approach (as proposed by comment #2) will dampen the sensitivity to errors in individual products, during for instance wintertime, being however aware of the fact that these errors are likely systematic and shared by all data products. In the revised manuscript, this issue is explicitly discussed.

In text, Sect. 3.1: …incoming radiation during winter months. <u>However, in those latitudes, LAI retrievals are contaminated by snow cover signals. While focusing on the growing season could solve this issue, the CSGC requires continuous time series. Because in wintertime, due to limitations in solar radiation, plant growth is inhibited in northern latitudes, most variability captured at monthly scales will be dominated by the more dynamic spring and summer periods; therefore, our results suggests that radiation still dominates the behaviour of vegetation at these latitudes. This dominant high-latitude radiation control was not reported by Papagiannopoulou et al. (2017b), who, based on a non-linear Granger causality framework, found</u> that 61% of the vegetated land…

6. The relevance of the multi-temporal scale needs to be clarified, what is the added value of such analysis compared to previous studies focusing only on monthly scale.

We feel that the fact our results differ for different frequencies (time-scales) highlights by itself the need to consider these frequencies separately to better understand the driving role of climate in ecosystem dynamics. To better clarify this point, we revised the manuscript to explain why, conceptually, phenology scales and inter-annual variability also need to be considered separately when models are evaluated.

In text, Sect. 1: … <u>Despite efforts to identify the controls of vegetation, which showed that ESMs overestimate the annual LAI due to problems related to the timing of the phenological cycle (Anav et al., 2013; Murray-Tortarolo et al., 2013; Zhu et al., 2013; Forkel et al., 2014; Verger et al., 2016), ESMs remain in need of a better understanding of why these multi-temporal scale variabilities differ from the observations. *Rather than using correlation or regression techniques, a method capable of inferring causality can greatly aid our understanding of key climate-biosphere processes, which in turn can help enhance the ESMs (Runge et al., 2019).*</u> *In a recent example,…*

Specific comments:

Page 1

- Paper of interest: https://www.nature.com/articles/s41467-019-10105-3 (Runge et al.: Inferring causation from time series in Earth system sciences, Nature communications, 10.1, 2553, 2019.).

At the time of submitting the first version of the manuscript, this article was not officially published yet, despite it being of interest for our manuscript. We've added it to the manuscript (see reply comment #6).

- Line 9: Are you referring to the onset, end of growing season, or what? Please clarify. LAI is not synonym of phenology.

As this is a recurring comment, we will clarify here what we mean by 'phenology'. We are aware that LAI seasonality is not a synonym of phenology, however, we do believe that LAI is highly sensitive to phenological changes, as also shown by Richardson et al. (2009) and Verger et al., 2016, just as Vegetation Optical Depth (VOD) is often used as a proxy of the vegetation total biomass due to its close proximity to the vegetation water content Liu et al. (2011). Here, if we speak of phenology, or phenological cycle, we mean the dynamics of LAI over the seasons. If CSGC points towards a certain climate control on vegetation at seasonal scale, this means that the variation in climate within a year, i.e. seasonality, contains information that can explain the behaviour of vegetation. For instance, in the northern latitudes, the seasonality of radiation precedes the seasonal pattern of vegetation, but these two are closely linked. One can state than that the total phenological cycle, e.g. the timing (start and end) of the growing season, the amplitude of the variations, etc. are strongly forced by radiation in this example. We incorporated this definition in the main manuscript, as we feel the abstract is not the right place to do so. (References not in manuscript: Liu et al. Global long-term passive microwave satellite-based retrievals of vegetation optical depth, Geophysical Research Letters, 38, L18402, 2011).

In text, Sect. 2.2.6: …differ from the short-term processes. <u>Hereafter, the terms phenology and phenological cycle are used to refer to the seasonal-scale variability in LAI. This reflects features such as the timing of the growing season or the amplitude of the intra-annual cycle (Richardson et al., 2009; Verger et al., 2016), since CSGC will react to variability in both the time and frequency domains. As explained in Sect. 2.2.3, CSGC allows a simultaneous analysis of the interactions at multi-temporal</u> scales, while no assumption…

In text, Abstract: …<u>The seasonal LAI variability</u> in energy-driven latitudes…

- Line 11: For completeness, can you also briefly refer to the role of temperature?

In text: … inter-annual than multi-month scales. <u>Globally, precipitation is the most dominant driver of vegetation at monthly scales, particularly in (semi-)arid regions. The seasonal LAI variability</u> in energy-driven latitudes is mainly controlled by radiation, while <u>air temperature controls vegetation growth and decay in the high northern latitudes at inter-annual scales</u>. The observational results…

- Line 13: Please, specify over which temporal scale?

In text: … semi-arid regions <u>at inter-annual scales</u>. Analogously,…

- Line 15: Again, it is not clear here to what phenology is referring to?

We refer to the comment of page 1, line 9 that tackled this issue and hope it helped to solve the confusion.

In text: … control of air temperature on <u>seasonal forest variability</u>. Overall…

- Line 17: I found a bit too much speculative the interpretation… Could not be just because the direct effect of climate on LAI is larger than the opposite feedback of vegetation on climate in nature? The fact that you are focusing on local scale without remote effect does not imply per se that the feedback of vegetation could be larger than the climate impact on vegetation.

We thank the reviewer for this remark. We did not mean to state that the feedback on climate is smaller as the climate impact on vegetation due to the local nature of our analysis. However, we do see how this statement could be interpreted this way. Therefore, we altered the statement slightly.

In text: …Overall, climate impacts on LAI are found to be stronger than the feedbacks of LAI on climate in both observations and models; <u>in other words, local climate variability leaves a larger imprint on temporal LAI dynamics than vice versa. Note however that while vegetation reacts directly to its local climate conditions, its dynamics may affect climate preferably downwind, especially in the case of precipitation. Consequently, the local (i.e. spatially collocated) character of the analysis does not allow for the identification of downwind or remote feedbacks, biophysical effects of vegetation on climate might be underestimated.</u> Nonetheless, the widespread…

Page 2

- Line 8 and 10: our biosphere → the biosphere, our Earth system → the Earth system

Agree, corrected in text.

- Line 12: You give per granted that models do not work well… I would reformulate the sentence… something like: models have shown limitations in capturing…

Agree, the statement was open to interpretation. We changed it in the text.

In text: <u>The different approaches to objectively evaluate the skill of Earth System Models (ESMs) in representing the two-way coupling between vegetation and climate have revealed several limitations</u> (Randerson et al., 2009; …

- Line 14: Consider to include the following publication: https://www.earth-syst-sci-data.net/10/1265/2018/ (Duveiller et al., Biophysics and vegetation cover change: a process-based evaluation framework for confronting land surface models with satellite observations, Earth System Science Data, 10, 1265-1279, 2018)

We thank the reviewer for this suggestion and added the article to the references.

- Line 15: Clarify why it is important “the representation of particular inter-variable sensitivities”

We agree we left this open for interpretation. It is important to study these links between variables in models to identify which processes are missing, or remain under-represented. In addition, ESMs have been shown to overestimate the mean annual LAI due to overestimation of the length of the growing season (see comment #6).

In text: …Most of these efforts focus on the evaluation of the magnitude and <u>short-term</u> dynamics of individual variables (such as LAI, and gross primary production, GPP), rather than on the inter-variable sensitivities, <u>which would be more informative on whether the interplay between vegetation and climate is reliably represented in these models. Furthermore, previous benchmark studies have typically focused on one specific time scale (typically annually or monthly), while the ecosystem response to (and feedback on) climate is expected to vary for different time scales; e.g. a model may accurately replicate the observed interplay between vegetation and climate at monthly scales, but still fail to capture the sensitivities that become relevant at seasonal or inter-annual time scales.</u>

- Line 24: Please, clarify why it is important to explore the multi-temporal issue. This would help the reader to follow your rationale and to better appreciate your findings. I would also stress here the challenges that you try to address. From what I understood, the multi-temporal scales and the explicit representation of causal relation between vegetation and climate represent the key novelty of your work. I would put more emphasis on these two aspects.

We thank the reviewer for this suggestion. We can see how the manuscript can benefit from stressing this more explicitly. We made some alterations in the text (see comment #6 and comment page 1, line 15).

- Line 25: I would mention that Papagiannopoulou et al. (2017b) do not address the seasonal and inter-annual scales in order to clearly differentiate your study from the previous work.

In text: In a recent example, Papagiannopoulou et al. <u>(2017a,b)</u> focused on evaluating multi-month vegetation variability in response to local climate, using a non-linear Granger causality framework <u>applied to optical remote sensing indices</u>. They showed that water availability and precipitation patterns primarily drive vegetation anomalies at monthly scales in more than 60% of the vegetated land<u>, but did not address the relevant drivers over longer time scales. The inter-annual variability in terrestrial</u> carbon fluxes has…

Page 3

- Line 1: I would suggest integrating your literature review with these relevant articles. https://science.sciencemag.org/content/351/6273/600 (Ramdane et al., Biophysical climate impacts of recent changes in global forest cover, Science, 351(6273), 600-604, 2016), https://www.nature.com/articles/s41467-017-02810-8 (Duveiller et al., The mark of vegetation change on Earth’s surface energy balance, 9, 679, 2018)

We thank the reviewer for this suggestion and added the references to the literature review.

In text, Sect. 1: … mainly due to high transpiration (Bonan et al., 2008; Forzieri et al., 2017). In fact, a net warming effect has been reported after tropical deforestation and agricultural expansion (Alkama et al., 2016; Duveiller et al., 2018). Furthermore, the biosphere…

- Line 18: In principle, it may serve also to detect where models work well. I would rephrase a bit the sentence in a more general way.

Agree.

In text: … (CMIP5) models (Taylor et al., 2012; see Sect. 3.2 and 3.3). By comparing the observational and model-based results, areas where certain processes and inter-variable sensitivities may be incorrectly represented in ESMs, as well as others that match the observed behaviour, are identified.

- Line 31: Remote sensing LAI data in winter season are affected by snow cover conditions. I'm wondering how you have addressed this issue. If you did not account for this, I think your results may be strongly affected by this bias.

We agree with the reviewer that snow cover conditions might affect LAI in winter season, especially in high northern latitudes. However, we strongly believe that our results from CSGC, after adopting an ensemble for the observations and optimising the shape parameter, are trustworthy. For a full response to this question, we refer to comment #5.

Page 4

- Line 4: Why do you not use the ESA-CCI land cover product (and conversion to pass to PFT)? In principle, this enables to track for changes in PFT over almost the entire period of study. The ESA-CCI product represent the state-of-the-art product aimed to improve the link between remote sensing users and climate modellers… https://www.esa-landcover-cci.org/

We are aware of the ESA-CCI land cover product, and its possibilities. However, due to the fact that our current CSGC framework does not allow to detect changes over time in inter-variable sensitivities between climate and vegetation (see Reviewer #1 comment #3), we felt that for now, such a state-of-the art land cover product was overqualified. Also, the IGBP product is widely used, which simplifies comparison of our results with already published ones. Finally, as with all choices regarding data, the final choice remains subjective. However, we do see potential to use the ESA-CCI land cover product in our current work focussing in changes of explained variation between climate and the biosphere. We hope the reviewer agrees with our decision of using the IGBP product in this manuscript.

- Line 8: Given the large differences amongst different products for some of the variables considered, I would strongly suggest to account for multiple products (https://onlinelibrary.wiley.com/doi/10.1111/gcb.13787 ; Jian et al., Inconsistencies of inter-annual variability and trends in long-term satellite leaf area index products, Global Change Biology, 23, 4133-4146, 2017). For instance, for LAI, data from GLASS, LTDR, GLOBMAP could also be included in the study. The same for precipitation which show large discrepancies – especially at inter-annual scale – depending on the dataset used. The use of ensemble of observational products would make your results more robust and substantially improve the work.

We strongly agree with the reviewer and adopted an ensemble for the observations. The manuscript and figures are updated accordingly. See comment #2 for more information.

- Line 9: Please clarify the value of using online model simulations in place of offline simulations. I see a potential limitation as in online ESMs the climate signal may largely determine the response of the land surface and then mask the interplay between vegetation and biophysical processes. Further reading: Blyth et al., A comprehensive set of benchmark tests for a land surface model of simultaneous fluxes of water and carbon at both the global and seasonal scale, Geoscientific Model Development, 4(2), 255-269, 2011. (https://doi.org/10.5194/gmd-4-255-2011) and Winckler et al., Robust identification of local biogeophysical effects of land cover change in a global climate model, Journal of Climate, 30(3), 1159-1176. (https://doi.org/10.1175/JCLI-D-16-0067.1)

We thank the author for this remark and for the articles of interest. Since CSGC is capable of unravelling interactions between variables without any assumption on the direction of these interactions, we saw the opportunity to use CSGC to investigate both the climate impacts on vegetation, and also the feedbacks of vegetation on climate. We also aimed to benchmark how these two-way interactions are represented in the ESMs, and therefore, we chose to work with online models as they do not only allow for climate to affect vegetation, but also for vegetation to provide a feedback on climate. In offline models, the separate parts of the models are driven by their necessary input, without any influence of the other parts. We added a brief description of this in the text.

In text: … account for dynamic vegetation (Anav et al., 2015). <u>Coupled model simulations are used to evaluate the full extent of vegetation feedbacks on climate.</u> Using the historical…

- Line 13: Please, clarify the selection, why only these 4 models are used here?

These models are selected based on a combination of three criteria. All CMIP5 ESMs are selected based on the use of their land surface components also present in TRENDY initiative to allow for comparison with studies using these models, such as Forzieri et al. (2018). Also, only ESMs accounting for dynamic vegetation are retained and the models must provide hourly climate output (precipitation, air temperature and radiation). These criteria results in the selection of four models (CCSM4, HadGEM2-ES, NorESM1-M and IPSL-CM5A-MR). We added these criteria to the revised version of the manuscript.

In text: <u>A selection of coupled ESMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) is assessed in their representation of climate—vegetation interactions. This includes the</u> Hadley Global… (CCSM4; Gent et al., 2011). This selection is based on (a) <u>use of similar land surface schemes as the Trends in Net Land-Atmosphere Exchange (TRENDY; Sitch et al., 2015) initiative, in order to allow for comparison with studies focussing on TRENDY models, (b) availability of hourly input data for air temperature, precipitation, and net radiation (aggregated to monthly values in this study), and (c) model consideration of dynamic vegetation (Anav et al., 2015).</u> Online model simulations…

- Line 15: Are all models run under a consistent modelling setup (e.g., same land cover changes, same climate forcing)? Please clarify. The consistency in modelling experiment is important to compare the different model results with each other

Yes, all models simulations where selected from the CMIP5 archive filtering for historical runs, ran with increasing greenhouse gas and sulphate aerosol concentrations, changes in solar radiation, forcing by volcanic aerosols, and time-evolving land-use changes (Anav et al., 2015).

- Line 17: Not sure this is correct. You basically used two different periods of analysis of observations and models: 1981-2015 (ca 35 years) for observations; 1956-2005 (50 years) for models. A part of the temporal shift between the two experiments, I would suggest to verify that the different length in the time series do not introduce a systematic bias between observational- and model-based results. Why you decided to start from 1956 for models? To me, it would be more logic at least to preserve the same length of observations (35 years). Please, check this and clarify your choices.

We agree that the change in period between observations and models may have an impact on our results. However, we analysed both observations and models for their overlapping period, and found no major changes to the results. The model results do faint for inter-annual scales due to the drastic decrease in sample points, but the general patterns remain, i.e. all regions show a similar climate control as for the 50-year period, albeit less clear due to the decreased sample size. Therefore, the models can be assumed to behave stationary and the period for models can be extended to 50 years to increase the robustness of the results. We added a brief description in the text and added the figures of the analysis for the overlapping period to the supplementary. For more information, we refer to the reply to reviewer #1, comment #6.

Page 5

- Line 24: In the present formulation of GC, the temporal lag m is implicitly assumed the same for all predictors. In practice, I expected that the legacy effects may differ depending on the predictor. Can this be included in the formulation? Please, discuss the implications.

To clarify, this formula refers to traditional Granger Causality, and not to the (Conditional) Spectral Granger Causality as calculated by Dhamala et al. (2008). CSGC, as proposed by Dhamala et al. (2008), is non-parametric and consequently no longer requires prescribing a specific lag; the dominant lag is in fact resolved by the formulation. For traditional Granger causality in the time domain, the parameter m represents the maximum temporal lag which best represents the dynamic of the system. This does not mean that all predictors have significant effect up to the lag m. A predictor might influence the system up to a lag k<m, which means that, for that predictor, the coefficients of the autoregressive model from k+1 to m will equal zero. So if the parameter m is chosen big, all possible legacy effects can be included in a multivariate case, and the most dominant lags will have the largest coefficients, and not necessarily at the same lag. However, by raising the maximum lag, also the computation costs increase. Therefore, a trade-off between included memory effects and computational cost needs to be taken into account with traditional Granger Causality. We hope resolves the remark. We also added a shorter version of this rationale to the manuscript.

