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Interactive comment on "Summarizing the state of the terrestrial biosphere in few dimensions" *by* Guido Kraemer et al.

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Replies to the Anonymous Referees

Guido Kraemer, Gustau Camps-Valls, Markus Reichstein, and Miguel D. Mahecha

November 11, 2019

Contents

1 Anonymous Referee #1

The authors thank the reviewer for the his time and thorough comments, we think that the comments greatly improved the manuscript. We have addressed them below.

1.1 General Remarks

I appreciated reading the discussion paper Summarizing the state of the terrestrial biosphere in few dimensions by Guido Kraemer and colleagues. The paper presents an approach for summarizing key variables on the terrestrial biosphere into fewer independent components using established multi-variate methods. They exemplify their

approach by showing several trajectories across space and time and by highlighting some major anomalies visible in their data.

While the work is well presented and scientifically sound, I have some major concerns regarding the publication of the manuscript in its current form:

1.1.1 Authors' reply

We thank the reviewer for his positive and very thorough review and the very helpful comments that we have now addressed the open issues as we will show below. We especially thank the reviewer for the detailed review of the overall structure of the manuscript and the many small details that have been improved due to is comments.

1.2 Concerns

1.2.1 1) The number of dimensions

The authors state that the first two components explain large parts of the variance and that the 'knee' is reached with the second component. However, inspecting Figure 1a, it seems that the 'knee' is reached with the third component, which still explains 9% of the variance. I was a little confused that the third component was disregarded throughout the whole manuscript, without giving a strong justification. Figure 2b indicates that the third component might be strongly connected to albedo. I encourage the authors to either expand their analysis to also include the third component, or to give a very strong argument for its exclusion. As it stands now, the decision to only inspect the first two components is very subjective.

1. Authors' reply The reviewer is right that the 3rd dimension still contains important information, therefore we included component 3 into the manuscript. We think

that the addition of the third component improved the manuscript substantially and want to thank the reviewer for this.

2. Changes:
   - Added axis 3 to the manuscript (for details, see the list of changes at the end of this letter).
   - Flipped axis 3 so that higher values for PC3 mean higher albedo

1.2.2 2) Scientific novelty and usefulness

I am missing a strong discussion/conclusion on how the manuscript advances scientific progress. Putting it into simple terms, the authors apply PCA – a widely used and established method – to a set of existing data sets. As such, it is not really a novel methodological development, but rather a demonstration of what could be done with global datasets as provided though the Earth System Data Lab. While this is not a deal-breaker per sé, the authors could greatly advance their manuscript by explaining how this approach can be used by other scientists, that is how it will advance the science of the terrestrial biosphere.

1. Authors' reply Thank you for this critique and comment which has many dimensions. At first glance the reviewer is right: we simply applied a PCA to a highly curated global data set - a data cube contained in the Earth system data lab. But, altough the method is similar to EOFs in climatology, where the matricization (the flattening of the 4th order tensor, variables $\times$ time $\times$ longitude $\times$ latitude, to a matrix) happens maintaining time, there are some differences in our approach: We are maintaining both, space and time and reduce only over the variables, as far as the authors are aware, this has not been done on global data. This is in our view an innovation, as we account, for the first time, for the many redundancies in

high-dimensional Earth observations. We have carefully reviewed the literature, but do not find a study that has investigated the global covariations of multiple Earth observation data streams. This is the main novelty of our work. Also, the use of a simple PCA algorithm is not incidental here: we seek for a method that learns a data transformation that is invertible, and allows us to measure/compute the reconstruction error in meaningful physical units. This cannot be done with more complicated/sophisticated nonlinear machine learning methods, where the (probably more accurate) transform is hard to analyze. We have included a comment in that direction, and pointed out the advantages and shortcomings of PCA versus other nonlinear dimensionality reduction methods in section 3.1.

2. L201, Added:

1.3 Differences from other PCA-type analyses

One of the most popular applications of PCA in meteorology is the EOF analysis, which are typically done with single variables, i.e. on a data set with the dimensions $lat \times lon \times time$, althought EOFs can be calculated from multiple fields. The resulting vector of indicators is calculated by multiplying the original data with the eigenvectors (typically only the first one), which represents the state of the entire spatial extent at a certain point in time and reducing over the spatial dimension. This is a PCA analysis that is very similar from a mathematical standpoint but very different from how we interpret the result. In an EOF, eigenvectors form maps that represent standing oscillations which are uncorrelated, while in the present study, the eigenvectors represent the influence of variables on the final indicators. Another important difference consists in EOFs maintaining the temporal dimension, while the present study maintains the spatial dimensions as well as the time dimension.

Ecological analyses often compare different sites, i.e. a spatial dimension, if the site measurements have repetitions in time. The observed variables often are species assemblages or environmental properties, which is the feature that is being reduced by the method of dimensionality reduction. The maintained dimensions therefore are space and, if present, time. Therefore the ecological application of dimensionality reduction is more similar to the present analysis than EOFs, the main difference lies in the type of features used, here we use variables that describe the exchange of ecosystems with their environment, while ecological analyses usually use species assemblage data. Another important difference lies in scale and type of data, ecological analyses usually use plot level data, observed at certain points, while our analysis uses global data that is arranged in a grid.

The present analysis uses multivariate data streams that are not bound to a certain point in time or space and removes the redundancies in these data streams and leaves the user with fewer indicators to worry about. In the future the number of data streams and the amount of data will only increase and therefore the utility of such a method will increase, too.

1.3.1 3) Too many results in the appendix

Many of the results are buried in the Appendix but never picked-up in the main text. In fact, Figure A1, B1, D1 and C1 were never referenced in the main text. The authors thus present many results in the Appendix that are not discussed in the main manuscript and thus the reader is left alone with her own interpretation. As some of the results are quite crucial for evaluating the method (e.g., the errors presented in B1), I strongly encourage the authors to thoroughly discuss them in their manuscript.

1. Authors' reply: Thank you for the observation! We agree that we have a lot of results in the appendix. To improve this situation, we have moved parts of the

appendix into the main text. We have also added references to the figures into the text.

2. Changes:
   - Moved the section "Reconstruction Error" from the appendix to L201.
   - Moved figure C1 ("bowen ratio") into the text.
   - We added the corresponding references. L340: A1, L183: B1, L195: C1 (was already there), L210: D1 (was already there, L339: E1 (was already there).

1.3.2 4) Writing

The writing needs improvement for turning this already good manuscript into an excellent manuscript. For example, the authors often describe their figures, instead of the results (Figure X shows...). It would be much more interesting to read about the main result instead (A influences B (Figure X)). I am sure the senior authors of this manuscript can do a great job in revising the manuscript to make it more accessible and exciting for the reader.

1. Authors' reply: We thank the reviewer for the pointing this out, and have revised many aspects of the paper, we hope that we have corrected the manuscript accordingly.

1.3.3 5) Spelling/grammar

There are some wording and spelling/grammar issues, some of which listened below:

1. Autors' reply Thanks for the thorough revision provided. We have corrected all suggested minor changes, and commented further on the critical ones below.

2. L. 16: Suggest removing 'the' before 'global'.
   (a) Authors' reply: Additionally added a "negative" for emphasis.
   (b) Change: the global impacts -> negative global impacts
3. L. 27: Spring is not a phenological event. Could use onset of bud-flush or similar.
   (a) Authors' reply: Thanks for catching this detail.
   (b) Changed from: In general, phenological patterns are changing in the wake of climate change, leading primarily to changes in the onset of spring (**??**).
   (c) Changed to: Changes in the onset of spring and autumn (**?**) change the length of the growing season, and cause large scale changes in phenological patterns ({**?**)schwartzgreen-wave1998, parmesanecological2006}.
4. L. 74: Not clear how standardization accounts for differences in scales. What scales? Spatial? Temporal?
   (a) Authors' reply: In deed, the wording is a bit ambiguous. We have changed it to make clear that we mean scale in a statistical sense here.
   (b) Changed from: In this study, each variable was normalized globally to zero mean and unit variance to account for the differences in scales. Because the area of the pixel changes with latitude, the pixels were weighted according to the represented surface area.
   (c) Changed to: In this study, each variable was normalized globally to zero mean and unit variance to account for the different units of the variables, i.e. transform the variables to have standard deviations from the mean as the common unit.
5. L. 138: The breakpoint detection comes out of the blue. Why is this done? What was the rational behind? This needs a decent introduction.

   (a) Authors' reply: The reviewer is right that we do breakpoint detection without properly introducing it. We have added a reference to fig. A1 and some introduction.
   (b) Added:
      i. End of Section 3.2.5 We added a paragraph at the "Trends in Trajectories" section to show the reader that trends are not the only way to detect changes in a trajectory and reference fig. A1
      ii. L29, added: Extreme events are temporary shifts, shifts where ecosystems changes their qualitative state permanently can also occur due to changing environmental conditions or direct human influence (**?**), detecting these changes is of vital importance for their mitigation (**?**).
6. L. 142: Same as above. The term hysteresis is never introduced before, but then explained in the results section (L. 239). As a reader, I would love to hear the details upfront, instead of reading about them in the results/discussion.
   (a) Authors' reply: This was missing from the introduction, we thank the reviewer for noticing this, we have remedied the situation.
   (b) Changes:
      - Moved the definition of "Hysteresis" to the "Methods" section and changed the first paragraph of Section "Hysteresis" to:
        "The alternative return path between ecosystem states forming the hysteresis loops arise from the ecosystem tracking seasonal changes in the environmental condition, e.g. summer–winter or dry–rainy seasons (fig. **??**b))."
      - Added to the introduction (L 27):
        "Hysteresis in ecosystems requires a better understanding as it can give us important information on limiting factors (**?**) and memory effects

({?)mahechacharacterizing2007, blonderpredictability2017} and may inhibit the return of ecosystems to the original state."

7. L. 148: Maybe include an example figure here, instead of referencing to the results already.
   (a) Authors' reply: The hysteresis may be a complex topic for people not familiar with it, we thank the reviewer for pointing this out and have added a conceptual figure that hopefully makes the concept easier to understand.
   (b) Changes: Added an example figure (Figure 1 in the new version of the manuscript, "Methods" section) with the four most common cases and changed the reference.
8. L. 151: 'We see that. . . ' is not a good opener. Directly describe the result, be precise and upfront (e.g., The first two components explained 73% of the variance (Figure 1a))
   (a) Authors' reply: Removed "We see that"
9. L. 160: What is the pre-imaging problem? Please do not assume that the reader reads up the details in the reference provided. Either avoid naming it or give a brief description.
   (a) Authors' reply: Again we thank the reviewer for pointing out that this is a topic that the target audience may not be acquainted to. We have improved the description and hopefully made the concept understandable to everyone.
   (b) Changed from: The salient feature of PCA is that an inverse projection is well defined and allows for a deeper inspection of the errors, which is not the case for nonlinear methods due to the pre-imaging problem (**??**).
   (c) Changed to: The salient feature of PCA is that an inverse projection is well defined and allows for a deeper inspection of the errors, which is not the

case for nonlinear methods which learn a highly flexible transformation that is hard to invert. Therefore interpretability of the transform in meaningful physical units in the input space is often not possible. In the machine learning community, this problem is known as the “pre-imaging problem” (**??**) and is a matter of current research.

10. L. 162: Again, not the best opener. The first sentence of a paragraph should summarize the main point of the paragraph (topic sentence), allowing the reader to skim through the manuscript. This sentence just describes where the reader can find a result, but nothing about the result itself.
    (a) Authors' reply: Thanks for pointing this out, we have changed some thing and hope that the manuscript is more readable now.
    (b) Changes:
        - Removed the sentence.
        - Added a reference to the rotation matrix equation to the caption of the first figure in the results. (Eq. **??**)
        - added ". . . , see fig. **??**b." at the descriptions of the components (L. 163, and L. 174)
11. L. 164: Odd formulation (two times related).
    (a) Authors' reply: Thank you for noticing! We have changed the sentence accordingly.
        i. From: These variables are related because they are all directly related to primary productivity.
        ii. To: These variables are related due to their importance for primary productivity.

12. L. 174ff: his paragraph actually described the indicators used and does not discuss the results. This could go into the methods description or should be more clearly related to the actual results.
    (a) Authors' reply: This paragraph describes PC2 and discusses how the variables that make up PC2 are related, therefore we have decided to leave it in as a discussion of PC2.
13. Figure 2: What are 'some points'? How were they chosen?
    (a) Authors' reply: It says so in the caption: "The trajectories were chosen to fill a large area in the space of the first two principal components."
    (b) Changes: "fill" -> "cover"
14. L. 139: As said before, this is rather introduction than results/discussion. I would have very much appreciated reading this in the introduction.
    (a) Authors' reply: This is the wrong line number, the Reviewer is probably referring to the description of the Bowen ratio as this should be mentioned in the introduction, indeed. We have added the Bowen ratio to the introduction and changed the paragraph to highlight the main result.
    (b) Changed L. 43
        i. from: Extracting the dominant dynamics from high-dimensional observations is a well-known problem in many disciplines. In climate science, for example, it is common to summarize atmospheric states using Empirical Orthogonal Functions (EOF), also known as Principal Component Analysis (PCA; **?**).
        ii. to: Extracting the dominant features from high-dimensional observations is a well-known problem in many disciplines, one approach is to

manually define indicators that are know to represent important properties, such as the "Bowen Ratio" (**?**), another one consists in using machine learning to extract these features. In climate science, for example, it is common to summarize atmospheric states using Empirical Orthogonal Functions (EOF), also known as Principal Component Analysis (PCA; **?**).
    (c) Moved the the following sentence from L. 201 to L. 194 The Bowen ratio embeds well into the subspace spanned by the first two PCs, see fig. **??**.
15. L. 258: rephrase: ... and can therefore be interpreted...
    (a) Authors' reply: Thank you for finding this, rephrased the entire sentence.
        i. From: These anomalies have a directional component and can be therefore be interpreted the same way as the original PCs which contain information of the underlying variables that were affected. In this sense, one can infer the state of the ecosystem during an anomalous state.
        ii. To: These anomalies have a directional component which makes them interpretable the same way as the original PCs, therefore one can infer the state of the ecosystem during an anomaly.
16. L. 282: Again, put the result in the spotlight, not the figure showing the result.
    (a) Authors' reply: The reviewer is right, this also counts for some of the other paragraphs describing that figure, thank you for pointing this out. We hope to have remedied the situation with the following changes:
    (b) Added L. 282: The seasonal amplitude of the trajectory in the Brazilian Amazon increases due to deforestation and crop growth cycles.
    (c) Added L. 290: The 2010 Russian heatwave has a very clear signal in the trajectories, ...