In text: …where m defines the <u>maximum</u> order of the autoregressive model (with m <= n), i is the time lag, a_i are the coefficients describing the linear interaction between different time steps, and ϵ_t is the prediction error. <u>Note that the order m defines the maximum lag that is investigated, which does not necessarily imply that all predictors have an effect up to time step m. By increasing m, more lags are included, at the cost of increasing the computational demand.</u>

- Line 27: In principle, data could be aggregated at seasonal or annual level and the GC applied to such values. I presume that the limited sample size hampers the use of GC in such an “aggregated” mode. Please clarify.

Yes, in principle, this is possible, and this is also roughly what Spectral Granger Causality does (but in a more elegant way). SGC decomposes the data in a time and frequency space using wavelet transformation. Then, instead of constructing the autoregressive models for each new time series at each determined frequency (which would require setting the parameter m arbitrarily, keeping in mind the computational costs), SGC is calculated the non-parametric way as described by Dhamala et al. (2008). Aggregating the data to seasonal and annual time series would create a limited sample size to determine GC, and would also generate abrupt breaking points in the data. Therefore, we apply Conditional Spectral Granger Causality instead of running the traditional Granger Causality in an aggregated mode. We shortly described this in the text as a justification to switch to Spectral Granger Causality.

In text: <u>Despite traditional Granger causality being capable of addressing short-term interactions, simply aggregating time series to their seasonal or annual equivalents prior to following a traditional Granger causality approach does not necessarily lead to realistic causation inference at larger temporal scales.</u> Consequently, Granger causality frameworks that are defined in the time domain…

Page 6

- Line 2: …assess <u>temporal</u> scale-dependent…

Adapted in text.

- Line 19: I believe that Eq. 7 needs more clarification for readers not familiar with the method.

We thank the reviewer for the concern and agree that a reader unfamiliar with the method needs more clarification. The method starts with traditional Granger Causality, followed by a description of Spectral Granger Causality, and ends with Conditional Spectral Granger Causality. We feel that further explanation of SGC won’t benefit the reader, but refer to, in our opinion, excellent introductory material on the method and its application to ecological problems. Readers that are truly interested in understanding the method are better suited in studying this material rather than trying to understand it from the limited space we have available in this manuscript.

In text: … using matrix factorisation (Wilson, 1972). <u>For more information on SGC, we refer to Ding et al., (2006), Dhamala et al. (2008) and Detto et al. (2012; 2013).</u>

- Line 29: Zp in place of Xp

A minor mistake did indeed slip into the formula. We corrected for it. We thank the reviewer for noticing it.

Page 7

- Line 14: I would clearly mention that CSGC does not allow to quantify the sign of causal relation. It is already mentioned in results… but I would also mention here – or somewhere in the method section – because important.

We agree with the reviewer and added a sentence stating that CSGC can only detect that there is a relation between variables, but not the sign of the causal relation. However, we also like to clarify that the sign of causality is less meaningful in time series analyses, where the concept of positive and negative interactions is substituted by the phase angle. For example, a positive interaction between time series corresponds to a zero phase angle (the series are in phase or perfectly synchronised, i.e. when one goes up, to other goes up as well). Conversely, a negative interaction implies that the series are out of phase (one goes up, the other goes down). These series would have an arbitrary angle of 180° or -180°. These phase angles can be determined using co-spectral analyses, but not directly from the Granger causality measure.

In text: ... However, if there is a direct causal influence of X on Y at a specific frequency f, $CSGC_{X\rightarrow Y|Z_1,Z_2\ldots Z_p}(f) > 0$. *Using Eq. 10, it is possible to determine if X (Granger-) causes Y, but no information on the sign of the causal relation can be extracted.*

Page 9

- Line 3: I would refer to seasonal LAI variability here and in the rest of the manuscript. Phenology implies other metrics that are not accounted for in this work.

We sincerely thank the author for the concern. We hope our reply to the comment on page 1, line 9 clears the confusion.

- Line 8: Please clarify this upper value.

*Theoretically, +∞ is the largest timescale, calculated using extrapolation. However, the first real maximum value equals 16.5 years due to the discretisation of the frequency phase by CSGC. The frequency phase is discretised in angular frequency from 0 to π, in 100 values (default). As frequency [1/month] equals the angular frequency divided by 2π, and since scale [years] equals 1/(Frequency*12), the maximum scale (corresponding to an angular frequency of π/99) equals 16.5 years. By tweaking the discretisation level, the maximum real scale could be raised to exactly 17 years (half of the total period for observations). However, since 16.5 years is extremely close to 17 years, and as we do not study the inter-decadal patterns, we opted for using the default value of 100 discrete frequencies, evenly spaced throughout the angular frequency space. We added a brief description to the method section.*

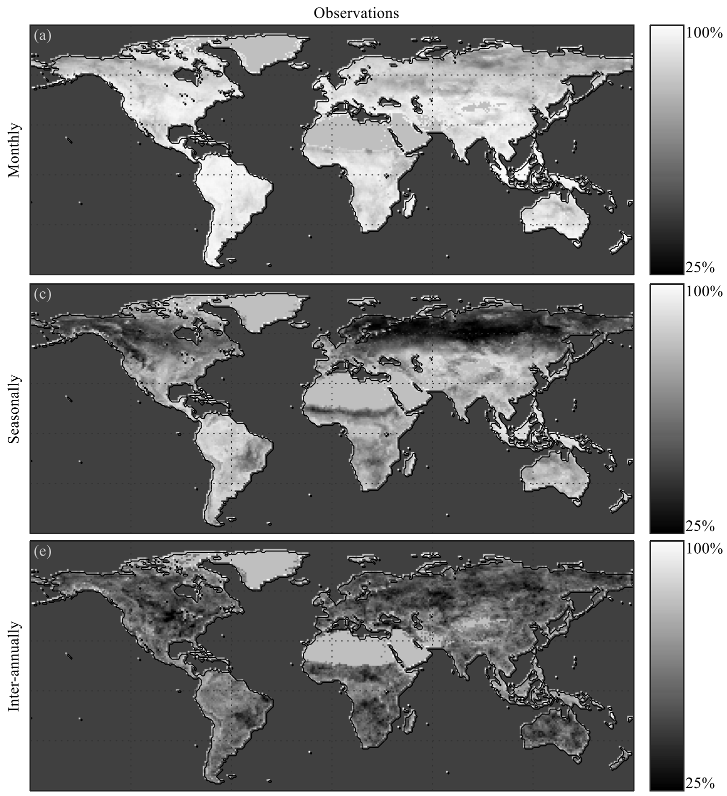
In text: …between climate and vegetation. Moreover, based on the characteristics of the climate data used in this study, CSGC can be applied to assess causality over a wide range of temporal scales, starting at 2 months (twice the temporal resolution) and going up to 16.5 years (maximum temporal scale due to discretisation of the frequency space; can be adjusted if needed, especially for longer time series).

Page 10

- Line 9: Could irrigation or land enlargement, particularly relevant in some regions of the globe, partially explain some patterns (e.g. India and China). Should the irrigated lands not be factored out?

https://www.nature.com/articles/s41893-019-0220-7 (Chen et al., China and India lead in greening of the world through land-use management, Nature Sustainability, 2, 122-129, 2019)

We thank the reviewer for this comment. We could factor out irrigated lands and other disturbed surfaces, but chose to only exclude non-vegetated areas such as desserts. We acknowledge that practices such as irrigation can impact the results. Here, only three dominant climate drivers are addressed, meaning that if human activities, such as e.g. irrigation, are the main driver of vegetation in an area, as could be in India and China, these regions probably get an energy-related driver attributed to them. However, if maps would be created of the part of variance that is not explained by the (considered) climate variables, areas with high human impact would be highlighted (see figure below, showing the variability in LAI not driven by climate). As can be seen, areas such as India and China show close to 100% of variation in LAI not driven by climate (white colors) at monthly scales. We chose not to show these maps in the supplementary, to avoid an abundance of plots. However, if the reviewer finds it necessary to include these maps, we can add them. In the manuscript, we chose not to exclude these areas, as also irrigated lands remain partly driven by climate, albeit to a limited extent. We added a paragraph to the manuscript to discuss this issue (see reviewer #1 comment #4)



- Line 16: I presume that if you mask irrigated lands, this fraction will increase. Can you please comment on this?

Yes, if irrigated lands are masked, the percentage of water limited regions would probably increase. Also, if irrigation would have been included, the percentage of water limited area would be higher. However, although we do not include irrigation as a driver, we strongly believe that are findings are valid, as irrigation is performed with the intention to resolve a water limitation, consequently making the vegetation more dependent on the energy constraints. We added a brief description to the manuscript.

In text: Here, our monthly-scale <u>results also show a dominant role of precipitation, yet more moderate;</u> 51% of vegetated land is primarily controlled by precipitation, with radiation being the primary control factor in 40% as well. When the analysis…

In text: … as opposed to the use of precipitation only in this study. <u>Note that not accounting for irrigation explicitly, does net necessary bias our results, since irrigation is intended to increase the energy-dependence of LAI dynamics, and will still reflect on a larger dominance of air temperature and net radiation in our analysis</u>. A final difference…

- Line 17: same detrending and deseasonalisation approach used for the predictors, right?

We agree that it is not clear from the text that also anomalies are calculated for the predictors and clarified it in the text.

In text: … When the analysis targets vegetation anomalies by detrending linearly and subtracting the average seasonal cycle <u>for both LAI and climate</u> (as was done in Papagiannopoulou et al. (2017a, b)), the results…

- Line 22: compared to what? Fig A1? Papagiannopoulou et al. (2017)?

We mean compared to Papagiannopoulou et al. (2017b). We rearranged this statement to clear this up. We also reduced the comparison of the findings of Papagiannopoulou et al. (2017b) with previous studies, and added a short comparison with our findings.

In text: …net radiation in our analysis. <u>A final difference with Papagiannopoulou et al. (2017b) is the consideration in the latter of snow water equivalent as a water availability driver, which explains the divergence with our results in higher latitudes. Our results can also be reconciled with previous studies, such as Nemani et al. (2003), Wu et al. (2015), and Seddon et al. (2016); regional differences may relate to the specific focus of those studies on one temporal scale only, their calculation of covariances instead of inferring causality in a more formal manner, or the use of different variables to assess water availability drivers.</u>

- Line 22: also the methods used to quantify the causal relations differ

We agree with the reviewer, the methods do differ substantially. Whereas we use raw data and a spectral variant of Granger Causality, Papagiannopoulou et al. (2017a, b) used an adapted non-linear Granger Causality framework on anomalies. However, this concern is valid for every study, as no study is repeated exactly in the same fashion. We do, however, agree that caution has to be taken when concluding from the comparison of both studies.

- Line 23: Should the snow precipitation not be already considered in CRU data that is used here?

Snow precipitation is considered in CRU, but snowmelt, and thus the delayed availability of water, is not considered by CRU. Papagiannopoulou et al. (2017b) did consider snowmelt as an additional climate driver related to water availability.

- Line 24: battery → set

Resolved due to rearranging and condensing the paragraph (see reply comment page 10, line 22).

Page 11

- Line 1: forcing on vegetation

Resolved due to changes in the results and rephrasing.

In text: … however, using incoming radiation as driver instead, leads to a similar 54% dominance (see Fig. B1). Compared to monthly scales, <u>seasonal precipitation control is less widespread, as only 33% of the vegetated land is primarily controlled by precipitation (compared to 51% at monthly scales; Fig. 2a and 2c). This reduced importance of precipitation can be attributed to the observed temperature-driven hotspot in the Sahel regions, but more importantly to increase of radiation control over the south of Eurasia and in tropical forests. Furthermore, the patterns in</u> Amazonia tend to agree

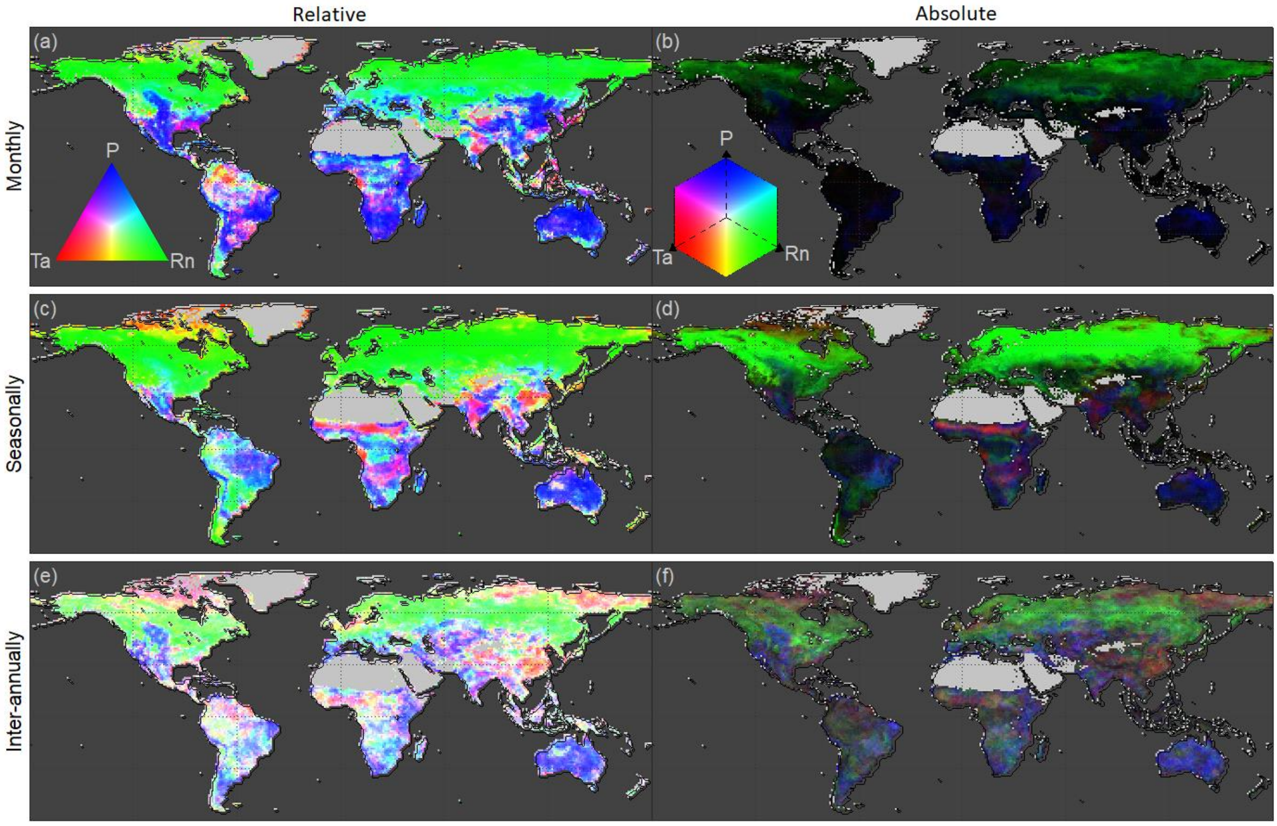
- Line 6: I find a dominance of precipitation very elusive… There are no clear patterns emerging at inter-annual scales. Probably the P control is just a bit over the other driver… but to me what emerges from Fig. 2e is a major co-dominance of multiple drivers. Please, can you please comment on this.

We strongly agree with the concern of the reviewer. From Fig 2e, a major co-dominance of all three drivers is observed at inter-annual scales, with precipitation being slightly higher in some regions. However, due to adopting an ensemble for the observations (see comment #2), and by adjusting the shape parameter for the wavelet transformation (see comment #3), clear patterns emerged in line with what was stated before. However, compared to monthly and seasonal scales, some co-dominance remains, so the manuscript is altered to account for this.

In text: Finally, at inter-annual scales, <u>despite co-dominance of multiple drivers in some regions</u>, global ecosystems tend to be water limited <u>with 43%</u> of the vegetated land surface being primarily dominated by precipitation (Fig. 2e), <u>especially in the subtropics</u>. Although patterns…

- Line 28: To me, the comparison performed only on these numbers is misleading because they refer to the relative contribution to the total explained variance. Therefore, ESMs could be in principle represent well the variability of the T control on vegetation in absolute terms, but could overestimate the P control on vegetation in absolute terms. This would lead to an underestimation of the T control in relative terms over the globe… Again, not because they fail to represent the T control but because they fail the P or Rn controls. The analyses should be complemented with the comparison in absolute terms.

We agree that a relative contribution does not tell the complete story, and can result in regions that are falsely identified with poor model performance. If, for example, Ta is correctly captured by the models, but P is overestimated in absolute terms, Ta would indeed appear to be underestimated in relative terms. Therefore, we chose to add the latitudinal profiles, which show how much vegetation is driven by climate in absolute terms. If a systematic overestimation of one driver would occur, this would be noticeable in the latitudinal profiles. Also, the spiderplots show the behavior per biome in absolute terms, which complements Fig. 2 and 3 in our opinion. We have thought of showing the global maps in absolute terms, where red still means pure control by Ta, green by Rn and blue by P. However, by doing so, we would transfer from a triangular colorscheme to a 3D-colorcube, where black means no climate control by all three drivers and white means *maximum climate control by all three drivers (not possible in practice as we use a conditioned measure of Granger causality, so theoretically, the sum of the explained variance by all three drivers has as maximum value 100%). As often only one driver controls vegetation dominantly, the other two bands of the RGB plot remain (close to) zero, resulting in a grey-tinted figure. One could threshold this figure in order to get it more bright, but also then oversaturation is a problem. The figure below illustrates this, as on the left the relative contributions of each driver are shown for the observations (identical to Fig 2, but without dotting for significance), while on the right the absolute explained variance is shown. Here, a simple thresholding was performed by multiplying each figures with a factor 2, so bright green here means that not 100% of vegetation variation is controlled by net radiation, but 50% is. Without this simple thresholding, all figures are mainly black or grey-tinted. As it is impossible to find an ideal threshold for all three temporal scales, we opted for showing the relative contributions in the maps in the manuscript, which implies that we lose the ability the compare the absolute value between pixels. But we can compare the ranking of the drivers over pixels. The latitudinal profiles in Fig. 2 and 3 and the spiderplots (Fig. 4 and 5) complement these maps with absolute values.*



Page 12

- Line 1: Clarify what you mean? Precipitation and air temperature?