(d) Added L. 300: The 2003 European heatwave is reflected in the trajectories just a the 2010 Russian heatwave.

17. L. 305: Occur instead of occurring.

    (a) Authors' reply: Changed, thanks.

18. L. 312: Move 'especially' after 'showed'.

    (a) Authors' reply: Changed, thank you.

19. L. 313: Repeats methods.

    (a) Authors' reply: Thanks for noticing, we have removed the phrase and added ... patterns of trends ... to the next sentence.

20. L. 320: Why did you calculate the trends from the full data? Would it have been better to use the growing season as well to facilitate comparison? Please give a reasoning why you do it differently.

    (a) Authors' reply: The reviewer is right, that usually these kind of analyses are made on the growing season only. Because of simplicity of the analysis we opted to do the analysis this way, just as with the breakpoints we did not want to develop complicated methods for detecting the growing season from PC1 because this is not the scope of this paper. The analyses on the resulting indicators are simple and straightforward because of their exploratory nature. The next question would have been, how to limit PC2 and PC3? Use the wet/dry season for PC2 because it shows water, and summer/winter for PC3, or also use the growing season? Using growing season data only, we probably could have found stronger trends in PC1, but this could be an interesting topic for future research.

21. L. 324: Something odd with the sentence starting with 'Inside...'.

    (a) Authors' reply: Thanks for finding this one, fixed!
        i. From: The finding of **?** is not reflected in our data, especially compared to the areas surrounding the Congo basin, we can find only minor browning effects. Inside the basin and our findings are more in line with the global greening (**?**), which show a browning mostly outside the Congo basin.
        ii. To: The finding of **?** is not reflected in our data, especially compared to the areas surrounding the Congo basin, we can find only minor browning effects inside the basin and our findings are more in line with the global greening (**?**), which show browning mostly outside the Congo basin.

22. L. 327: Remove 'a' before 'browning'.

    (a) Authors' reply: Removed, thank you.

23. L. 349: The breakpoints are actually never shown, nor discussed. The conclusion is thus not really based on data here.

    (a) Authors' reply: The reviewer is right, we have added the breakpoints to the introduction, thank you for pointing this out.
    (b) L. 29, added: Extreme events are temporary shifts, shifts where ecosystems changes their qualitative state permanently can also occur due to changing environmental conditions or direct human influence (**?**), detecting extreme events and breakpoints is of vital importance for their mitigation (**?**).

24. L. 352: in, not 'ina'.

    (a) Authors' reply: Changed, thank you.

2 Anonymous Referee #2

The authors thank the reviewer for the his time and thorough comments, we think that the comments greatly improved the manuscript. We have addressed them below.

2.1 General Remarks

2.1.1 General assessment

This is a very interesting paper addressing some important issues of big data analysis for ecology studies. It is rich in analyses and provides some new views on an old method (PCA). I particularly liked the analysis of trajectories that I found quite powerful, notably for case studies.

1. Authors' reply We thank the reviewer for this positive review, we have addressed all the concerns below.

2.1.2 Key research question

Yet I found it difficult to understand what key research questions are addressed in this paper. This is important to clarify at the end of the introduction as the authors is providing us with a suit of analyses that may resemble (for non PCA-expert) an attempt of addressing many (all?) questions without real rationale. The readers need to have a clear (concise) view of the objectives of this paper, and they need to be guided through the analyses by referring back to the main research questions.

1. Authors' reply: Thank you for pointing this out, the reviewer is right, the paper may appear to try to solve too many problems. We have added a paragraph at the end

of the introduction to clarify the focus of the paper. The main motivation and goal of this paper is the lack of a systematic data-driven approach to explain the main features in Earth system data cubes in the literature. We first introduce a method to create such summarizing indicators in the form of a simple yet effective PCA, then we apply the method to a global set of representative variables describing the biosphere. Finally, to prove the effectiveness of the method, we give interpretations of the resulting set of indicators and explore the information contained in the indicators by analyzing them in different ways and relating them to well known phenomena. We have explicitly declared such motivation and approach at the end of the introduction section. Thanks for pointing this out.

2. L. 65 Added: First we introduce a method to create such indicators, then we apply the method to a global set of variables describing the biosphere. Finally, to prove the effectiveness of the method, we give interpretations of the resulting set of indicators and explore the information contained in the indicators by analyzing them in different ways and relating them to well known phenomena.

2.1.3 Input data may cause the resulting axes

In addition, I also have a major concern related to the set of inputs data used to feed the PCA. I agree that PCA is a powerful tool to deal with correlated variables, yet I have difficulties understanding why the authors have decided to include variables that are obviously highly correlated. To my opinion, vegetation productivity proxies are overrepresented as well as those related to water availability and stress. It puts some doubts in my head as to whether the finding of PC1 (primary productivity) and PC2 (surface hydrology) driving the state of the biosphere in space and time is truly original (or just purely mathematical). It is therefore important for the authors to justify the set of original variables. A suggestion could also be to decrease the number of input variables (removing obvious redundant proxies) as the amount of data to be condensed is mainly coming from the 8days interval used for the analysis.

1. Authors' reply: PCA extracts correlated variables, therefore the resulting axes will not change much if more or less variables are added that represent a certain aspect of the ecosystem. What does change are the explained variances of the resulting axes, i.e. including more variables that are proxies for primary productivity will cause this axis to explain more variance. The set of covariates we chose constitutes a large complementary and representative set that describe the exchange of mass and energy of the biosphere with the atmosphere. We have added a justification for the used variables:
   - The data was chosen from the entirety of the variables in the ESDL (at the time of analysis), meteorological variables were discarded (e.g. air temperature and precipitation), as well as variables with obvious problems in their distribution (e.g. burnt area contains too many zeros).
   - The used variables are mostly describing the mass and energy exchanges of the ecosystem with the atmosphere and we have shown that here, the most important drivers are found by a PCA.
2. L. 73 Added: For this study we chose all the variables available in the ESDL v1.0 (the most recent version available at the time of analysis), divided the available variable into meteorological and biospheric variables and discarded the biospheric variables. We also discarded variables with distributions that are badly suited for a linear PCA (e.g. burnt area contained too many zeros) and variables with too many missing values. The only data set that was added post hoc was fAPAR which represents an important aspect of vegetation which was not available in the data cube at the time on analysis (it is part of the data cube now).

2.2 Detailed comments

Finally I also have other comments and concerns - notably related to the structure of the manuscript - that would need to be addressed by the authors prior publication of their research (see attached report for details).

2.2.1 (1) Abstract

The authors start off the abstract by mentioning the importance of detecting abrupt and gradual changes in terrestrial ecosystem but do not develop further in the introduction. In the method section, the detection of breakpoints reappears but no results are presented or discussed (except for the appendix A). The authors should decide whether to consider the detection of abrupt changes as a real research question for this study.

1. Authors' reply: The reviewer is right, do not really go into detail in the analysis of breakpoints. To remedy this, we have changed the first sentence and made it clear that there is a proof of concept analysis in the appendix.
2. Changed the first sentence to: In times of global change, we must closely monitor the state of the planet in order to understand the full complexity of these changes.
3. L. 339 added: Another way to detect changes to the biosphere consists in the detection of breakpoints, which has been applied successfully to detect changes in global NDVI time series (**??**), or generally to detect changes in time series (**?**). A proof of concept analysis can be found in fig. **??**, we hope that applying this method to indicators instead of variables can detect a wider range of breakpoints analyzing a single time series.

2.2.2 (2) Introduction

As stated in my main comment, I find that there is somewhat a mismatch between the introduction and the method section. In the introduction, the authors touch upon many issues related to assessing and attributing changes of biosphere properties. However apart from creating a new set of independent, 'essential' variables, they do not clearly mention what other research questions this study is going to address; whereas in the methods they mention PCA, trend and breakpoints analyses. Clearly stating the research questions for this study would help the readers to understand the rationale behind each analysis.

1. Authors' reply: The reviewer is right, we have added the research questions to the introduction. We have extended L. 22–31 to contain the research questions.
2. L. 22ff, changed to: Regional trends of vegetation greening and browning that have been attributed to fertilization effects on the one hand, and long-term climate change on the other, need to be understood (???). Changes in the seasonal cycles of primary production, e.g. decreased seasonal amplitudes in "cold" ecosystems due to warmer winters (?) or increased seasonal amplitude in agricultural areas due to the so called "green revolution", are expected (??). Changes in the onset of spring and autumn (?) change the length of the growing season, and cause large scale changes in phenological patterns (??). Hysteresis in ecosystems requires a better understanding as it can give us important information on limiting factors (?) and memory effects (??) and may inhibit the return of ecosystems to the original state. Additionally, we are confronted with cascading effects induced by today's increasing frequencies and magnitudes of extreme events (??) which are yet to be fully understood (??). Extreme events are temporary shifts, shifts where ecosystems changes their qualitative state permanently can also occur due to changing environmental conditions or direct human influence (?), detecting extreme events and breakpoints is of vital importance for their

mitigation (?). The question is, how to uncover and summarize effects of this kind from the wealth of available global data streams? Do we need to develop specific solutions for every observed phenomenon or can we develop a single approach to uncover a wide variety of phenomena?

Extracting the dominant features from high-dimensional observations is a well-known problem in many disciplines, one approach is to manually define indicators that are know to represent important properties, such as the "Bowen Ratio" (?), another one consists in using machine learning to extract these features.

2.2.3 (3) Data and methods

1. Better description of the data The description of the data slightly too minimalistic, including in the appendix F. Mentioning the input data (satellite, climate or others) feeding into each dataset would be helpful. The observation period used for this study is also not mentioned.
   (a) Authors' reply: We thank the reviewer for pointing this out. We have added the limits of the time dimension and the type of grid in
   (b) L 72, changed to: The data streams are harmonized as analysis ready data on a common spatiotemporal grid (equirectangular 0.25° in space and 8 days in time, 2001–2011), forming a 4d hypercube, which we call a data cube.
   (c) Appendix F: Was augmented with the origins of the data
2. L. 75, Mention projection This statement is not always valid (e.g. in the case of equal-area projection). The sentence would be clearer if the authors would mention the projection system used here.
   (a) Authors' reply: We thank the reviewer for pointing this out. See previous response.

3. L77. Better explanation of PCA The authors mentioned that they used a modified PCA, reading from the description given in the following lines, the PCA applied here seems to be standard. Could the authors provide some explanations to why / how the PCA has been modified? It should also clarify whether they applied the PCA in s or t-mode.

   (a) Authors' reply: We have clarified the PCA analysis by discussing it in the context of frameworks describing PCA in the context of climatology and ecology and hope that this will help with the understanding of the method.
      - The PCA is a decomposition of the correlation matrix.
      - Building the correlation matrix is not standard due to the big data aspects,
      - and the spatial extension, both of which require a lot of care in the calculation of the covariance matrix, which is described in the "Methods" section.
      - The dimensions we summarize are new, there are a number of different frameworks (S- vs. T-mode in climatology, Q- vs. R-mode in ecology, and primal vs. dual modes in machine learning) that describe standard applications of PCA, none of which give an exact description of the analysis done here. We have added a section describing the relation of the present analysis with these frameworks.

   (b) L201, added:

      2.3 Relations to other PCA-type analyses

      One of the most popular applications of PCA in meteorology is the EOF analysis, which is typically done with single variables, i.e. on a data set with the dimensions $lat \times lon \times time$, althought EOFs can be calculated from multiple fields.

      EOFs can be calculated in S-mode and R-mode. If we matricize our data cube X so that we have time in rows and $lat \times lon$ in columns, then S-mode PCA works on the correlation matrix of the combined variable and space dimension. In T-mode, the PCA works on the correlation matrix formed the time dimension (**?**). The PCA presented here works slightly different: (1) We did a different matricization ($lat \times lon \times time$ in rows and variables in columns) and then (2) the PCA works on the correlation matrix formed by the variables, therefore in this framework we could call this a V-mode PCA.

      Ecological analyses use PCA usually with matrices of the shape $object \times descriptors$, when calculating the PCA on the correlation matrix formed by the objects, then we it is called a Q-mode analysis, when the PCA is applied on the correlation matrix formed by the variables, then it is called an R-mode analysis (**?**). The PCA done in this study is closest to an R-mode analysis, in the present case the descriptors are the various data streams and the objects are the spatiotemporal pixels.

4. Per-pixel analysis It would be nice here to make a link to the (extended – see comment above) research questions in order to understand directly the rationale for such analyses.

   (a) Authors' reply: The link was really unclear, we have added more research questions to the introduction (see previous replies) and are now mentioning the research questions.

   (b) L. 127, added: We calculated the trends of the indicators and the trends of the seasonal amplitude of the indicators, for the trends we used the Theil–Sen estimator.

   (c) L. 138, added: When looking for disruptions in trajectories, breakpoint detection provides a good framework for analysis.