The statement was indeed not clear. We altered it in the manuscript.

In text: Seasonally, a larger control <u>of precipitation and air temperature</u> on vegetation phenology is noticeable over the equator for ESMs…

- Line 20: I found the patterns from observations very jeopardized across all analysed temporal scales, and in particular at seasonal and inter-annual scales. It is really difficult to believe that in the real world you pass from one dominant control to another one while remaining in the same environmental conditions. This heterogeneity should be better explored and understood. The use of ensemble of combination of different observational products of LAI, P, T and Rn could help to derive more robust and spatially consistent patterns.

We agree with the reviewer that the patterns appear extremely heterogeneous. Adopting the ensemble for the observations greatly improved the patterns (see comment #2) as did optimizing the shape parameter of the wavelet transformation (see comment #3). We hope that with these changes, all concerns are addressed.

Page 13

- Line 13: more clear → clearer

Resolved due to rephrasing and changes in the results.

In text: <u>At seasonal scales, an increase of feedbacks on temperature is observed in the Northern Hemisphere, and feedbacks on precipitation remain limited to the tropics, although practically no statistical significance is reached outside the tropics (Fig. 3c). Finally, at inter-annual scales,</u> the observations-based results…

- Line 19: You could move figure 6 earlier and refer to it.

We thank the reviewer for the suggestion, but we see Fig. 6 more as a synthesis of all our findings to conclude the manuscript. If the reviewer agrees, we would like to keep it in the conclusion. We are aware this is not standard practice.

- Line 25: ESMs capture correctly the LAI effects on net radiation throughout most of the Northern hemisphere. How do you reconcile with results from Forzieri et al. (2018)? (Forzieri et al., Evaluating the interplay between biophysical processes and leaf area changes in land surface models, Journal of Advances in Modelling Earth Systems, 10(5), 1102-1126, 2018.)

This difference could arise from the use of online (here) ESMs and offline (Forzieri et al., 2018) land surface models (LSMs), as the latter force the model with climatic data and carbon dioxide concentration, without any feedbacks of the land surface on climate. However, after using an ensemble for the observations (see comment #2) and optimising the shape parameter (see comment #3), the patterns did change. From Fig. 3, one could state that the feedbacks on vegetation seem to be well captured by the ESMs in the northern latitudes, however, as this figure shows the relative feedbacks, one can only with certainty state that ESMs correctly identify the feedback on net radiation to be the strongest in these regions. When looked at Fig. 5 (the spiderplot showing the feedbacks per biome), one can clearly see that, especially at seasonal and monthly scales, needleleaf forests (both evergreen and deciduous) seem to overestimate the absolute feedback on net radiation, which is in line with the findings of Forzieri et al. (2018). Overall, the result section changed slightly due to adopting the ensemble for the observations, and the alteration of the shape parameter.

In text: In general, ESMs <u>seem to correctly capture the spatial extent of LAI effects on net radiation throughout most of the Northern Hemisphere, but underestimate feedbacks of vegetation on air temperature, which</u>

originates from either an actual underestimation of the air temperature feedback by ESMs, or an overestimation of the feedback on net radiation in these regions, as reported by Forzieri et al. (2018) and confirmed by the latitudinal profiles (Fig. 3b,d,f), which masks the vegetation feedback on air temperature. Despite the overestimation, models do agree with each other on the influence of LAI on net radiation at polar latitudes (see dotted pixels), and the overall mean ensemble patterns for monthly and seasonal time scales also agree with observational results. *Interestingly, while observations….*

In text, Sect. 3.4: …Nonetheless, the effect of needleleaf forests on the radiation budget tends to be overestimated by most CMIP5 models, especially at monthly and seasonal time scales, which aligns with the findings of Forzieri et al. (2018). ESMs also overestimate…

Page 14

- Line 9: I would say only for EBF, DNF, DBF, MF. For the rest of classes, the data-model comparison is fine…

We agree with this remark. However, due to the updates of the figures, the patterns changed slightly, aggravating the difference between observations and models even more for mixed forests (MF), deciduous broadleaf forests (DBF), deciduous needleleaf forests (DNF) and evergreen broadleaf forests (EBF). The overestimation is strongest for broadleaf forest in that sense that even the minimum model simulations exceed the maximum observed impact of air temperature on LAI. A short description of these findings is added to the manuscript.

In text: …In regards to the influence of air temperature, strong differences with observations can be noticed at seasonal time scales for forest biomes; this is most remarkable for broadleaf forests, both evergreen and deciduous (EBF and DBF), which show a model overestimation of the control of temperature on LAI dynamics, even for the minimum modelled temperature control. Interestingly, models…

- Line 19: Only when averaged at biome level. Maps in Fig. 3 differ substantially. Maybe this concept would merit to be expanded a bit. Results from ESMs and satellite tend to converge when averaged at biome level… can you please comment on this?

We agree with the statement that feedbacks of vegetation seems to be well modelled by ESMs if the response is averaged at biome level. When looked at the maps in relative terms, such as Fig. 3, patterns tend to be masked sometimes, probably due to the under- or overestimation of a single driver. However, at biome level, these errors are lost in the average biome response. We also refer to the comment of page 13, line 25, which already tackled these differences between patterns in relative and absolute terms. We added a comment on this in the manuscript.

In text: On the other hand, short-term feedbacks of LAI on climate seem to be better represented in ESMs, as small differences can be seen when compared to the observational results in Fig. 5. Note that this statement only holds if looked at biome-averaged patterns, as comparison of observations and models in Fig. 3 does indicate to clear regional differences. Deciduous needleleaf forests (DNF) and evergreen needleleaf forests (ENF) exhibit …

- Line 30: Can you please reconcile or at least interpret these divergences?

We agree this section stops abrupt. However, due to changes in the results, this statement was no longer correct and it was altered.

In text: The strength of the effect of LAI on precipitation is overall lower than its impact on net radiation and air temperature<u>, partly due to the non-consideration of downwind influences in this analysis. However, similar to the results of Green et al. (2017), a strong influence of LAI on precipitation can be observed in savannah regimes.</u>

Fig 2 and 3 and appendices: I suggest a different color palette because colours tend to saturate quickly and differences can not be appreciated well.

We thank the author for his concerns, however, as stated in the reply to comment page 11, line 28, the other option is using absolute numbers, which darken the maps and also make them hard to compare.

Figure 4: change order of variables consistently with figure legend.

We agree with the reviewer and changed the order in the legend so it is consistent with the figures, also for Fig. 5.

Global ~~biosphere~~biosphere-–climate interaction: a ~~multi-scale~~ multi-temporal scale appraisal of observations and models

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Abstract. Improving the skill of Earth System Models (ESMs) in representing climate–vegetation interactions is crucial to enhance our predictions of future climate and ecosystem functioning. Therefore, ESMs need to correctly simulate the impact of climate on vegetation, but likewise, feedbacks of vegetation on climate must be adequately represented. However, model predictions at large spatial scales remain subjected to large uncertainties, mostly due to the lack of observational patterns to benchmark them. Here, the bi-directional nature of ~~climate-vegetation~~ climate–vegetation interactions is explored across multiple temporal scales by adopting a spectral Granger causality framework that allows identifying potentially co-dependent variables. Results based on global and multi-decadal records of remotely-sensed leaf area index (LAI) and observed atmospheric data show that the climate control on vegetation variability increases with longer temporal scales, being higher at inter-annual than multi-month scales. ~~The phenological cycle~~ Globally, precipitation is the most dominant driver of vegetation at monthly scales, particularly in (semi-)arid regions. The seasonal LAI variability in energy-driven latitudes is mainly controlled by radiation, while ~~in (semi-)arid regimes precipitation variability dominates at all temporal scales. However, at~~ air temperature controls vegetation growth and decay in high northern latitudes at inter-annual scales~~, the control of water availability gradually becomes more wide-spread than that of energy constraints. The~~ . These observational results are used as a benchmark to evaluate ESM simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5). Findings indicate a tendency of ESMs to over-represent the climate control on LAI dynamics, and a particular overestimation of the dominance of precipitation in arid and semi-arid regions at inter-annual scales. Analogously, CMIP5 models overestimate the control of air temperature on ~~forest seasonal phenology~~seasonal forest variability. Overall, climate impacts on LAI are found to be stronger than the feedbacks of LAI on climate in both observations and models~~, arguably due to the local~~ ; in other words, local climate variability leaves a larger imprint on temporal LAI dynamics than vice versa. Note however that while vegetation reacts directly to its local climate conditions, its dynamics may affect climate preferably downwind, especially in the case of precipitation. Consequently, since the local (i.e. spatially collocated) character of the analysis ~~that~~ does not allow for the identification of downwind or remote ~~vegetation feedbacks~~feedbacks, biophysical effects of vegetation on climate might be underestimated. Nonetheless, ~~wide-spread effects~~ the widespread effect of LAI variability on radiation~~are~~ , as observed over the northern latitudes ~~, presumably related~~ due to albedo changes, ~~which are well-captured~~ is overestimated by the CMIP5 models.

Overall, our experiments emphasise the potential of benchmarking the representation of particular interactions in online ESMs using causal statistics in combination with observational data, as opposed to the more conventional evaluation of the magnitude and dynamics of individual variables.

1 Introduction

The biosphere is a key actor in the global carbon and water cycles, mainly through its impact on the energy balance at the Earth's surface and the chemistry of the atmosphere (McPherson, 2007; Pearson et al., 2013; Le Quéré et al., 2018). Long-term patterns in temperature, incoming radiation and water availability strongly control the global distribution of biomes, while vegetation in turn alters climate via a series of local and remote feedbacks (Kottek et al., 2006; Bonan, 2008). In boreal regions, for example, vegetation is thought to preferentially warm the atmosphere (positive feedback) by lowering the surface albedo, while in tropical regions, it is ~~expected~~ thought to have a local net cooling effect (negative feedback), mainly due to high transpiration (Bonan, 2008; Forzieri et al., 2017). ~~Furthermore, our~~ In fact, a net warming effect has been reported after tropical deforestation and agricultural expansion (Alkama and Cescatti, 2016; Duveiller et al., 2018b). Furthermore, the biosphere also provides a ~~strong negative feedback to the the global carbon cycle~~ negative climate feedback by acting as a net carbon sink (Schimel et al., 2015). This strong regulating power of vegetation in ~~our~~ the Earth system indicates the need to ~~properly~~ accurately incorporate biosphere–climate interactions in the models used to predict changes in terrestrial ecosystems and future climate (Piao et al., 2013; Pachauri et al., 2014; Le Quéré et al., 2018). ~~As~~ The different approaches to objectively evaluate the skill of Earth System Models (ESMs) ~~are expected to imperfectly capture the sensitivity of vegetation to climate, and vice versa (Green et al., 2017), different approaches have been followed to objectively evaluate their skill in representing these interactions (Randerson et al., 2009; Weiss et al., 2012; Murray-Tortarolo et al., 2013; Alessandri et al., 2017; Forzieri et al., 2018)~~ in representing the two-way coupling between vegetation and climate have revealed several model limitations (Randerson et al., 2009; Weis . Most of these efforts focus on the evaluation of the magnitude and short-term dynamics of individual variables (such as ~~leaf area index,~~ LAI, and gross primary production, GPP), rather than on the ~~representation of particular~~ inter-variable sensitivities~~.~~ , which would be more informative on whether the interplay between vegetation and climate is reliably represented in these models. Furthermore, previous benchmark studies have typically focused on one specific time scale (typically annually or monthly), while the ecosystem response to (and feedback on) climate is expected to vary for different time scales; e.g. a model may accurately replicate the observed interplay between vegetation and climate at monthly scales, but still fail to capture the sensitivities that become relevant at seasonal or inter-annual time scales.

Nonetheless, a first and necessary requirement towards improving the predictive skill of ESMs is the availability of data that can be used as reference. Satellite observations of our biosphere, hydrosphere and atmosphere are now widely available, providing multi-decadal records of climatological and environmental variables at global scale that can be used as benchmark. Several studies have already focused on identifying short- and long-term global impacts of climate on vegetation using observational data, mostly from satellites (Nemani et al., 2003; Zhao and Running, 2010; Forkel et al., 2014; De Keersmaecker et al., 2015; Wu et al., 2015; Seddon et al., 2016; Papagiannopoulou et al., 2017b). ~~Nonetheless, studies focusing on how the dominant interactions vary as a function of temporal scale (e. g., monthly, seasonally and inter-annually) are still lacking, and so is the evaluation of this inter-scale variability in ESMs~~Despite efforts to identify the controls of vegetation, which showed that ESMs overestimate the annual LAI due to problems related to the timing of the phenological cycle (Anav et al., 2013; Murray-Tortarolo et al., 2013; Zhu et al., 2013; Forkel et al., 2014; Verger et al., 2016), ESMs remain in need of a better understanding of why these multi-temporal scale variabilities differ from observations. Rather than using correlation or regression techniques, a method capable of inferring causality can greatly aid our understanding of key climate–biosphere processes, which in turn can help enhance the ESMs (Runge et al., 2019). In a recent example, ~~Papagiannopoulou et al. (2017b)~~ Papagiannopoulou et al. (2017a, b) focused on evaluating multi-month vegetation variability in response to local climate, using a non-linear Granger causality framework applied to optical remote sensing indices. They showed that water availability and precipitation patterns primarily drive vegetation anomalies at monthly scales in more than 60% of the vegetated land~~. While this study evaluated the ecosystem response based on optical remote sensing indices, the influence of climate on terrestrial ecosystem~~ , but did not address the relevant drivers over longer time scales. The inter-annual variability in terrestrial carbon fluxes has also been intensively explored in recent years, with apparent contradictions in the findings regarding the importance of water availability ~~for inter-annual~~ and air temperature for biosphere dynamics (Jung et al., 2017; Humphrey et al., 2018; Green et al., 2019; Stocker et al., 2019). In addition, most studies to date have either attributed the covariance of vegetation and climate dynamics to the role of atmospheric processes driving biosphere variability (e.g., Nemani et al., 2003; Zhao and Running, 2010; Forkel et al., 2014; De Keersmaecker et al., 2015; Wu et al., 2015; Papagiannopoulou et al., 2017b), or to the opposite processes, i.e. the feedbacks of vegetation on climate (e.g., Forzieri et al., 2017; Zeng et al., 2017)~~. To~~ ; to the authors knowledge, the study by Green et al. (2017) is the only exception in which the causal directionality of vegetation–climate interactions has been formally disentangled at global scales. In ~~this~~ that study, a linear Granger causality approach was used to successfully unravel impacts and feedbacks between biosphere and climate at multi-month scales. However, the traditional Granger causality framework is unsuited to identify which interactions dominate at different temporal scales, thus to differentiate between the dominant causes and effects at multi-month, seasonal and inter-annual scales (Detto et al., 2012).

Here, we investigate climate–vegetation interactions over the global domain using an innovative variant of Granger causality, referred to as Conditional Spectral Granger Causality (CSGC) – see Dhamala et al. (2008) and Detto et al. (2012). CSGC relies on transforming time series from the time domain into a time–frequency space using the continuous wavelet transform, enabling the simultaneous analysis of interactions that are active at different temporal scales, from (e.g.) monthly to inter-annual. In addition, this technique allows for evaluating the contribution of any variable while conditioning on the others, and, because CSGC can cope with lagged responses, it enables the assessment of bi-directional interactions (Dhamala et al., 2008; Detto et al., 2012; see Sect. 2.2). The latter implies that the vegetation feedback on climate can be quantified separately from the climate impact on vegetation. In this study, CSGC is first applied to satellite observations to reveal useful insights regarding the global, ~~multi-scale~~multi-temporal scale, bi-directional interaction between vegetation dynamics and local climate (Sect.

3.1 and 3.3). Next, to benchmark the ESM representation of these biosphere–climate interactions, the approach is replicated using the outcome from online simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5) models (Taylor et al., 2012; see Sect. 3.2 and 3.3). By comparing the observational and model-based results, areas where certain processes and inter-variable sensitivities may be incorrectly represented in ESMs, as well as others that match the observed behaviour, are identified.

2 Data and methods

2.1 Data

Multiple satellite-based ~~datasets~~ data sets are used to evaluate the representation of climate–vegetation interactions in ESMs. The focus is on the key climatic drivers of vegetation growth, here assumed to be precipitation, net radiation and air temperature, consistent with previous studies (Nemani et al., 2003; Seddon et al., 2016; Jung et al., 2017; Papagiannopoulou et al., 2017b). Vegetation dynamics are diagnosed using LAI; in the following, when vegetation (state) is mentioned, the latter refers to LAI unless stated otherwise. All datasets have global coverage, are processed into $0.5°$ spatial resolution via bilinear interpolation, and are averaged to monthly values prior to the application of CSGC.