2.3.1 (4) Results

1. General comment: I highly suggest to split the results and discussion into two separate sections. It will facilitate the reading and will allow the authors to emphasise better the originality of their work. Example: L155-161, L164-173, L175-182, L235-246, etc. should not be in a results section s.s., but would rather belong to a discussion (or even introduction or method). Please consider at least moving all methods description and introduction to new concepts to the respective adequate sections.
   (a) Authors' reply We thank the reviewer for this suggestion, but we think that a joint results and discussions section is the better choice, as it allows for the results and their discussions to be closer and easier to follow.
2. L153 and Figure 1 The authors mentioned that there is a knee at component 2. I believe it is rather at component 3. This component still contribute to the total variability to a share of almost 10%, therefore the authors should either include it in the rest of the analysis or provide an adequate justification not to. Also I generally miss a figure presenting together the temporal and the spatial patterns for the main PCs. This could be put as supplementary material. In the caption of Fig.1 I would recommend to change the term axis 1 and 2 by PC1 and 2. The comment also applies to the text itself (Ex. L190).
   (a) Authors' reply: The third component was missing, indeed. We have added it to the paper, we thank the reviewer for pointing this out, as it improved the manuscript substantially. The spatiotemporal figure was also missing and we have added it, this was an oversight of our part and we corrected it. We have also unified the terminology, axis is now never used to describe principal components.
   (b) Changes:

      - We have added the third component to the manuscript.
      - Added appendix F with joint time and space patterns.
      - Removed the term axis when in designated a component in the entire manuscript.
3. L183 Please describe in the first sentence what the triangle is made of.
   (a) Authors' reply We have provided a better description of the figure.
   (b) Changed to: The bivariate distribution of the first two principal components form a triangle (gray background in fig. **??**a).
4. L203 'movement of a spatiotemporal pixel in variable space', please rephrase. A pixel cannot be moving spatiotemporally, like in a sliding puzzle.
   (a) Authors' reply The pixel is moving in the vector space, this formulation is easily misunderstood and we have changed it therefore. We thank the reviewer for pointing this out.
   (b) From: The principal components may be used to summarize the movement of a spatiotemporal pixel in variable space, so that they represent the current state of the ecosystem at a certain location in space and time (fig. **??** left column) or time of year of the mean seasonal cycle of the pixel (fig. **??** right column).
   (c) To: Because the first few principal components represent most of the variability of the space spanned by the observed variables, they summarize the state of a spatiotemporal pixel efficiently. This means that they track the state of a local ecosystem over time (fig. **??** left column) or, in case of the mean seasonal cycle, time of the year (fig. **??** right columns). For a representation of the state of the first three components in time and space, see appendix fig. **??**.

5. L221-224 This should be described in the methods section and should be linked to a key research questions.
    (a) Authors' response We thank the reviewer for pointing out this oversight. We have added a definition of the means seasonal cycle to the methods and mention it in the introduction.
    (b) L. 56, changed to: Here, we aim to summarize these high-dimensional surface dynamics and make them accessible to subsequent interpretations and similar analyses as the original variables, such as mean seasonal cycles(MSC), anomalies, trend analyses, breakpoint analyses, and the characterization of ecosystems.
    (c) L. 126, added: The mean seasonal cycle at a certain day of year is the mean of all values of a variable at a certain day of year and describes the average characteristics of a location. The anomaly of the mean seasonal cycle is the observed value at a certain point in time minus the mean seasonal cycle. The anomaly gives an idea, if there is the current value is normal or extreme.

2.3.2 (5) Conclusion

1. L341 The results of the breakpoints analyses were not reported or discussed in the main text, therefore the statement 'To monitor gradual and abrupt changes in times of global change' do not hold.
    (a) Authors' reply: We thank the reviewer for pointing this out and hope that we have remedied the situation.
    (b) Changed the beginning of the conclusion to: To monitor the complexity of the changes occurring in times of an increasing human impact on the environment . . .

2. Appendixes Some results presented in the appendixes do not appear in the main text, e.g. Figures A1 and B1. The authors should maybe decide on the key results to be presented here and maybe save some others for a follow-up paper?
3. Authors' reply: We thank the reviewer for pointing this out and all appendices should be referenced in the text now.

2.3.3 (6) Two final comments for reflexion:

1. Legacy effects: The authors have applied PCA on time series of 8day variables without considering any lag or accumulation effect in the response of a given variable. Would it be fair to say that legacy effects might not be captured adequately by such analysis?
    (a) Authors' reply: The method ignores lag and memory effects, lag effects may still be captured implicitly in the components but there will never be a "memory axis". Something like this may be captured using a combination of autoencoders and LSTMs but as far as the authors know, no one ever attempted an analysis like this.
2. Operationalization: The authors refer to the MEI in the introduction as an example of a successful PCA-based indicator. Could the authors elaborate on the requirement for operationalising their methods (e.g. if one would like to use the new indicators operationally, how frequently should the PCA be updated?).
    (a) Authors' reply: Applying a trained PCA is very simple and computationally efficient, the trained PCA should also be quite stable and therefore we assume that updates don't have to happen frequently. The implementation with 'WeightedOnlineStats.jl' would theoretically allow a very efficient update with every step, but we assume that this will not be necessary. For a real time

application of the method, the most important limitation is that only real time data can be used. This limits the type of data that that can be used, as most of the data we used here are created years after collecting the satellite or field observations.

3 Anonymous Referee #3

The authors thank the reviewer for the his time and thorough comments, we think that the comments greatly improved the manuscript. We have addressed them below.

3.1 General Remarks

This manuscript entitled "Summarizing the state of the terrestrial biosphere in few dimensions" is well-thought and well-written, and fits the scope of Biogeosciences, so overall, I am favourable to get it published there. I do have some concerns which I would like to see addressed by the authors, and I also have several recommendations to improve the manuscript before getting it published. Please find these points below.

3.1.1 Authors' reply:

We thank the reviewer for the positive comment and hope that we can address all mentioned concerns and recommendations.

3.2 Better explanation for the interpretation

My first point regards the interpretation of the first to PCA components. Having the first related to productivity and the second to water availability is indeed interesting and

useful to summarize that state of vegetation. However, I believe some more effort is needed to more clearly separate these 2 in their interpretation. Productivity is inevitably dependent on water availability, so in principle, one wonders why these would be the first 2 components, which by definition should be orthogonal and 'unrelated'. I suppose this is perhaps because these refer to signals at different scales, PC1 describing an overall general state of potential productivity of the system at that location, while PC2 describes more events of water shortages and or excesses that are not directly related to the stationary potential productivity. Am I correct? Could you please clarify/elaborate on this to help readers better understand how these two axes should be 'read'.

Much related to the previous point, isn't it surprising that the 2 first principal components have such similar spatio-temporal patterns in Figure 3? These seem very highly correlated, which is something I would not have expected from the first two components which explain the maximum of variance in two orthogonal direction. Can you help me grasp this apparent paradox? In a way having such similar patterns make me wonder how useful having 2 PC is instead of only 1? Of course you do show the value of the 2D space in figure 2, but even there, much of the variation goes along the PC1 axis. Your selected cases in the anomalies in Figure 5 also generally go in the same direction of lower productivity coinciding with dryer conditions (Russian heatwave, droughts in Amazon), or vice versa (Floods in horn of Africa). Perhaps a stronger focus in general throughout the paper should be made on highlighting the much more specific cases where the two PCs give different but complementary information rather that going in the same direction.

3.2.1 Authors' response:

While the reviewer is right that ecosystem productivity is dependent on water availability, the availability of water can be restricted due to several reasons which are reflected by PC2. We have added a paragraph to explain this more extensively.

1. L 189 added: PC2 separates the two most important factors that limit water availability: The lack of available water and frozen water. The first two components are (due to their construction by PCA) orthogonal, if we only took ecosystem with a dry season, then the “water component” would explain much less variance or even disappear, because ecosystem productivity would have a strong negative correlation with dryness. This would be equivalent to removing the lower left corner of the distribution triangle in fig. ??a and b. If we only looked at ecosystems that ceased productivity in winter, then we would find a strong positive correlation with the current "water component" and ecosystem productivity and the component would explain much less variance or even disappear. This would be equivalent of removing the lower left corner of the distribution triangle in fig. ??a and b. But because we have both relations, which can be seen from the triangle in the background shading of fig. ??a and b, the “water component” is (1) orthogonal to the productivity component and (2) is the second most important component.
2. L 232 added: Although the principal components are globally uncorrelated, they covary locally (see fig. ??). Ecosystems with a dry season have a negative covariance between PC1 and PC2 while ecosystems that cease productivity in winter have a positive covariance.

3.3 Explain component 3

I think you should also explore the third component. It does represent 9% of the variance, which is not so little, but above all it seems to be quite different from the first 2 in that it reacts much more to the albedo, which you hardly mention in the entirety of the manuscript. Could this be related to biophysical effects that vegetation could have on the climate? E.g. to understand where radiative vs non-radiative mechanisms dominate their effect on local temperature, for instance.

3.3.1 Authors' response:

This is really a good suggestion and we added component three.

3.4 Include static variables?

The behavior of the biosphere is much related to the elevation. While I know the effect of elevation should be reflected in the other variables, this is still dependent of modelling assumptions that may end up diluting the effect of elevation. Yet elevation is a variable that is very well measured, and which could contribute to summarizing the terrestrial biosphere. So why not including such a variable in the PCA? I know changes in elevation are minimal (and probably very difficult to detect) and having a static variable with respect to all the other dynamic ones you propose is a bit odd, but still, what are your arguments for not doing so? I think some discussion on this is warranted.

3.4.1 Authors' response:

We thank the reviewer for this suggestion, but we are only including variables that are affected by the biosphere, it is true that elevation has a strong effect on the biosphere, the biosphere has no impact on elevation (excluding long term effects, such as erosion).

3.5 General structure

The paper generally could be improved by curating more the structure. Several points on this:

- Section 3.2 could benefit from some introduction naming what you intend to calculate first (get trends, test significativity, get breakpoints, hysteresis) before going in the details. This part could also be more pedagogic, providing more rational on why you do these things.

- Parts of the ‘discussion’ should be much further after the ‘results’, such as lines 155-162 which should come in some kind of ‘caveats and perspective about the method’ section
- Section 3.2 is very unbalanced with respect to 3.1. Probably best to reorganize to avoid ‘sub-sub-sections’ and have subsections from 3.1 to 3.5
- Parts describing concepts, such as Hysteresis (lines 235-246) should not appear in the results but before, either in methods or introduction.

3.5.1 Authors’ response:

We thank the reviewer for these suggestions and hope that we have addressed satisfactorily.

3.5.2 L 205: Added introduction to section 3.2

Because we exchange the variables for (fewer) components we can do the same kinds of analysis on the components as we usually do on variables. In the following apply some of the commonly used methods of analysis on the components to analyze their general properties. First we calculate the mean seasonal cycle to analyze the general behavior of the components, we see if we can find hysteresis effects and explore their origins, we calculate anomalies to find extreme events. We analyze single trajectories to find non-obvious changes, and apply a number of change detection algorithms, i.e. trend detection, breakpoint detection and trends in amplitudes.

3.5.3 L183:

The mentioned paragraph is too short for an entire section, we moved it further back, after a paragraph comparing PC1 and PC3, where we observe that PC3 could probably be avoided by using a nonlinear method.

3.5.4 Reordering Section 3.2

Section 3.2 is about trajectories and therefore we thought it would be useful to keep these in a shared hierarchy level.

3.5.5 Move the description of Hysteresis into Methods

Moved the description of Hysteresis into the "Methods" section, see comment of previous reviewer.

3.6 Minor stuff

3.6.1 Lines 74, 75:

how do you manage intermittent gaps in the data? Does this affect your averages and your normalization? Also, please clarify if the normalization is based on the entire data cube for each variable, or is the normalization done per time frame?

1. Authors’ response: We should mentionthis, this was partially already addressed by responses to previous reviewers.
2. L75, added: Spatiotemporal pixels with missing values were ignored in the cal-

culation of the covariance matrix.

3.6.2 Line 182:

don't you mean sensible heat instead of latent heat?

1. Authors' response: Yes, thank you for noting this, changed.

3.6.3 Figure 1:

caption could be more instructive, perhaps somehow say there what the reader should understand/read from the "rotation matrix".

1. Authors' response: Thank you for pointing out that the term rotation matrix may not be understood by everyone. We have added the word "loadings", which is the standard jargon for PCA and an explanatory sentence.
2. Added the following sentence: The columns of the rotation matrix describe the linear combinations of the (centered and standardized) original variables that make up the principal components.

3.6.4 Figure 7:

surprised to see the strong pattern in Eastern Australia. Is this corroborated in other studies?

1. Authors' reply This is indeed interesting, we added a paragraph describing the reasons for this particular trend:

2. L328 Added: In eastern Australia we find a strong wetness and greenness trend which is due to Australia having a "milennium drought" since the mid nineties with a peak in 2002 (**??**) and extreme floods in 2010–2011 (**?**).

3.6.5 Mention the time period for trend analysis.

Regarding all trend analyses, make sure you more clearly mention in the captions the extend of the period you are considering, as these are not long-term trends and could thus be misinterpreted.

1. Authors' reply: Good point, added the year to the captions of fig. E1 and 8

3.6.6 Add contour for coast lines

For clarity and readability, figures with maps could benefit from either a dark background on the oceans or a line vector showing the coasts, as many of the colour scales use very light colours which are confounded with the white background.