2.1.1 Observational data

~~Observations of LAI come from the Global Inventory Modelling and Mapping Studies 3rd generation (GIMMS3g; Zhu et al. , 2013). Bimonthly LAI data at $1/12°$ spatial resolution is produced using aneural network between GIMMS3g Normalised Difference Vegetation Index (NDVI) and LAI from the Moderate Resolution Imaging Spectroradiometer (MODIS) . The final dataset covers the period July 1981 – December 2015. Climate data is obtained from the Climate Research Unit - National Centers for Environmental Prediction (CRU-NCEP) version 7 (Viovy, 2018). CRU-NCEP provides atmospheric data obtained through merging the CRU TS3.2 observations and NCEP reanalysis data, resulting in a $0.5°$ product, available from 1901 up to 2016. Finally, for the comparison of the results between observations and models, the International Geosphere-Biosphere~~ To avoid product-specific biases and artefacts, an ensemble of multiple observation-based products for each variable is created, consisting of: (a) four LAI, (b) two air temperature, (c) two net radiation, and (d) three precipitation data sets. The larger ensemble of data sets here adopted to characterise LAI and precipitation is motivated by the larger disparity among the different products of these variables (Jiang et al., 2017; Sun et al., 2018). Tab. 1 provides an overview of the available data sets. Finally, the International Geosphere–Biosphere Program (IGBP) land cover classification (Loveland and Belward, 1997) is used to determine biome-specific behaviours. At a biome-level, the mean observed and modelled interactions are calculated, and the range in ESM results is determined. These biomes include mixed ~~forests~~ forest (MF), deciduous broadleaf forest (DBF), deciduous needleleaf forest (DNF), evergreen broadleaf forest (EBF), evergreen needleleaf forest (ENF), barren or sparsely vegetated (BSV), cropland or natural vegetation mosaic (CNVM), ~~croplands~~ cropland (C), ~~grasslands~~ grassland (G), ~~savannas~~ savanna (S), woody ~~savannas~~ savanna (WS), and open ~~shrublands~~ shrubland (OS).

Table 1. Summary of global data sets used for vegetation, i.e. LAI, and climate, i.e. air temperature (Ta), net radiation (Rn), and precipitation (P).

Product	Minimum resolution		Variable	Reference
	Spatial	**Temporal**		
Global Inventory Modelling and Mapping Studies 3rd generation (GIMMS3g)	1/12°	1982–2015; bimonthly	LAI	Zhu et al. (2013)
NOAA/AVHRR Thematic Climate Data Record (TCDR) Reflectance	0.05°	1982–2018; daily	LAI	Claverie et al. (2016)
GIMMS3g + Terra/MODIS C5 reflectance (GLOBMAP)	1/13.75°	1982–2017; 28-day	LAI	Liu et al. (2012)
NOAA/AVHRR LTDR + Terra/MODIS C5 reflectance (GLASS)	0.05°	1982–2015; 8-day	LAI	Xiao et al. (2016)
ECMWF ERA5	32km	1979–...; hourly	Ta, Rn and P	Hersbach and Dee (2016)
Climate Research Unit - National Centers for Environmental Prediction (CRU-NCEP) version 7	0.05°	1901–2016; 6-hour	Ta, Rn and P	Viovy (2018)
Global Precipitation Climatology Centre (GPCC)	0.5°	1891–2016; daily	P	Schneider et al. (2011)

2.1.2 Earth System Model data

A selection ~~ESMs, i. e.~~ of coupled ESMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) is assessed in their representation of climate–vegetation interactions. This includes the Hadley Global Environment Model 2 - Earth System (HadGEM2-ES; Collins et al., 2011), Institut Pierre Simon Laplace - Component Models 5 - Medium Resolution (IPSL-CM5A-MR; Dufresne et al., 2013), Norwegian Earth System Model 1 - Medium Resolution (NorESM1-M; Bentsen et al., 2013), and Community Climate System Model 4 (CCSM4; Gent et al., 2011)~~, from the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) is assessed in their representation of climate–vegetation interactions.~~ . This selection is based on (a) use of similar land surface schemes as the Trends in Net Land-Atmosphere Exchange (TRENDY; Sitch et al., 2015) initiative, in order to allow for comparison with studies focusing on TRENDY models, (b) availability of hourly input data for air temperature, precipitation and net radiation (aggregated to monthly values in this study), and (c) model consideration of dynamic vegetation (Anav et al., 2015). Coupled model simulations are used to evaluate the full extent of vegetation feedbacks on climate. Using the historical input climate data, one realisation was used for each model to simulate vegetation dynamics, resulting in a monthly time series of LAI. Due to the discontinuation of historical simulations in 2005, the overlap with the observational record is limited to 24 complete years. To enhance the robustness of the results, the analysis period considers the entire ~~1956-2005~~ 1956–2005 in the case of ESMs, under the assumption that the sensitivities are stationary (see e.g. Green et al., 2017). Sect. 3.2 addresses the validity of this assumption. Nonetheless, we acknowledge that the non-stationarity associated with changes in land use and land cover may induce divergences between the observation and model results.

2.2 Methods

~~Multi-frequency~~ Multi-temporal scale interactions between climate and vegetation are here explored using CSGC. To describe the method comprehensively, we first introduce the Granger causality in its classical formulation (parametric in the time domain; Sect 2.2.1), followed by the derivation of its spectral counterpart (non-parametric in the time-frequency domain; Sect. 2.2.2 and 2.2.3).

2.2.1 Granger Causality: Time domain formulation

According to Granger (1969), causality can be inferred if a predictor X ($[x_1, x_2 ... x_{n-1}, x_n]$), with n the number of time steps, contains information in past terms that aids the prediction of a target variable Y ($[y_1, y_2 ... y_{n-1}, y_n]$), while this information is not contained in any other predictor or past values of the target variable itself. To assess the predictive power of X on Y, the self-explanatory power of Y, i.e. the autocorrelation, has to be determined first, so it can later be factored out. At time t, the auto-predictive power of Y can be calculated with the following univariate autoregressive equation:

$$y_t = \sum_{i=1}^{m} a_i y_{t-i} + \epsilon_t \tag{1}$$

where m defines the maximum order of the autoregressive model (with $m \leq n$), i is the time lag, a_i are the coefficients describing the linear interaction between different time steps, and ϵ_t is the prediction error. Note that the order m defines the maximum lag that is investigated, which does not necessarily imply that all predictors have an effect up to time step m. By increasing m, more lags are included, at the cost of increasing the computational demand.

The predictive power of X on Y can be assessed through construction of a second autoregressive model, containing a term capturing the contribution of X, given by:

$$y_t = \sum_{i=1}^{m} a_i y_{t-i} + \sum_{i=1}^{m} b_i x_{t-i} + \eta_t \tag{2}$$

with η_t representing the prediction error of the bivariate model. A drawback is the need to set the order m, which, if set non-optimal, can result in large estimation errors.

Granger causality is then typically defined as the natural logarithm of the ratio of two prediction error variances (Ding et al., 2006), σ_ϵ^2 and σ_η^2 for the univariate and bivariate model, respectively:

$$GC_{X \to Y} = \ln \frac{\sigma_\epsilon^2}{\sigma_\eta^2} \tag{3}$$

The null hypothesis of X causing Y (or vice versa), can be tested for significance against a preset p-value, typically 5%. Thus, if $GC_{X \to Y}$ exceeds the preset threshold, assuring that σ_η^2 is significantly smaller than σ_ϵ^2, X is said to have a causal effect on Y. Similarly, the causal effect of Y on X can be determined. Note that as the effect of autocorrelation is removed, a simple correlation between X and Y does not guarantee the presence of Granger causality as co-movement does not necessarily imply causality (Aldrich, 1995).

This framework can also be extended to the multivariate case, where the effect of predictors X, Z_1, Z_2 ... Z_p (with $p+1$ the number of predictor variables) on Y can be evaluated. In order to determine the effect of X on Y in a multivariate case, the performance of a model containing all predictors is compared against that of a multivariate model from which X is excluded, as given by:

$$y_t = \sum_{i=1}^{m} a_i y_{t-i} + \sum_{j=1}^{p}(\sum_{i=1}^{m} b_{j,i} z_{j,t-i}) + \epsilon_{x,t} \tag{4}$$

$$y_t = \sum_{i=1}^{m} a_i y_{t-i} + \sum_{j=1}^{p}(\sum_{i=1}^{m} b_{j,i} z_{j,t-i}) + \sum_{i=1}^{m} c_i x_{t-i} + \eta_t \tag{5}$$

The added value of incorporating X in the set of predictors (Z_1, Z_2 ... Z_p) to improve the prediction of Y can be expressed in terms of Granger causality as:

$$GC_{X\to Y} = \ln \frac{\sigma^2_{\epsilon_X}}{\sigma^2_\eta} \frac{\sigma^2_{\epsilon_x}}{\sigma^2_\eta} \tag{6}$$

2.2.2 Spectral Granger Causality

~~Inherent to the use of discrete time series,~~ Despite traditional Granger causality ~~can only address~~ being capable of addressing short-term interactions, ~~i.e. one variable at a past time-step affecting other variables in the current or future time-step~~simply aggregating time series to their seasonal and annual equivalents prior to following a traditional Granger causality approach does not necessarily lead to realistic causation inference at larger temporal scales. Consequently, Granger causality frameworks that are defined in the time domain ~~,~~ – such as the ~~newly-developed framework of Papagiannopoulou et al. (2017a), all fail~~ framework by Papagiannopoulou et al. (2017a), are not designed to capture low-frequency processes. To assess temporal scale-dependent processes, transforming the data into a frequency-dependent domain is crucial as it allows ~~to differentiate between~~ for a differentiation of interactions active at various temporal scales. Therefore, we propose the use of CSGC, which enables to simultaneously condition for other predictors, thus factoring out co-dependency among variables, while addressing processes active at different scales.

The ~~spectral Granger causality~~ Spectral Granger Causality (SGC) is ~~an~~ a non-parametric extension of the Granger causality theory in which ~~timeseries~~ time series are first transformed into a frequency domain, resulting in a spectral analogue of Granger causality (Geweke, 1982). A well-known example of such a transformation is the Fourier transformation, where a time series is decomposed in a space solely consisting of frequency. This allows for highlighting strong spectral features, but comes at the cost of time localisation, i.e. the ability to differentiate between processes active at different times. To prevent the loss of the time dimension, SGC adopts a wavelet transformation, which decomposes the original time series into a time–frequency space, thus allowing for both spectral (i.e. temporal scale-dependent) evaluation and time localisation of interactions between predictors and target variable. ~~To~~ In order to perform the time–frequency decomposition, the Morlet wavelet is used and a balance between the time and frequency resolutions is obtained by setting the shape parameter to a value of 6, as in Torrence and Compo (1998), or Casagrande et al. (2015). Moreover, to overcome the limitation of assigning an arbitrary order of the system given by Eq. 1 and 2, Dhamala et al. (2008) developed a non-parametric method to express ~~spectral Granger causality~~ Spectral Granger Causality based on spectral properties of the variables without the need to estimate the model order, given by:

$$SGC_{X\rightarrow Y}(f) = \ln \frac{S_{yy}(f)}{S_{yy}(f) - \left[\Gamma_{xx} - \left(\frac{\Gamma_{yx}^2}{\Gamma_{yy}}\right)\right] |H_{yx}(f)|^2} \tag{7}$$

where $S_{yy}(f)$ equals the spectral density (power spectrum) of the target variable Y at frequency f, which can be estimated from the wavelet transform. Using the variables X and Y, the error covariance matrix Γ and the spectral transfer function matrix $H(f)$ can be calculated using matrix factorisation (Wilson, 1972). For more information on SGC, we refer to Ding et al. (2006), Dhamala et al. (2008), and Detto et al. (2012, 2013).

2.2.3 Conditional Spectral Granger Causality

Eq. 7 is only valid to determine the effect of a variable X on Y, without taking into account that other variables might influence both the predictor and target, consequently inducing an apparent causal relationship. To tackle this issue, conditionality between variables has to be taken into account, for which the SGC framework can be extended to ~~conditional spectral Granger causality~~ Conditional Spectral Granger Causality (CSGC). In other words, SGC can be adapted to CSGC to assess if X causes Y given that Z_1, Z_2 ... Z_p may cause Y and X, resulting in a conditioned measure of spectral causality $\cancel{CSGC_{X\rightarrow Y|Z_2,Z3...Z_p}(f)}CSGC_{X\rightarrow Y|Z_1,Z_2...Z_p}(f)$. For a multivariate problem with p+2 variables (Y, X, Z_1, Z_2 ... Z_p), the system can be written, after spectral transformation and Wilson factorisation (Wilson, 1972), as:

$$\mathbf{S}(Y,X,Z_1,Z_2...Z_p,f) = \mathbf{H}(f)\,\boldsymbol{\Sigma}\,\mathbf{H}^*(f) \tag{8}$$

$$\mathbf{U}(Y,Z_1,Z_2...\cancel{Xp}Z_p,f) = \mathbf{G}(f)\,\boldsymbol{\Gamma}\,\mathbf{G}^*(f) \tag{9}$$

with $\mathbf{S}$ and $\mathbf{U}$ representing the spectral matrices of the complete system and the system with the variable whose causality is tested being excluded, i.e. X in this case, respectively. Similarly, $\mathbf{H}$ and $\mathbf{G}$ are the spectral transfer function matrices, while $\cancel{\sum}$ $\boldsymbol{\Sigma}$ and $\boldsymbol{\Gamma}$ equal the error covariance matrix of the full and incomplete system of variables, respectively, and where * indicates matrix adjoint.

From Eq. 8 and 9, CSGC of X on Y given Z_1, Z_2 ... Z_p can be calculated as:

$$CSGC_{X\rightarrow Y|Z_1,Z_2...Z_p}(f) = \ln \frac{\Gamma_{yy}}{|Q_{yy}(f)\Sigma_{xx}Q^*_{yy}f|} \tag{10}$$

where:

$$\mathbf{Q} = \begin{pmatrix} \tilde{G}_{YY} & 0 & \tilde{G}_{YZ_1} & ... & \tilde{G}_{YZ_p} \\ 0 & 1 & 0 & ... & 0 \\ \tilde{G}_{Z_1Y} & 0 & \tilde{G}_{Z_1Z_1} & ... & \tilde{G}_{Z_1Z_p} \\ ... & ... & ... & ... & ... \\ \tilde{G}_{Z_pY} & 0 & \tilde{G}_{Z_pZ_1} & ... & \tilde{G}_{Z_pZ_p} \end{pmatrix}^{-1} \begin{pmatrix} \tilde{H}_{YY} & \tilde{H}_{YX} & ... & ... & \tilde{H}_{YZ_p} \\ \tilde{H}_{XY} & ... & ... & ... & ... \\ ... & ... & ... & ... & ... \\ ... & ... & ... & ... & ... \\ \tilde{H}_{Z_pY} & \tilde{H}_{Z_pX} & ... & ... & \tilde{H}_{Z_pZ_p} \end{pmatrix} \tag{11}$$

In Eq. 11, $\tilde{\mathbf{H}}(f) = \mathbf{H}(f)\mathbf{P}^{-1}$ and $\tilde{\mathbf{G}} = \mathbf{G}\mathbf{P}_2^{-1}$ represent corrected transfer function matrices to separate the directional interactions (Geweke, 1982). The rotation matrices $\mathbf{P}$ are normalisation matrices needed to transform the multivariate systems in their canonical form with uncorrelated errors (Detto et al., 2013). For more information on CSGC, we refer to Dhamala et al. (2008) and Detto et al. (2012, 2013).

Using Eq. 10, ~~spectral Granger causality~~ Conditional Spectral Granger Causality of X on Y can be determined, given the influence of Z_1, Z_2 ... Z_p on both X and Y. If X is not directly affecting Y, but for example Z_1 is forcing both X and Y, the numerator in Eq. 10 will equal the denominator, thus resulting in a Granger causality measure of zero. However, if there is a direct causal influence of X on Y at a specific frequency f, $CSGC_{X \to Y|Z_1,Z_2...Z_p}(f) > 0$. Using Eq. 10, it is possible to determine if X (Granger-) causes Y, but no information on the sign of the causal relation can be extracted.

2.2.4 Significance testing of CSGC

Despite the ability of Eq. 10 to account for conditional effects between variables, it fails to determine how robust the found interactions are. Therefore, the robustness of the determined CSGC values needs to be tested against the null hypothesis that X has no causal effects on Y. In case of Granger causality in the time domain, significance of the determined statistic, e.g. GC, can be tested by a bootstrapping scheme in which the time series are randomly shuffled before determining the GC-values. By repeating this procedure n times, the distribution of GC can be determined. By selecting a p-value, typically 5%, the determined Granger causality of X on Y can be tested against the null hypothesis of no causal interaction.