1. Authors' reply: Done, improved the figures quite a bit, thanks for the suggestion!

3.6.7 Move breakpoint detection to SI, including description

I wonder if the breakpoint detection is really useful if it is not more mentioned and elaborated in the main text and just left in appendix. I would recommend to bring it in as a main figure if something strong can be extracted from there, and otherwise remove it entirely from the methods. Eventually you could include it in supplementary, but then include the description of the breakpoint methodology only there.

1. Authors' reply The breakpoint detection is an example analysis that showcases one of the possible set of changes that can occur and that can be detected, therefore we think it has it's place in the paper as an example what can be possible, without going into too much detail.

3.6.8 Move Fig C1 into the main text

On the other hand, I would strongly recommend to integrate the Figure C1 in the main text as you do talk in detail about the Bowen ratio and how the 2 PCs do characterize it well.

1. Authors' reply Thank you for the good suggestion, we have moved the figure into the main text.

3.6.9 Unify scale ranges for fig D1

Figure 1D I have a bit of a hard time to make good use of it as it is. Are the values in normalized units or absolute values? Would it not be prefereable to have the same scale for MSC min and MSC max? Do you refer to this figure in the main text.

1. Authors' reply Thank you for this suggestion, but this figure is entirely about showing, that very different ecosystems can be very similar at certain points in time, for this, we don't need to compare across subfigures and therefore a single scale won't help for this, they will just remove contrast, especially across MSC min and MSC max.

3.6.10 Typos

There are some typos in several places. Make sure to address them.

1. Authors' reply We have fixed many and hope we did not forget any.

4 Anonymous Referee #4

The authors thank the reviewer for the his time and thorough comments, we think that the comments greatly improved the manuscript. We have addressed them below.

4.1 General remarks

The authors present a well-written manuscript on the analysis of two principal components derived from a set of biosphere variables, one related to vegetation productivity and the other one related to water stress. The trajectories of those components over time reveal interesting seasonal patterns, inter-annual changes and anomalies, and can be used to track extreme events and state shifts of ecosystems/biomes. Therefore, I believe that this is a novel and relevant contribution to Biogeosciences.

4.1.1 Authors' reply:

We thank the reviewer for the positive comment.

4.2 Major concern

4.2.1 Advantage of PCA

My major concern lies in the fact that the authors select mainly variables related to productivity and water availability, and thus not surprisingly the PCA shows those two major axes. I wonder whether just selecting for example GPP and evaporative stress for the analysis of time trajectories would give the same results, but it might be easier to interpret than principal components representing a mix of variables. Can the authors elaborate in more depth what is the advantage of using PCs in this context?

1. Authors' reply There are multiple advantages,
    - Having to observe less dimensions.
    - Information on the covariance structure of the covariates.
    - If some event happens only on one of the variables constituting a component, then it can still be observed on the final component.
    - Directional information, when observing extremes.

4.2.2 More data streams

For describing the state of the terrestrial biosphere, I think the authors are missing a very important component related to biodiversity, habitat quality, intactness, forest degradation and fragmentation. These aspects are crucial to describe the state of the terrestrial biosphere. There is still research needed to develop these as operational data streams, but a few examples are available at least at one point in time, e.g. Global Habitat Heterogeneity from EarthEnv, datasets from Global Forest Watch, Dynamic Habitat Indices DHI from Silvislab. This might not be sufficient (in terms of temporal

resolution) to include it for this analysis, but the results from this study could be compared to those datasets (especially the DHI) and the need and relevance of global biodiversity and habitat intactness/quality information should be discussed.

1. Authors' reply We think that the reviewer has a very relevant point here, we would have loved to include more data streams that are relevant to the biosphere. The major problem is the availability of relevant of open data streams at a sufficiently high resolution in space and time which is currently very limited. As we want to track the change of the indicators over time, including static variables did not really make sense in this analysis. Including variables that have a yearly temporal resolution would require to aggregate our data by year which would also have made for a very interesting analysis but outside of the scope of this study.

4.3 Minor comments

4.3.1 L18:

new satellite missions, add: Schimel, D., Schneider, F., Bloom, A., Bowman, K., Cawse-Nicholson, K., Elder, C., . . . Zheng, T. (2019). Flux towers in the sky: global ecology from space. New Phytologist, nph.15934. https://doi.org/10.1111/nph.15934

1. Authors' reply: added

4.3.2 L25:

green revolution, add: Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R. K., . . . Myneni, R. B. (2019). China and India lead in greening of the world through land-use management. Nature Sustainability, 2(2), 122–129. https://doi.org/10.1038/s41893-019-0220-7

1. Authors' reply: added

4.3.3 L27:

changes are not only occurring in the onset of spring, but also browning trends, see:

- Garonna, I., de Jong, R., de Wit, A. J. W., Mücher, C. A., Schmid, B., & Schaepman, M. E. (2014). Strong contribution of autumn phenology to changes in satellite-derived growing season length estimates across Europe (1982 - 2011). Global Change Biology, 20(11), 3457–3470. https://doi.org/10.1111/gcb.12625
- Garonna, I., de Jong, R., & Schaepman, M. E. (2016). Variability and evolution of global land surface phenology over the past three decades (1982-2012). Global Change Biology, 22(4), 1456–1468. https://doi.org/10.1111/gcb.13168

1. Authors' reply: Thanks for the suggestion, we added the browning and changed the line to:

   In general, phenological patterns are changing in the wake of climate change, leading to changes in the growing season (**?**) due changes in the onset of spring (**??**) and autumn (**?**).

4.3.4 L35:

if a principal component is a mix of productivity measures, I don't necessarily think it's more intuitive to interpret than a simple GPP map.

1. Authors' reply: Thanks for pointing this out, changed the sentence to:

   The rationale is that dimensionality reduction only retains the main data features, which makes them easier accessible for analysis.

4.3.5 L63:

What do you mean by "of parts"? Parts of what?

1. Authors' reply: changed "parts" to "observations"

4.3.6 L75:

Isn't this dependent on the coordinate system and/or projection? What is the coordinate system used? And why not try to use an equal-area projection (e.g. equal earth projection)?

1. Authors' reply: Added the coordinate system, thank you for pointing out this oversight.
2. L 72, changed to: The data streams are harmonized as analysis ready data on a common spatiotemporal grid (equirectangular 0.25° in space and 8 days in time, 2001–2011), forming a 4d hypercube, which we call a *{data cube}*.

4.3.7 L152:

So what is contributing to the third component. It's still 9% of explained variance!

1. Authors' reply: Thank you for pointing this out, we have added the third component to the manuscript.

4.3.8 L162:

Figure 1b is not very intuitive to me. What exactly does it show and how do you read from this that the first component represents productivity and the second hydrology? The figure doesn't seem to show any clear patterns to me. Could you also show the biplots of PC1 and 2, and PC2 and 3?

1. Authors' reply: As biplots are the "standard" way do describe this type of information, we have thought about adding biplots, but decided against it for the following reasons: 1) Biplots don't really contain any information that is not already contained in fig 1b and fig. 2. 2) The number of observations is so high, that it would be impossible to add all the observations to a plot, we worked our way around this by showing bivariate histograms as a background shading in fig. 2. 3) The manuscript contains too many figures already.