However, for the spectral variant of Granger causality, a simple randomisation of the time series induces unwanted artefacts. Due to the spectral nature of the method, the power spectrum of the randomised time series must be preserved, i.e. to be equal to that of the original time series at each frequency. In other words, if the original time series are characterised by much high-frequency variation and less at lower frequencies, the time series used for significance testing need to show the same frequency-dependent variability. Therefore, surrogate time series exhibiting the same spectral power as the original time series need to be used. Here, iterative amplitude adjusted Fourier transform (IAAFT) surrogates are used in combination with Monte Carlo simulations, as CSGC is non-parametric (Detto et al., 2012), to test the determined CSGC-value against the null hypothesis of no causal interaction. Due to computational ~~restraints~~constraints, 100 runs with surrogates were ~~run~~ performed for each set of original time series (i.e. for each pixel), and will be used to test for significance (p-value < 0.05). However, to increase the robustness of the results, ~~a p-value of 1% is chosen to compensate for the limited amount of repetitions.~~ an ensemble of products is used for both the observations and models as explained in Sect. 2.1.

2.2.5 Explained variance

CSGC as defined by Eq. 10, compares the performance of two autoregressive models in explaining variation in a target variable Y. In other words, does X, given a set of predictors Z_1, Z_2 ... Z_p, improve the estimate of Y compared to a model that only uses Z_1, Z_2 ... Z_p. In this study, we are interested in quantifying how much of variance in the target variable is actually directly explained by a predictor, and not how much did the estimation error improve upon adding X to the set of the predictors. Therefore, we deviate from the traditional formulation of Granger causality and define a new measure, the fraction (F) of variance in the target variable Y that is explained by a predictor X. Ideally, the new formulation would be:

$$F_{X\to Y} = \frac{\sigma_X^2}{\sigma_Y^2} \times 100\% \tag{12}$$

with, σ_Y^2 representing the total variance of Y and σ_X^2 the variance in Y explained by X. However, a part of the variance in Y is not explainable by any predictor, as is is forced by the autocorrelation of Y ($\sigma_{Y,auto}^2$). Therefore, in order to account for the part of variance in Y that will not be able to be explained by any predictor, Eq. 12 is adapted to:

$$F_{X\to Y} = \frac{\sigma_X^2}{\sigma_Y^2 - \sigma_{Y,auto}^2} \times 100\% \tag{13}$$

As traditional Granger causality and CSGC determine a measure of causality that is defined in a similar way, Eq. 1 can be used to determine how F can be calculated from the actual Granger causality value. Considering the univariate model given by Eq. 1, the total variance in the target variable Y can be rewritten as:

$$\sigma_Y^2 = \sigma_{Y,auto}^2 + \sigma_\epsilon^2 \tag{14}$$

with σ_ϵ^2 representing the unexplained variance or prediction error variance. Substituting Eq. 14 into Eq. 13 results in:

$$F_{X\to Y} = \frac{\sigma_X^2}{\sigma_\epsilon^2} \times 100\% \tag{15}$$

This derivation can also be extended towards the multivariate case, and even to CSGC. As Eq. 15 equals $1 - e^{-GC_{X\to Y}}$, the conditional spectral variant of the fraction of variance in Y explained by X can be calculated as:

$$F_{X\to Y|Z_1,Z_2\ldots Z_p}(f) = \frac{\Gamma_{yy} - |Q_{yy}(f)\Sigma_{xx}Q_{yy}^{*}f|}{\Gamma_{yy}} \times 100\% \tag{16}$$

Using Eq. 16, the impact of climate on vegetation and the feedbacks of vegetation on climate can be quantified and reported in an intuitive manner (see Sect. 3).

2.2.6 Determining scales of interest

As pointed up in ~~the~~ Sect. 1, monthly interactions between climate and vegetation have been studied by many authors (Nemani et al., 2003; Wu et al., 2015; Papagiannopoulou et al., 2017b). On the other hand, the phenological cycle or inter-annual variability of climate and vegetation are also expected to interact, yet little is known about how these interactions differ from the short-term processes. ~~CSGC is ideal to assess these differences as it allows to simultaneously analyse interactions at different temporal~~ Hereafter, the terms *phenology* and *phenological cycle* are used to refer to the seasonal-scale variability in LAI. This reflects features such as the timing of the growing season or the amplitude of the intra-annual cycle (Richardson et al., 2009; Verger et al., 20 , since CSGC will react to variability in both the time and frequency domains. As explained in Sect. 2.2.3, CSGC allows a simultaneous analysis of the interactions at multi-temporal scales, while no assumption ~~has~~ needs to be made about the direction of the interplay between climate and vegetation. ~~However, CSGC determines the Granger causality at~~ Moreover, based on the characteristics of the climate data used in this study, CSGC can be applied to assess causality over a wide range of temporal scales, starting at 2 months (twice the ~~minimum temporal scale~~temporal resolution) and going up to 16.5 years (maximum temporal scale due to discretisation of the frequency space; can be adjusted if needed, especially for longer time series).

In order to determine which range of temporal scales better represents monthly, seasonal and inter-annual interactions, an experiment with synthetic monthly time series was performed. First, a predictor variable ($X1$) is constructed with imposed variability at the scales of interest (e.g. monthly, seasonal and inter-annual). Monthly variability is assumed to be random from month to month, while seasonality is defined as consecutive three-block periods of constant value. Inter-annual variation is defined as blocks of one year with a fixed value. The predictor $X1$ is constructed by randomly generating these three variabilities and adding them. Finally, a linear trend is added to $X1$ to be able to retrieve the maximum scale at which inter-annual variability can be observed. Next, a target variable ($Y1$) is constructed with a known causal relation to the predictor $X1$ by multiplying $X1$ with a random factor and then shifting $Y1$ in time so that $Y1$ lags $X1$ by one month. Using these two synthetic time series, SGC is used to determine the Granger causality of $X1$ on $Y1$. Note that SGC is used instead of CSGC as the scales at which the targeted interactions can be observed are identical for a bivariate and multivariate case.

In order to identify the scales that are most sensitive to monthly, seasonal and inter-annual interactions, a new predictor variable $X2$ is constructed as an identical copy of $X1$, except for one specific variability. For example, if the range of scales that capture monthly interactions is determined, $X2$ will be equal to $X1$, but with perturbed monthly variability. Next, a new target variable $Y2$ is constructed by multiplying $X2$ with a new random factor and again guaranteeing that $Y2$ lags $X2$ by one month. Then, SGC is used to determine if $X1$ Granger causes $Y2$, which will show a decrease in Granger causality at scales that capture the perturbed interaction compared to the Granger causality of $X1$ on $Y1$. Consequently, by repeating this procedure for all the interactions that are to be assessed (i.e. monthly, seasonal and inter-annual), comparison of the two Granger causalities allows to record the range of scales that capture these interactions. To increase robustness, this procedure is repeated 100,000 times, resulting in a clear delineation of scales representing monthly (0–0.32 years), seasonal (0.32–1.54 years) and inter-annual (1.54–9 years) interactions. Decadal patterns of trends cannot be investigated here due to length of the observational record (see Sect. 2.1), but are used in the determination of the ranges to fix the upper limit for inter-annual interactions. See Fig. 1 for an illustration of the resulting scales, which are considered to be time- and space-invariant. Results will be presented as mean patterns for each scale using the determined ranges. Selecting the maximum explained variance within each range, unwillingly results in the taking the CSGC at the highest scale of each interval, as the CSGC increases with the scale (for more information, see Sect. 3.1).

3 Results and discussion

3.1 Climate impact on vegetation in observations

Fig. 2~~illustrates~~ a,c,e illustrate the Granger causality of ~~precipitation, air temperatureand net radiation~~ air temperature, net radiation and precipitation on LAI dynamics, based on observations~~(Fig. 2a, 2c, 2e),~~ , globally and latitudinally. Results are shown separately for monthly (Fig. 2a), seasonal (Fig. 2c) and inter-annual (Fig. 2e) ~~time-scales~~ time scales using a tri-variate colormap according to the fraction explained by each climatic driver (see Sect. 2.2.5). Dotted pixels ~~highlight significance of the strongest climate impacton vegetation at a 1% -significance level~~indicate that in at least 75% of the ensemble members there is (a) agreement regarding the dominant climate impact, and (b) statistical significance (at the 5% level). At monthly scales, overall spatial patterns in the observation-based results (Fig. 2a) are in agreement with previous studies, showing the dominance of precipitation in arid and semi-arid regions, while radiation and temperature dominate in northern latitudes and rainforests, respectively (Nemani et al., 2003; de Jong et al., 2013; Seddon et al., 2016; Papagiannopoulou et al., 2017b). Strong radiation effects on vegetation can be observed over northern latitudes due to severe limitations in incoming radiation during winter months. ~~Recently, Papagiannopoulou et al. (2017b) reported ,~~ However, in those latitudes, LAI retrievals are contaminated by snow cover signals. While focusing on the growing season could solve this issue, the CSGC requires continuous time series. Because in wintertime, due to limitations in solar radiation, plant growth is inhibited in northern latitudes, most variability captured at monthly scales will be dominated by the more dynamic spring and summer periods; therefore, our results suggests that radiation still dominates the behaviour of vegetation at these latitudes.

This dominant high-latitude radiation control was not reported by Papagiannopoulou et al. (2017b), who, based on a non-linear Granger causality framework, found that 61% of the vegetated land surface is primarily driven by water availability at monthly time scales, while temperature and radiation are the primary factors in only 23% and 15% of the vegetated surface (respectively). These results ~~contrasted strongly~~ also contrasted with earlier studies, that pointed to a less dominant role of water availability for global ecosystems (Nemani et al., 2003; Wu et al., 2015). Here, our monthly-scale results also ~~highlight a more moderate~~ show a dominant role of precipitation, ~~which dominates (i.e is highest) in 41% of the vegetated land~~ yet more moderate; 51% of vegetated land is primarily controlled by precipitation, with radiation being the primary control factor in ~~41~~40% as well. ~~However, when~~ When the analysis targets vegetation anomalies by detrending linearly and subtracting the average seasonal cycle for both LAI and climate (as was done in Papagiannopoulou et al. (2017a, b)), ~~the results show precipitation and air temperature gaining~~ results show a similar dominance of precipitation, but air temperature gains importance over net radiation ~~as they are~~ (being the dominant driver over ~~45%, 21% and 33~~13%, and 36%, respectively, as indicated in Supplementary Fig. A1~~. Using anomalies results to a slight increase of the importance of precipitation, but Papagiannopoulou et al. (2017b) also accounted~~). The higher importance of water availability in Papagiannopoulou et al. (2017b) can be attributed to accounting directly for the effect of (root-depth) soil moisture as a driver of ~~water availability, consequently increasing the dominance of precipitation . Finally, the lower water limitation in the northern latitudes (Fig. 2a) relates to the fact that Papagiannopoulou et al. (2017b) considered also~~ vegetation, as opposed to the use of precipitation only in this study. Note that not accounting for irrigation explicitly, does not necessary bias our results, since irrigation is intended to increase the energy-dependence of LAI dynamics, and will still reflect on a larger dominance of air temperature and net radiation in our analysis. A final difference with Papagiannopoulou et al. (2017b) is the consideration in the latter of snow water equivalent as a water availability driver~~.~~ ~~Evenmore, the framework used by Papagiannopoulou et al. (2017b) incoporates a battery of remotely-sensed products, which can widely diverge and consequently lead to discrepancies in the results. This also reconciles the results in Papagiannopoulou et al. (2017b)~~ , which explains the divergence with our results in higher latitudes. Our results can also be reconciled with previous studies, such as Nemani et al. (2003), Wu et al. (2015), and Seddon et al. (2016)~~that focused on other temporal scales or used~~ ; regional differences may relate to the specific focus of those studies on one temporal scale only, their calculation of covariances instead of inferring causality in a more formal manner, or the use of different variables to assess water availability drivers.

As mentioned before, a key feature of CSGC is that it also enables the assessment of interactions at longer temporal scales, such as seasonally (Fig. 2c) and inter-annually (Fig. 2e). ~~Radiation~~ As expected, radiation is found to dominate the seasonal phenology over ~~51~~55% of the global vegetated land. The strong radiation control over northern latitudes is attributed to the amplitude of the solar cycle, which ultimately inhibits vegetation growth during wintertime. In this analysis, net radiation instead of incoming radiation has been used, in order to be consistent with the investigation of vegetation–climate feedbacks in Sect. 3.3; however, using incoming radiation as driver instead, leads to a similar ~~50~~54% dominance (see Fig. B1). Compared to monthly scales, ~~the importance of precipitation as a driver of vegetation decreases in regions such as the Mediterranean regionand western South America that still show the dominant role of radiation forcing vegetation phenology, while hotspots of~~ seasonal precipitation control is less widespread, as only 33% of the vegetated land is primarily controlled by precipitation (compared to 51% at monthly scales; Fig. 2a and 2c). This reduced importance of precipitation can be attributed to the observed temperature-driven ~~phenology are found over the Sahel region and south of the Congo rainforest~~hotspot in the Sahel region, but more importantly to increase of radiation control over the south of Eurasia and in tropical forests. Furthermore, the ~~results for seasonal scales~~ patterns in Amazonia tend to agree with the findings of ~~Saleska et al. (2007)~~Saleska et al. (2007, 2016), Phillips et al. (2009), ~~Hilker et al. (2014), and Saleska et al. (2016),~~ and Hilker et al. (2014), showing a dominance of water availability in the southeastern side, while radiation is more limiting in the northwest. ~~Overall, precipitation primarily controls ecosystem phenology in (semi-)arid regions, adding up to 30% of the vegetated land (Fig. 2c).~~

Finally, at inter-annual scales, despite co-dominance of multiple drivers in some regions, global ecosystems tend to be ~~more water limited : 46~~water limited with 43% of the vegetated land surface ~~is~~ being primarily dominated by precipitation (Fig. 2e), especially in the subtropics. Although patterns ~~appear highly heterogeneous~~exhibit some heterogeneity, not only arid and ~~semiarid~~ semi-arid regions show a (significant) dominant control by precipitation, but also substantial parts of ~~continental Eurasiaand North America, albeit the results for most of these regions are not statistically significant. This~~ southern Eurasia. This widespread inter-annual dependency ~~of ecosystem dynamics~~ on water availability of ecosystem dynamics may arise due to the large inter-annual variability of precipitation~~– compared to e.g, radiation –~~, and has already been documented in relation to the impact of precipitation of global carbon budgets (Poulter et al., 2014) and terrestrial evaporation (Miralles et al., 2014). ~~Air temperature thrives scattered~~ Moreover, it agrees with the results of Green et al. (2019) and Humphrey et al. (2018), yet it does not necessarily contradict the findings by Jung et al. (2017); the latter reported a dominant role of temperature at the global scale, yet showed a dominance of water availability at regional scales that is compensated when upscaling to global means. Inter-annually, the control of air temperature extends over the high northern latitudes and eastern China, dominating in ~~28~~20% of vegetated land, while radiation ~~is typically less crucial than the other two drivers at~~ remains the most crucial driver for 37% of the land surface, almost exclusively in the northern latitudes, likely affected by the strong seasonal patterns (Fig. 2e). Once the seasonality is removed, the inter-annual ~~scales, likely due to its lower inter-annual variability as mentioned above. Nonetheless~~dominance of radiation control falls down to 20% of the vegetated land surface (see Fig. A1c). Despite the heterogeneity, the overall control of climate on vegetation is higher at inter-annual scales than at shorter time scales, as can be observed in the latitudinal profiles, which show the total causality in absolute terms (Fig. 2). This is partly a consequence of the ~~time-frequency~~ time–frequency decomposition of CSGC, which generally results in higher values of explained variance at longer ~~timescales~~ time scales due to the increased time frame over which a predictor variable is assessed, thus increasing the chance of incorporating memory effects. However, ~~during~~ the significance test against the null hypothesis of exhibiting no causal effect, ~~the calculated threshold for significance also increases with the temporal scales, consequently ensuring~~ ensures that regions exhibiting significant responses can be compared over different ~~timescales. The dominant role of water availability at inter-annual scales, agrees with the results of Green et al. (2019) and Humphrey et al. (2018), yet it does not necessarily contradict the results by Jung et al. (2017); the latter reports a dominant role of temperature at the global scale, yet shows a clear dominance of water availability at regional scales, that is compensated when upscaling to global means~~time scales.

Noteworthy is that anthropogenic effects, which are not directly addressed here, can also impact vegetation and climate at short temporal scales. For example, irrigation and deforestation can result in a decoupling between climate and vegetation (Lawrence and Vandecar, 2015; Chen et al., 2019). In the tropics, deforestation results in a warming effect due to reduced plant transpiration, which in turn may induce a decline in precipitation, creating a warmer and drier regime (Lawrence and Vandecar, 2015). Irrigation allows for growing crops in water-limited regions, consequently inducing energy constraints which are captured by the CSGC. Note that due to the limited data record, the effects of global warming trends and carbon dioxide fertilisation – and the consequent trends in vegetation greening and water use efficiency (Reichstein et al., 2013; Wu et al., 2015; Zhu et al., 2016) – are not directly addressed in this study.

3.2 Climate impact on vegetation in models

Results of the observations are next used to benchmark CMIP5 ESM performance in representing the control of climate on vegetation (Fig. 2b, 2d, 2f). Dotted pixels indicate that at least three ~~models find the same climate driver to be the significant primary control of vegetation at a 1% -significance level. At monthly scales, comparison~~ out of four models reach agreement regarding (a) dominant climate impact, and (b) statistical significance (at the 5% level). Comparison of Fig. 2a and 2b shows that the monthly impact of air temperature on ecosystems is strongly overestimated by ESMs, with 17% and 26% of vegetated land being primarily dominated by temperature for observations and ESMs, respectively. This coincides with a lower effect of net radiation in central Eurasia and, more importantly, elevated air temperature control in the Amazon and Congo rainforests. These contrasting results with observations might hint towards problems in ESMs with respect to representing the behaviour of the tropics, but may also relate to the difficulties to retrieve LAI from satellites in dense ~~tropical~~ forests (Hilker et al., 2015).

Nevertheless, ESMs agree on the general patterns that highlight the strong radiation effects in northern latitudes (albeit less extended), and the water availability as main driver in arid and ~~semiarid regions~~ semi-arid regions at monthly time scales.

Seasonally, a larger control of ~~climate~~ precipitation and air temperature on vegetation phenology is also noticeable over the equator for ESMs (see latitudinal profile in Fig. 2d). The dominant control of radiation on vegetation phenology over northern latitudes is similar for all models (inter-model agreement and significance represented by the black dotting), and whereas the spatial extent agrees with the observational results, the magnitude is underestimated by the models (see Fig. 2c and 2d). Radiation is the primary driver of the seasonal LAI variation in ~~40~~45% of the vegetated land in models (compared to ~~51~~55% for the observations). The role of precipitation and air temperature as ~~a driver~~ drivers of the phenological cycle gains in importance in ESMs, at the cost of radiation, with ~~34% and 24~~40% and 15% of seasonal LAI variation being dominated by precipitation and air temperature variability, respectively, versus the ~~30% and 17~~33% and 12% in observations, respectively. Despite the overall similarities in the patterns of dominant drivers, regional differences between observations and models are still observed. Models point towards a water-limited phenological cycle in the Sahel, while observations hint also towards a dominant role of temperature ~~.~~ (compare Fig. 2c and 2d). Furthermore, whereas observations clearly highlight a south-to-north water-to-energy-limited gradient in Amazonia, models tend to disagree and point towards temperature as a key driver over most of the Amazonian rainforest at seasonal scales. These differences might indicate difficulties to model climate–vegetation interactions across the basin, yet they may again be influenced by the difficulties to retrieve LAI from satellites over dense canopies, as pointed above.

Similar to observations, the climate impact on LAI increases with longer temporal scales in ESMs. ~~More~~ However, more remarkable than in the observations ~~,~~ is the strong water limitation across the globe at inter-annual scales, which is not restricted to ~~the typical~~ arid and semi-arid regions (Fig. 2f). Water availability at inter-annual scales is dominant for vegetation over ~~52~~62% of land versus the ~~46~~43% found in observations (Fig. 2e)~~. However, this divergence~~ , and is also strongly overestimated in absolute terms at most latitudes, especially in the tropics. Further analysis shows that the divergence in the considered period between observations and models ~~is also influenced by the shorter record of satellite data, which, as mentioned above, is expected to affect the results at longer (e. g., inter-annual)temporal scales~~(see Sect. 2.1) does not substantially impact results; repeating the analysis for the overlapping time range for observations and models (1982–2005) yields very similar findings (Fig. C1).

3.3 Vegetation feedback on climate in observations and models

Analogous to the effect of climate on vegetation, vegetation can alter local (and remote) climate conditions via biophysical and biochemical feedbacks. These feedbacks arise from the effect of vegetation structure and physiological activity on the surface radiation budget, available energy partitioning into latent and sensible heat fluxes, aerodynamic conductance of the ecosystem, atmospheric chemical composition, and indirect processes affecting incoming radiation, atmospheric humidity and temperature (McPherson, 2007; Bonan, 2008). The representation of these feedbacks in ESMs remains in need for improvement to accurately predict future climate (de Noblet-Ducoudré et al., 2012; Zhang et al., 2016). Here, we unravel these feedbacks of LAI on different climate variables based on observations (Fig. 3a, 3c, and 3e) and ESM data (Fig. 3b, 3d, and 3f), and at different temporal scales, from monthly (Fig. 3a and 3b), to seasonal (Fig. 3c and 3d) and inter-annual (Fig. 3e and 3f). Dotted pixels indicate ~~significance at~~ that in at least 75% of the ~~1% -level of the strongest feedback (for observations, e.g. Fig. 3a, 3c, and 3e) , or three models agreeing on the significance of the strongest feedbacks (Fig. 3b, 3d, and 3f~~ensemble members there is (a) agreement regarding the dominant feedback, and (b) statistical significance (at the 5% level). To aid comparison to the strength of climate impacts on vegetation – measured in relative or absolute percentage of caused variance (see Sect. 2.2.5) – an identical tri-variate colormap to that in Fig. 2 is used.

Observed LAI feedbacks over the mid and high northern latitudes ~~mainly reflect on the direct impact on~~ concentrate on surface net radiation at monthly time scales (Fig. 3a). As vegetation lowers the ~~surface~~ albedo in boreal regions, it allows for more energy storage and less reflection back into the atmosphere; this increases surface net radiation and may lead to a net warming effect (e.g. Bonan, 2008; Forzieri et al., 2017). By repeating the analysis using only incoming (shortwave and longwave) radiation, instead of surface net radiation, the results indicate that the influence of LAI on (e.g.) cloud formation is limited, at least considering the local (in the sense of 'spatially collocated') scales revealed by the causal framework (see Fig. D1). Monthly feedbacks of vegetation on precipitation and air temperature are spatially ~~heterogeneous and weaker. Seasonally, two distinct areas of significant effect (see dotted pixels) of LAI on precipitation can be distinguished, namely southern Amazonia and the Congo rainforest. Patterns~~ less widespread, however, significant feedbacks on precipitation are observed, especially in tropical forests. The patterns in Amazonia suggest a more dominant effect of vegetation on radiation in the north, while precipitation feedbacks dominate in the south ~~.~~ (Fig. 3a). We note that the method does not differentiate whether higher or lower values of LAI cause more or less rainfall, only that a causal effect of LAI on rainfall exists. The south-to-north patterns in the Amazon agree with the larger dependency on precipitation recycling in the South (Dirmeyer et al., 2009; Zemp et al., 2014). Tropical forests are known to regulate local (and global) precipitation as their large use of water increases atmospheric humidity and results in cloud formation (Malhi et al., 2008). This also directly affects the incoming short- and long-wave radiation. ~~However~~Nevertheless, we restate that the method only focuses on the effects of LAI on its immediate climatic environment, not in neighbouring or remote locations. ~~Seasonal feedbacks are more clear for radiation and air temperature , although their~~

At seasonal scales, an increase of feedbacks on temperature is observed in the Northern Hemisphere, and feedbacks on precipitation remain limited to the tropics, although practically no statistical significance is ~~lower~~ reached outside the tropics (Fig. 3c)~~; however, these results do indicate to an effect of LAI on the seasonal cycle of the ecosystem energy budget, albeit less significant as for monthly interactions .~~

~~Finally, the observation-based results suggest that~~ . Finally, at inter-annual scales, the observation-based results show a north-to-south gradient over the Sahel region, with the north exhibiting feedbacks on precipitation, while strong vegetation feedbacks on temperature are observed in the south (Fig. 3e). However, despite the highly significant interactions in the tropics, and except for the feedback on radiation in the Northern Hemisphere, the inter-annual feedbacks cannot be clearly disentangled ~~at inter-annual scales~~ using the CSGC, as shown by the incoherent spatial patterns in Fig. 3e. This may occur due to the long integration time and the somehow limited observational record. Overall, and as expected, comparisons between Fig. 2 and 3 reveal that the impact of climate on vegetation consistently exceeds the strength of the vegetation feedback on climate. This means that local climate variability leaves a larger imprint on LAI dynamics than vice versa. This can be partly attributed to the fact that only local interactions are considered here: while vegetation reacts to its most immediate environment, vegetation can lead to remote effects on climate that are not addressed in our analyses ~~(Dirmeyer et al., 2009; Guillod et al., 2015)~~ (Dirmeyer et al., 2009; **?**). Nevertheless, these results show the importance of LAI variability in explaining the variance in local climate at intra-annual scales – mainly through impacts on the net radiation induced by albedo changes – and the potential of the CSGC framework to disentangle the bi-directional interaction between vegetation and climate.

~~ESMs capture correctly the~~ In general, ESMs seem to correctly capture the spatial extent of LAI effects on net radiation throughout most of the Northern Hemisphere~~. While models only~~ , but underestimate feedbacks of vegetation on air temperature, which originates from either an actual underestimation of the air temperature feedback by ESMs, or an overestimation of the feedback on net radiation in these regions, as reported by Forzieri et al. (2018) and confirmed by the latitudinal profiles (Fig. 3b,d,f), which masks the vegetation feedback on air temperature. Despite the overestimation, models do agree with each other ~~in~~ on the influence of LAI on net radiation ~~in very high northern~~ at polar latitudes (see dotted pixels), ~~the~~ and the overall mean ensemble patterns ~~agree well with observational results, for both~~ for monthly and seasonal ~~timescales~~time scales also agree with observational results. Interestingly, while observations show significant impacts of LAI on precipitation in ~~the edges of the~~ tropical forests, these effects are not entirely reproduced by ESMs, which tend to show a larger influence of LAI on temperature in ~~the tropics~~those regions. This may suggest a lower dependency of tropical forests on rainfall recycling (Malhi et al., 2008; Hilker et al., 2014; Zemp et al., 2017) and/or an overall wet bias in the ESMs (Mueller and Seneviratne, 2014); the latter is however not supported by the results in Fig. 2 that indicate an overall overestimation of water limitations in models. Nonetheless, these local feedbacks on temperature and precipitation are overall weak – both in observations and models – as indicated by the absolute magnitudes shown in the latitudinal profiles ~~.~~ (Fig. 3).

3.4 Biome-specific interactions

Finally, to better visualise the ~~multi-scale~~ multi-temporal scale vegetation–climate interactions in observations and models, results are presented averaged per biome type. Fig. 4 shows the biome-averaged absolute observed and modelled climate control on LAI dynamics, while Fig. 5 presents the vegetation feedbacks on climate. ~~Both boreal and tropical forests are~~ Forest ecosystems are generally found to be ~~mostly~~ energy-driven, in agreement with previous studies (Nemani et al., 2003; Seddon et al., 2016; Papagiannopoulou et al., 2017b). ESMs tend to agree with the observations on the magnitude of the response of ecosystems to radiation at all temporal scales, with the exception of the over-sensitivity of evergreen broadleaf forests (EBF) at monthly scales and for most models. In regards to the influence of air temperature, ~~even though ESMs agree with each other,~~ strong differences with observations can be ~~observed at seasonal timescales for most~~ noticed at seasonal time scales for forest biomes; this is most remarkable for broadleaf forests, both evergreen and deciduous (EBF and DBF), which show a model overestimation of the control of temperature ~~control~~ on LAI dynamics, even for the minimum modelled temperature control. Interestingly, models also overestimate the sensitivity of broadleaf forests (EBF and DBF) to precipitation~~at seasonal and~~ , especially at inter-annual ~~time-scales~~time scales. Observation results show limited water stress in tropical and mid-latitude forests, arguably due to the deep rooting system and mild climate. However, this apparent model over-dependency of broadleaf forests on climate may also emerge from the under-sensitivity of the observational results due to the saturation of the greenness signal received by satellites in dense canopies. Models unambiguously overestimate the importance of water availability for LAI in most biome types ~~, and for all three timescales, with the exception of open shrublands (OS) and grasslands (G). This~~ at inter-annual time scales, and to a more limited extent at monthly and seasonal scales – this appears in contrast with the results of Green et al. (2017). As expected, savannas are found to be mainly driven by precipitation across all ~~timescales~~ time scales both in observations and models, although models strongly disagree among each other, as reflected by the large error bars in Fig. 4.

On the other hand, short-term feedbacks of LAI on climate seem to be ~~well~~ better represented in ESMs, as small differences can be seen when compared to the observational results in Fig. 5. ~~Deciduous~~ Note that this statement only holds if looked at biome-averaged patterns, as comparison of observations and models in Fig. 3 does indicate to clear regional differences. Deciduous needleleaf forests (DNF) and evergreen needleleaf forests (ENF) ~~needleleaf forests~~ exhibit the strongest feedback on net radiation (and temperature) at all temporal scales; once again this appears related to albedo changes and not impacts on, e.g., cloud formation (see Fig. D1). Nonetheless, the effect of needleleaf forests on the radiation budget tends to be overestimated by most CMIP5 models, especially at monthly and seasonal time scales, which aligns with the findings of Forzieri et al. (2018). ESMs also overestimate the influence of ecosystem phenology on net radiation in mixed forests (MF), open shrublands (OS), and woody savannas (WS); yet, large inter-model disagreements exist on the seasonal influence of LAI on net radiation for almost all biomes, as illustrated by the large error bars Fig. 5~~)~~. The strength of the effect of LAI on precipitation is overall lower than its impact on net radiation and air temperature, partly due to the ~~less localised influence and the~~ non-consideration of downwind influences in this analysis. ~~Contrary~~ However, similar to the results of Green et al. (2017), ~~no particular~~ a strong influence of LAI on precipitation can be observed ~~for semi-arid regions, although these regions have been found to be able to offset decreases in precipitation when considering non-local mechanisms (Miralles et al., 2016)~~ in savannah regimes.

4 Conclusion

Here, bi-directional interactions between climate and vegetation in global remotely-sensed observations were analysed at different temporal scales using ~~conditional spectral Granger causality~~ Conditional Spectral Granger Causality (CSGC) with the aim to benchmark the representation of these interactions in ESMs. Three main climate variables are considered, namely air temperature, net radiation and precipitation, while LAI is used as a proxy for vegetation state. While CSGC is not in principle designed to cope with non-linear interactions, it has the advantage of being able to assess both the climate impact on vegetation and the vegetation feedback on climate, while differentiating simultaneously between different temporal scales. Our findings for monthly interactions agree with those of earlier studies (Nemani et al., 2003; Wu et al., 2015; Papagiannopoulou et al., 2017b), with (semi-)arid regions showing a primary control by water-availability, while the tropics and high northern latitudes being primarily energy-limited. Fig. 6 gives an overview of the overall global interactions between climate and biosphere. Averaged over continental vegetated land, radiation is found to dominate vegetation dynamics at seasonal scale, but models seem consistently incapable of reproducing the strength of this dependency. ~~At longer timescales, precipitation control gains in importance, but modelstend to overestimate this~~ Precipitation control is most dominant at monthly scales and is, overall, well captured by models, but ESMs strongly overestimate the inter-annual control of water availability. On the other hand, vegetation feedbacks are found to be ~~most widespread~~ locally more predominant for net radiation over all ~~timescales~~time scales, mainly due to the strong interplay between radiation and vegetation at northern latitudes. As shown by the summary in Fig. 6, ~~the range of feedbacks as estimated from the ESM output includes the feedbacks from the observations, except for feedbacks on precipitation, which~~ ESMs tend to overestimate the feedbacks on the radiation budget, while feedbacks on local precipitation are often underestimated. Finally, interactions ~~,~~ in both ways ~~, were~~ are found to increase with increasing ~~timescales~~time scales, and feedbacks of vegetation on climate explain a lower ~~percentage of variance, as expected, than the climate impact on vegetation~~fraction of the variance in the latter than vice versa.

Despite the clear advantages over traditional statistical analysis, the application of CSGC is subject to a series of assumptions. Firstly, CSGC can condition for other variables to exclude effects due to co-dependency, but this implies that the variable has to be considered. Here, we limited the potential drivers of vegetation to air temperature, net radiation and precipitation, but vegetation is also affected by other factors such as nutrient availability, atmospheric carbon dioxide concentrations etc. ~~Secondly~~Second, only local interactions are considered, meaning that interactions are assumed to ~~occur within a pixel~~be spatially collocated. This assumption might be valid for the impact of climate on vegetation, but is certainly an oversimplification regarding the vegetation feedbacks on climate which are rarely of local nature, especially when it refers to cloudiness and rainfall. Finally, ~~errors in the observations~~ despite the use of observation ensembles, errors due to difficulties in retrieving LAI over dense canopies, ~~such as tropical forests, may falsely point towards process misrepresentations in ESMs, which overall show a good agreement with the observational results in our analyses~~and biases in LAI products outside the growing season might affect our results. Adapting the causal framework to resolve changes in sensitivities over time would allow the consideration of these and other aspects, and increase the potential of the method to address scientific challenges related to changes in sensitivity of different climate factors over time. That would enable, for instance, a benchmarking of the ESM skill to reproduce changes in ecosystem resilience to climate.

Code availability. Our scripts can be accessed via https://github.com/lhwm.

Appendix A: Climate impact on vegetation in anomalies of observations

Appendix B: Climate impact on vegetation in observations using incoming radiation instead of net radiation

Appendix C: Climate impact on vegetation in observations and ESMs during 1982–2005

Appendix D: Vegetation feedback on climate in observations using incoming radiation instead of net radiation

Author contributions. DGM and JC conceived the study and led the writing. JC conducted the analysis. MDem contributed to the data-processing. AM and MDet contributed to the implementation of the method. All co-authors contributed to the design of the experiments, interpretation of results and editing of the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This work is funded by the Belgian Science Policy Office (BELSPO) in the framework of the STEREO III programme, projects SAT-EX (SR/00/306) and SAT-EX Wave (SR/02/367). Diego G. Miralles acknowledges funding from the European Research Council (ERC) under grant agreement 715254 (DRY–2–DRY). We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP. We also thank the climate modelling groups for their effort in producing and making available of their model output.

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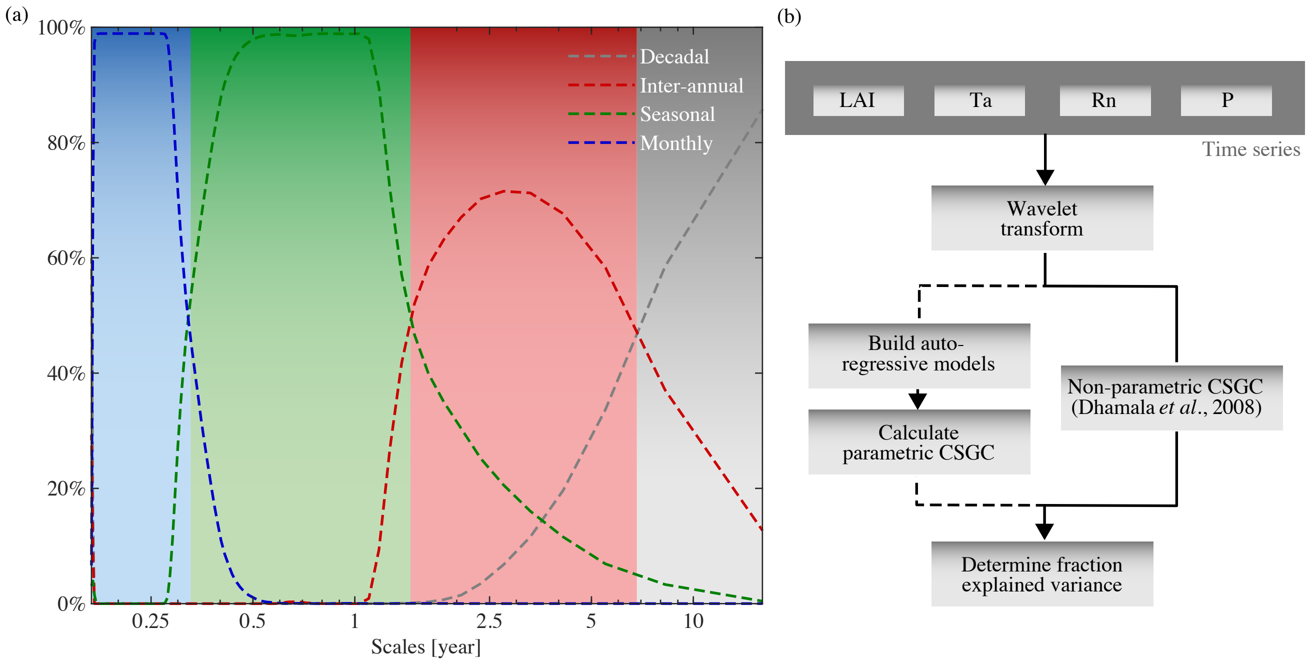

Figure 1. (a) Scales affected by perturbation of variability in synthetic time series at a particular temporal scale. Coloured lines show for each perturbed variability the scales that changed most compared to the unperturbed runs as a percentage of runs out of 100,000. The shaded colours indicate the ranges adopted for each temporal scale in the analysis. **(b)** Schematic overview of the principle of CSGC, with the extension of calculating the fraction of explained variance.

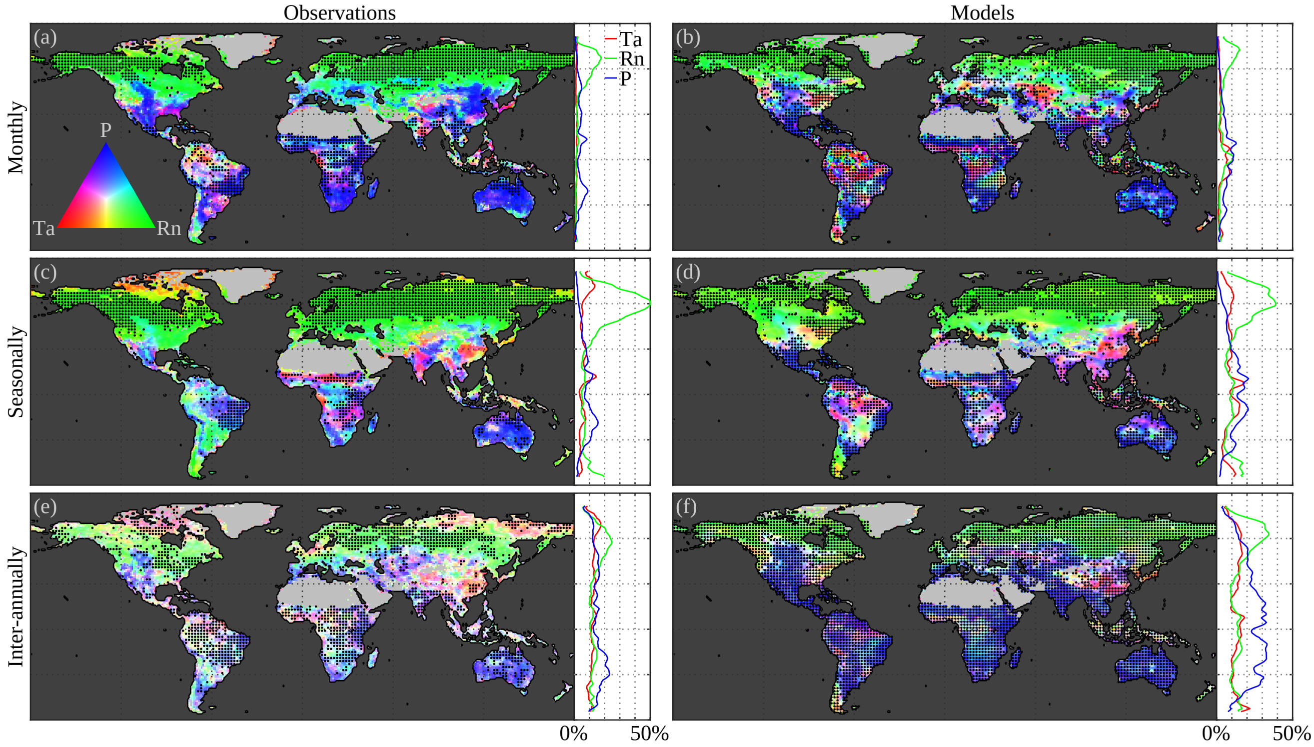

Figure 2. Global climate impact on vegetation. Variability in **(a, c, e)** observed and **(b, d, f)** modelled LAI caused by ~~precipitation (P),~~ air temperature (Ta)~~and~~ , net radiation (Rn) and precipitation (P) at **(a, b)** monthly, **(c, d)** seasonal, and **(e, f)** inter-annual ~~timescales~~time scales. Maps show the causality in relative terms with respect to the dominant driver at each pixel, while the latitudinal profiles show the absolute impact of each driver. The period ~~1982-2015~~ 1982–2015 is taken as reference for the observations, while models span ~~1956-2005~~1956–2005. ~~Modelled maps~~ Maps show the mean from the ensemble of the observations or four CMIP5 models: CCSM4, HadGEM2-ES, NorESM1-M, IPSL-CM5A-MR. Dotted pixels indicate a significant (p-value = ~~1~~5%) primary driver ~~(or~~ agreed upon by at least ~~three models agreeing on~~ 75% of the ~~significant primary driver)~~ensemble members.

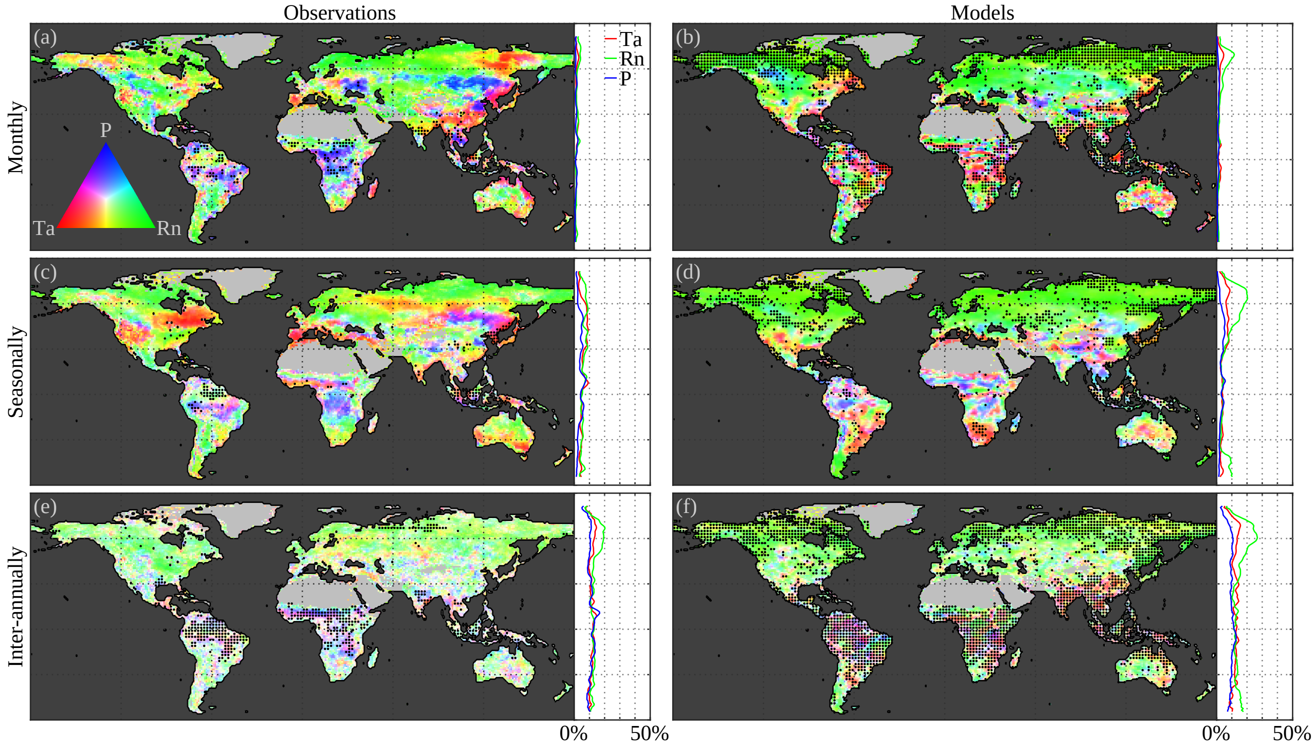

Figure 3. Global vegetation feedback on climate. Variability in ~~precipitation (P),~~ air temperature (Ta)~~and~~ , net radiation (Rn) and precipitation (P) that is caused by (**(a, c, e)** observed and **(b, d, f)** modelled LAI at **(a, b)** monthly, **(c, d)** seasonal, and **(e, f)** inter-annual ~~timescales~~time scales. Maps show the causality in relative terms with respect to the strongest feedback at each pixel, while the latitudinal profiles show the absolute feedback on each driver. The period ~~1982-2015~~ 1982–2015 is taken as reference for the observations, while models span ~~1956-2005~~1956–2005. ~~Modelled maps~~ Maps show the mean from the ensemble of observations or four CMIP5 models: CCSM4, HadGEM2-ES, NorESM1-M, IPSL-CM5A-MR. Dotted pixels indicate a significant (p-value = ~~1~~5%) strongest feedback ~~(or~~ agreed upon by at least ~~three models agreeing on~~ 75% of the ~~significant strongest feedback)~~ensemble members.

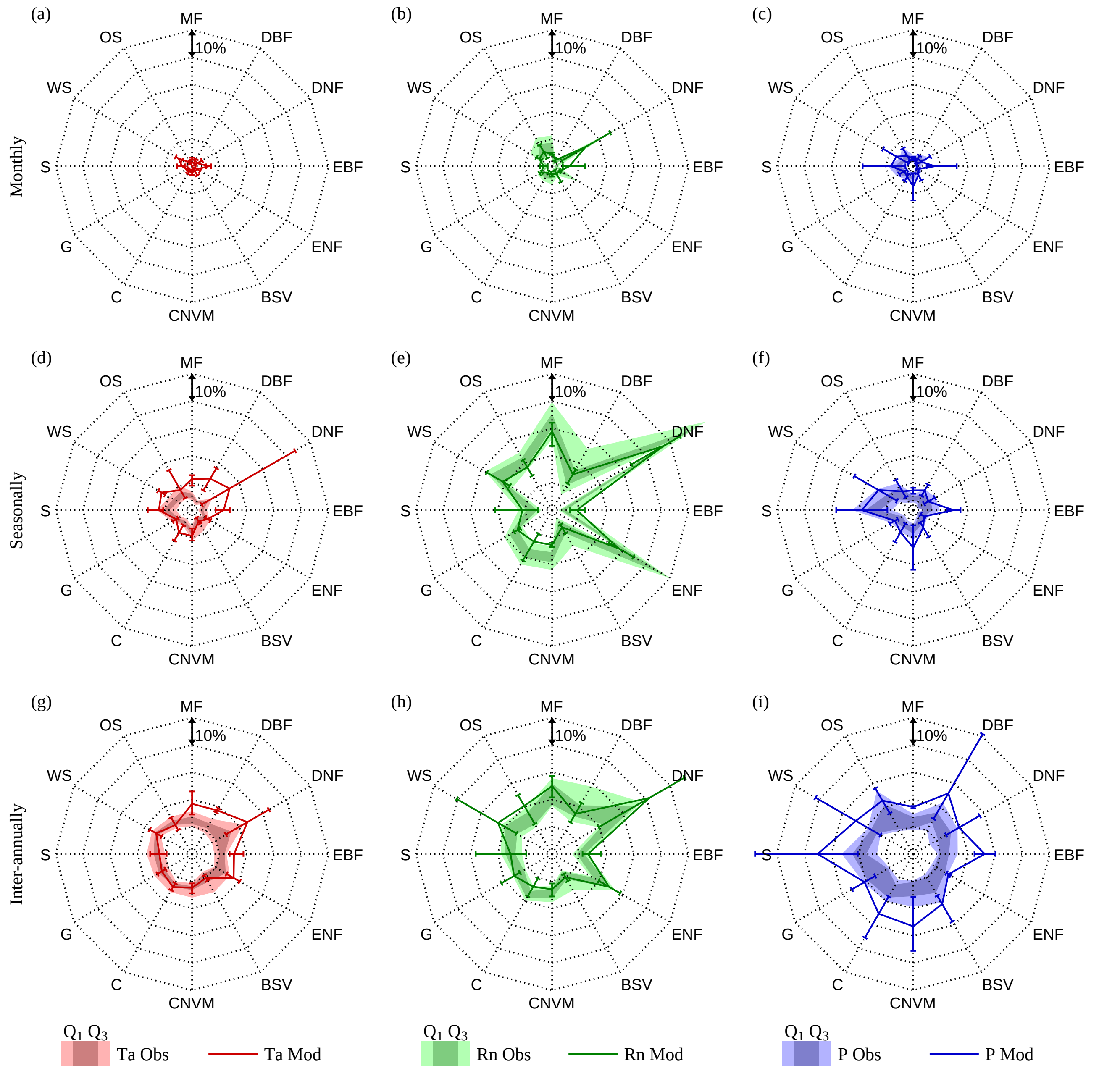

Figure 4. Climate impact on vegetation per biome. Biome averages of absolute observed (filled polygons) and modelled (lines) variation of LAI caused by ~~precipitation (P),~~ air temperature (Ta)~~and~~ , net radiation (Rn) and precipitation (P), at monthly **(a, b, c)**, seasonal **(d, e, f)**, and inter-annual **(g, h i)** ~~timescales~~time scales. Observations present the total range over all ensemble members, and the 25%- (Q_1) and 75%-percentile (Q_3). Models present an error-bar indicating the inter-model maximum, minimum and average results of four CMIP5 models (CCSM4, HadGEM2-ES, NorESM1-M, IPSL-CM5A-MR). Represented biomes are mixed forests (MF), deciduous broadleaf forest (DBF), deciduous needleleaf forest (DNF), evergreen broadleaf forest (EBF), evergreen needleleaf forest (ENF), barren or sparsely vegetated (BSV), cropland or natural vegetation mosaic (CNVM), croplands (C), grasslands (G), savannas (S), woody savannas (WS), and open shrublands (OS).

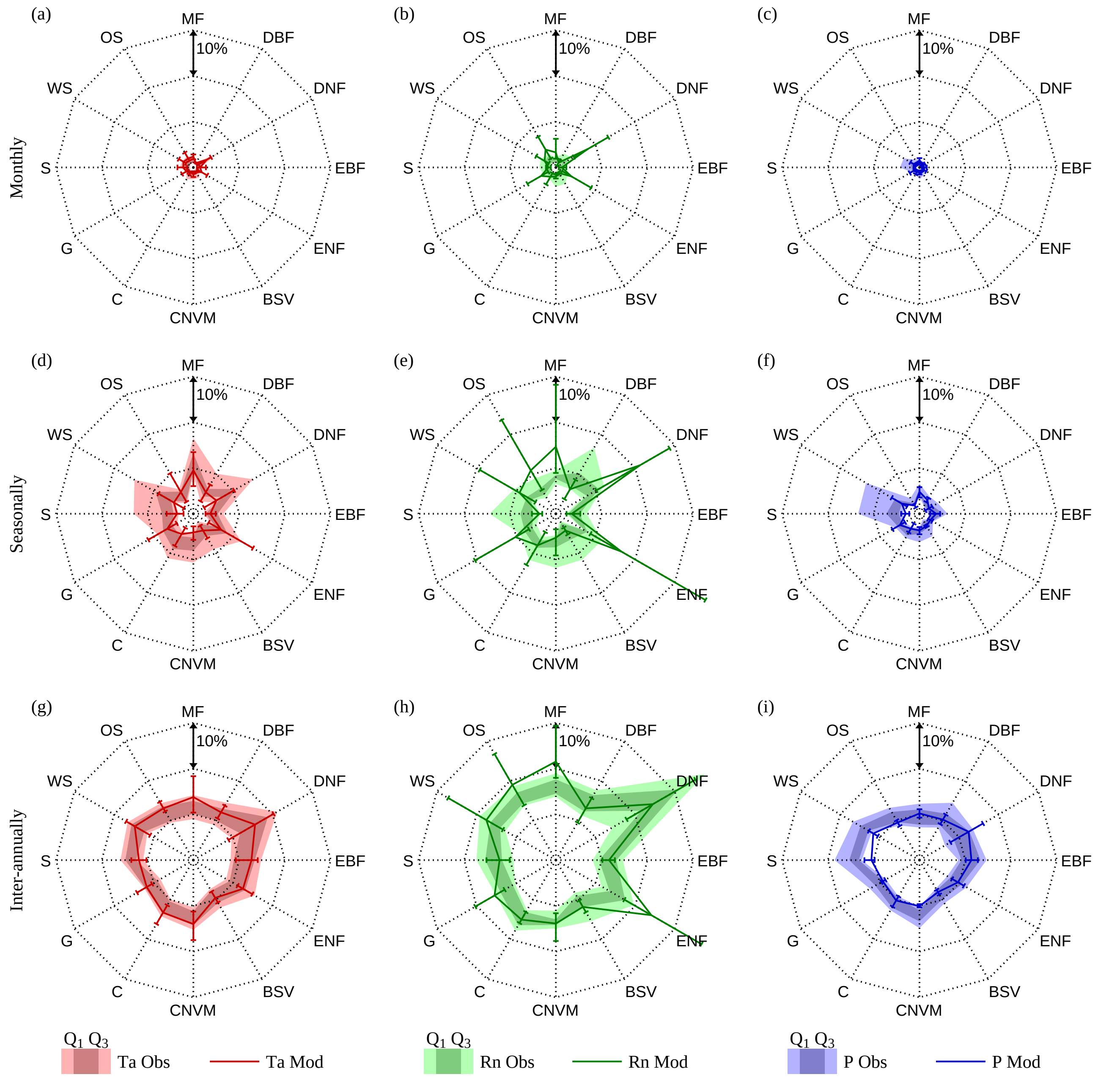

Figure 5. Vegetation feedback on climate per biome. Biome averages of absolute observed (filled polygons) and modelled (lines) variation of ~~precipitation (P),~~ air temperature (Ta)~~and~~, net radiation (Rn) and precipitation (P) caused by LAI, at monthly **(a, b, c)**, seasonal **(d, e, f)**, and inter-annual **(g, h i)** ~~timescales~~time scales. Observations present the total range over all ensemble members, and the 25%- (Q_1) and 75%-percentile (Q_3). Models present an error-bar indicating the inter-model maximum, minimum and average results of four CMIP5 models (CCSM4, HadGEM2-ES, NorESM1-M, IPSL-CM5A-MR). Represented biomes are mixed forests (MF), deciduous broadleaf forest (DBF), deciduous needleleaf forest (DNF), evergreen broadleaf forest (EBF), evergreen needleleaf forest (ENF), barren or sparsely vegetated (BSV), cropland or natural vegetation mosaic (CNVM), croplands (C), grasslands (G), savannas (S), woody savannas (WS), and open shrublands (OS).

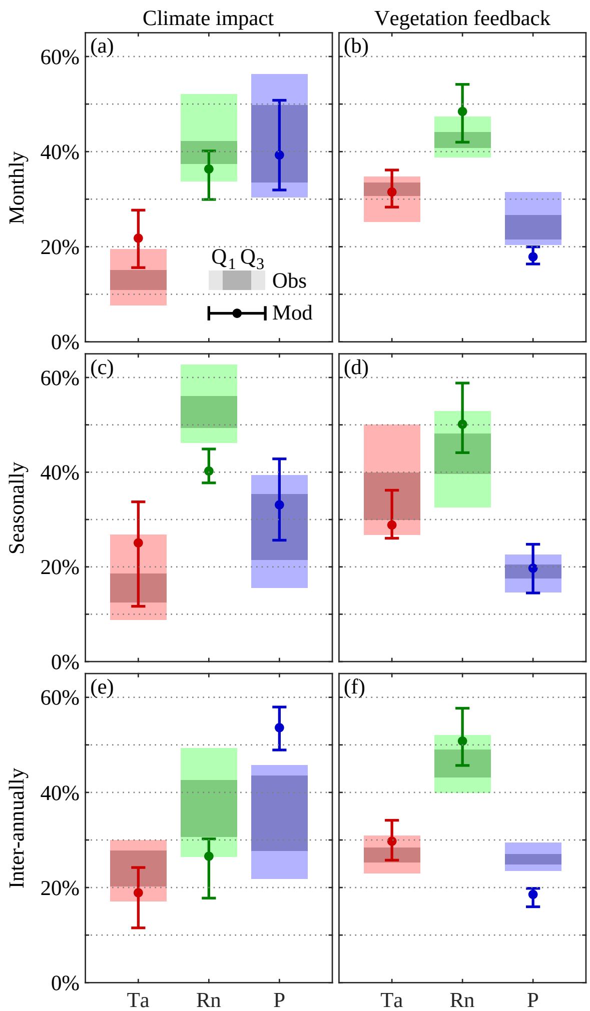

Figure 6. Continental average climate impact on vegetation and vegetation feedback on climate. Continental averages of absolute observed (filled rectangles), and modelled (lines) variation in vegetation **(a, c, e)** (climate **(b, d, f)**) caused by climate (vegetation), at monthly **(a, b)**, seasonal **(c, d)**, and inter-annual **(e, f)** ~~timescales~~time scales. Models present an error-bar indicating the inter-model maximum, minimum and average results of four CMIP5 models (CCSM4, HadGEM2-ES, NorESM1-M, IPSL-CM5A-MR).

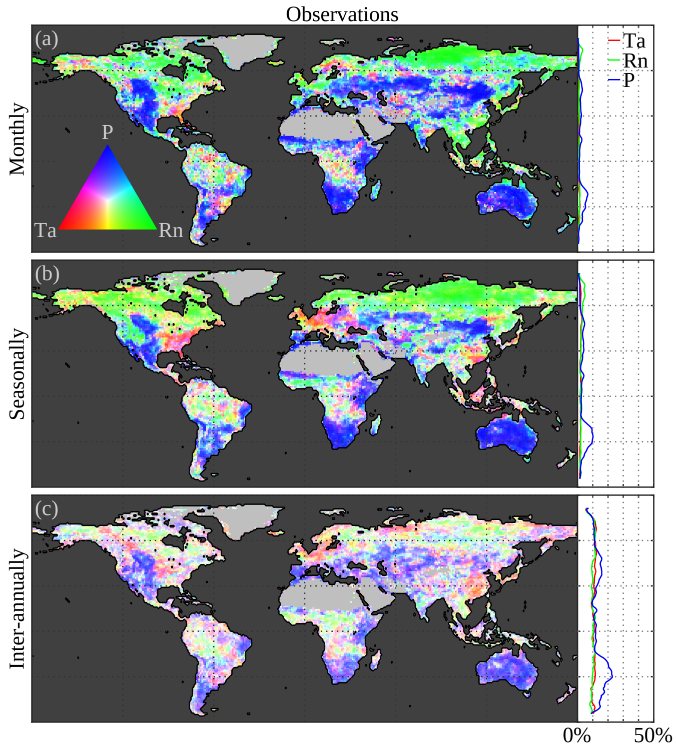

Figure A1. Global climate impact on anomalies of vegetation. Variability in observed anomalies of LAI caused by anomalies in ~~precipitation (P),~~ air temperature (Ta)~~and~~, net radiation (Rn) and precipitation (P) at **(a)** monthly, **(b)** seasonal, and **(c)** inter-annual ~~timescales~~time scales. Maps show the causality in relative terms with respect to the dominant driver at each pixel, while the latitudinal profiles show the absolute impact of each driver. The period ~~1982-2015~~ 1982–2015 is taken as reference for the observations.

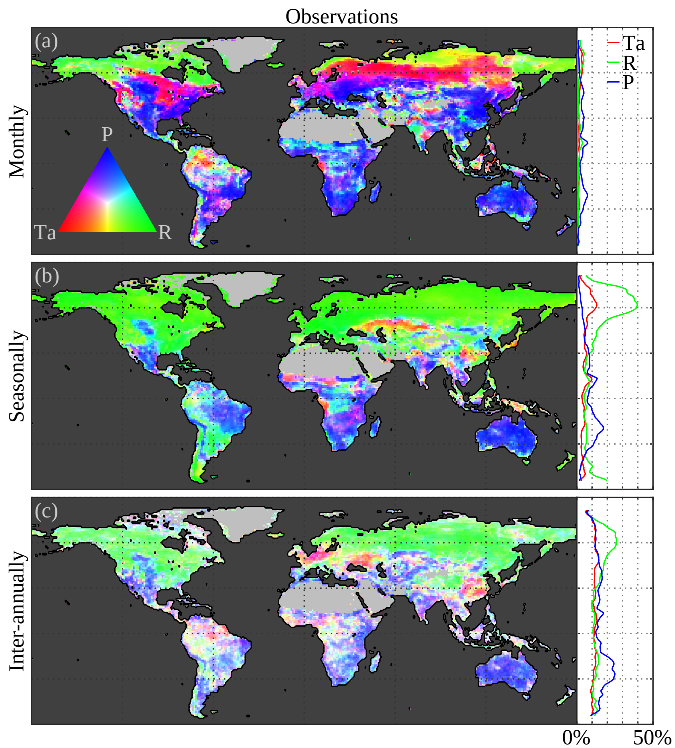

Figure B1. Global climate impact on vegetation using incoming radiation instead of net radiation. Variability in observed LAI caused by ~~precipitation (P),~~ air temperature (Ta)~~and~~ , incoming radiation (~~Rin~~R) and precipitation (P) at **(a)** monthly, **(b)** seasonal, and **(c)** inter-annual ~~timescales~~time scales. Maps show the causality in relative terms with respect to the dominant driver at each pixel, while the latitudinal profiles show the absolute impact of each driver. The period ~~1982-2015~~ 1982–2015 is taken as reference for the observations.

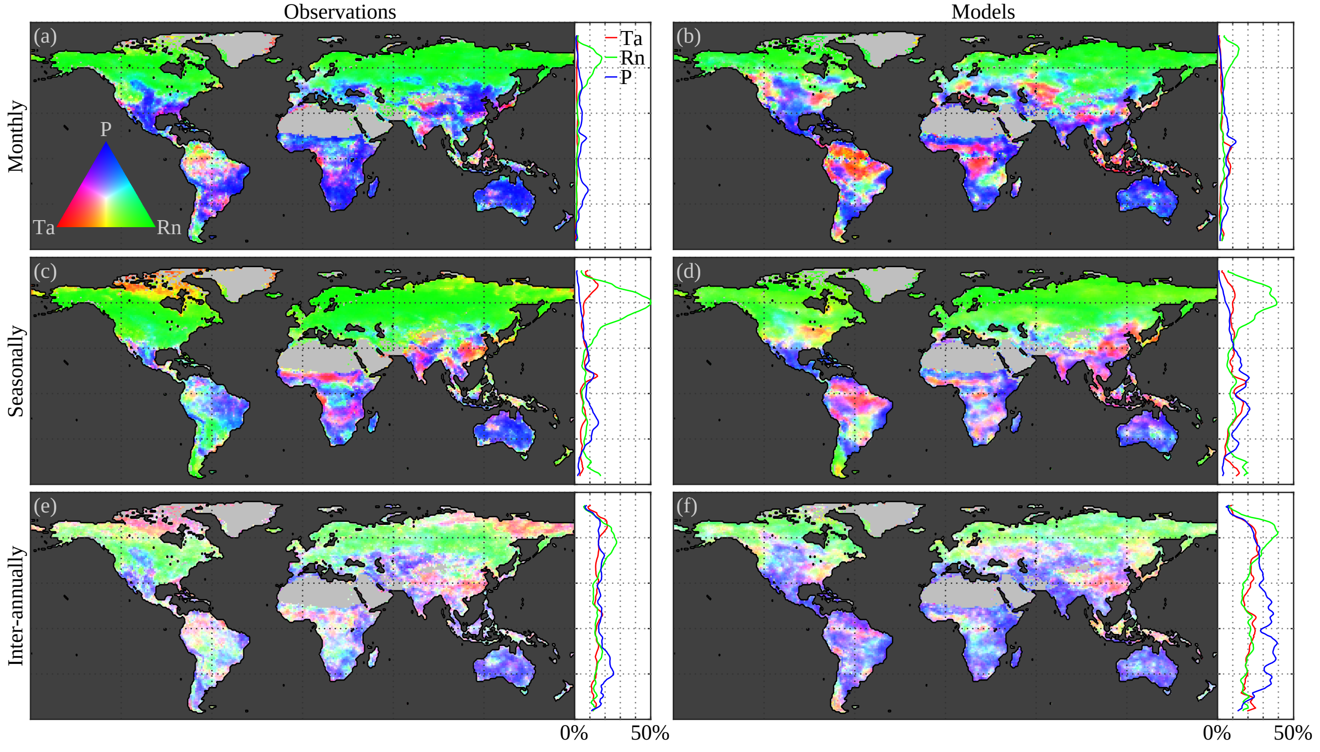

Figure C1. Global climate impact on vegetation during 1982–2005. Variability in **(a, c, e)** observed and **(b, d, f)** modelled LAI caused by air temperature (Ta), net radiation (Rn) and precipitation (P) at **(a, b)** monthly, **(c, d)** seasonal, and **(e, f)** inter-annual time scales. Maps show the causality in relative terms with respect to the dominant driver at each pixel, while the latitudinal profiles show the absolute impact of each driver. Maps show the mean from the ensemble of the observations or four CMIP5 models: CCSM4, HadGEM2-ES, NorESM1-M, IPSL-CM5A-MR.

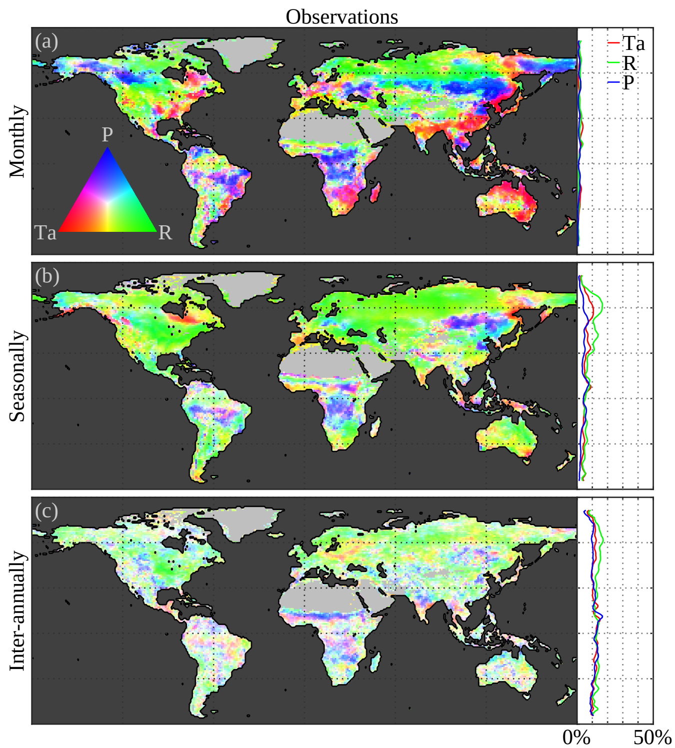

Figure D1. Global vegetation feedback on climate using incoming radiation instead of net radiation. Variability in ~~precipitation (P),~~ air temperature (Ta)~~and~~, incoming radiation (~~Rin~~R) and precipitation (P) that is caused by observed LAI at **(a)** monthly, **(b)** seasonal, and **(c)** inter-annual ~~timescales~~time scales. Maps show the causality in relative terms with respect to the strongest feedback at each pixel, while the latitudinal profiles show the absolute feedback on each driver. The period ~~1982-2015~~ 1982–2015 is taken as reference for the observations.