4.3.9 L177/178:

check spelling

1. Authors' reply: Thanks for finding this!
2. Changed to: While surface moisture is a rather direct measure, evaporative stress is a modeled quantity summarizing the level of plant stress: A value of zero means that there is no water available for transpiration, while a value of one means that transpiration equals the potential transpiration (**?**).

4.3.10 Figure 2:

Very interesting figure! A degraded or stressed system might show different trajectories, could you somehow visualize the difference between intact and degraded ecosystems?

1. Authors' reply: Thank you for the positive comment, in this figure we are trying to show trajectories that are diverse. You can see a comparison between a degraded and non-degraded trajectory in fig. 6a.

4.3.11 L258:

check spelling

1. Authors' reply: Thanks for finding this one. This sentence was changed in reply to another comment.

4.3.12 Figure 5:

third line, the effects of the drought

1. Authors' reply: Changed drought -> floods. Thank you for finding this mistake.

4.3.13 Figure 6:

This figure is a bit confusing to me. Could you improve the legends? I don't see an increase in seasonal amplitude in 6a, but maybe I just don't read this figure correctly.

(b-c-d) seem to show the mean seasonal cycle and an event, but what do we see in 6a?

1. Authors' reply: Thank you for pointing out that this may be confusing, we have added an explanatory sentence to the caption.
2. Added: The red line shows the trajectory before 2003, the blue line the trajectory 2003 and later, a strong increase in seasonal amplitude can be observed after 2003.

4.3.14 L305:

changes that occurring?

1. Authors' reply: Thank you for finding this, this sentence was changed in reply to another comment.

4.3.15 L340:

Additional research is needed to better represent biodiversity, habitat quality and intactness, forest degradation and fragmentation, etc. . . See:

- Jetz, W., Cavender-Bares, J., Pavlick, R., Schimel, D., Davis, F. W., Asner, G. P., . . . Ustin, S. L. (2016). Monitoring plant functional diversity from space. Nature Plants, 2(3), 16024. https://doi.org/10.1038/nplants.2016.24
- Chiarucci, A., & Piovesan, G. (2019). Need for a global map of forest naturalness for a sustainable future. Conservation Biology, 00(0), cobi.13408. https://doi.org/10.1111/cobi.13408

- Nicholas C. Coops, Michael A. Wulder, (2019). Breaking the Habit(at), Trends in Ecology & Evolution, Volume 34, Issue 7, https://doi.org/10.1016/j.tree.2019.04.013.

1. Authors' reply: We think that the reviewer has a very valid point here, it would be very desirable to include these variables into the analysis. Unfortunately these variables do not exist, yet
2. L356, changed to: Future research should consider nonlinearities, adding data streams that represent different aspects (e.g. biodiversity, and habitat quality), and work to include different subsystems, such as the atmosphere or the anthroposphere.
3. L201, added: Because the number of available data streams that describe the biosphere globally in a sufficiently high resolution in space and time is limited, the resulting components reflect the dimensions contained in these data streams. The used data streams mostly describe the exchange of energy and matter of ecosystem with the atmosphere. Data streams that describe the biology more closely, such as habitat fragmentation (**??**), diversity (**??**), and ecosystem intactness (**?**) have great potential to be included into analyses like the present but still require substantial amounts of research.

4.3.16 L352:

detected ina a similar fashion

1. Authors' reply: Thanks for finding this one.

5 List of other changes

5.0.17 L8:

1. Reason: PC 3
2. From: We find that two indicators account for 73% of the variance of the state of the biosphere in space and time.
3. To: We find that three indicators account for 82% of the variance of the state of the biosphere in space and time

5.0.18 L11:

1. Reason: PC 3
2. Added Sentence: The third indicator represents mostly changes in albedo

5.0.19 L31:

1. Reason: Typo.
2. From: Do we need to develop specific solutions for every observed phenomenon or can we develop a single approach to uncover a wide variety of phenomena.
3. To: Do we need to develop specific solutions for every observed phenomenon or can we develop a single approach to uncover a wide variety of phenomena?

5.0.20 L58:

1. Added: These indicators should also be uncorrelated, so that one can study the system state by looking and interpreting each indicator independently.

5.0.21 L151:

1. Reason: PC 3

2. From: We see that the first two components explain 73% of the variance from the 12 variables; additional components contribute little $< 10 variance each. This results in a “knee'' at component 2, which suggests that two indicators are su$
$We see that the first three components explain 82\% of the variance from the 12 variables; additio$
$7 variance each. This results in a “knee'' at component 3, which suggests that three indicators are s$

5.0.22 Figure 1:

1. Reason: PC 3
2. Change: Flipped component 3 so that it is positively correlated with albedo.

5.0.23 Caption Figure 1:

1. Reason: PC 3; Changes Figure 1.
2. From: (a) Fraction of explained variance of the PCA by component. Components three and higher do not conrtibute much to total variance. (b) Rotation matrix of the global PCA model, axis one describes primary productivity related variables, axis two describe water availability.

3. To: (a) Fraction of explained variance of the PCA by component. Knee at component three suggest that components four and higher do not contribute much to total variance. (b) Rotation matrix of the global PCA model (also called *loadings*, eq. ??). The columns of the rotation matrix describe the linear combinations of the (centered and standardized) original variables that make up the principal components. PC1 is dominated by primary productivity related variables, PC2 two by variables describing water availability, PC3 by variables describing albedo. }

5.0.24 L183:

1. Reason: PC 3
2. Added: We observe that the third axis is most strongly related to albedo (fig. ??b). Albedo describes the overall reflectiveness of a surface. Light surfaces, such as snow and sand, reflect most of the incoming radiation, while surfaces that have a high liquid water content or active vegetation absorb most of the incoming radiation. Local changes to albedo can be caused by a large array of reasons, e.g. snow fall, vegetation greening/browning, autumn leaf shedding or land use change.

   The third axis can be seen as an axis that introduces the binary decision of snow cover into the model and should be used mostly as such. On a global scale, effects on PC 3 are dominated by snow cover because they represent the highest absolute change in albedo. The relation to productivity and hydrology are counterintuitive to what we would expect from an albedo axis. In fig. ??b we can also observe that albedo also plays significant roles on PC 1 and PC 2. Because vegetation uses radiation as an energy source, albedo is negatively correlated with the productivity of vegetation, hence the negative correlation of albedo with PC 1. Albedo is also negatively correlated with PC 2, because surfaces with a higher water content absorb more radiation. We can observe that PC 1 and PC 2 are

positively correlated with PC 3 on the positive portion of their axes (see fig. ??d and f), which means counterintuitively that the index representing albedo is positively correlated with primary productivity and moisture content. Finally we can observe that PC 1 and PC 2 have a much higher reconstruction error in snow covered regions, which is strongly improved by adding PC 3 (see fig. ??f). This could probably have been avoided by using a nonlinear method to better compress the nonlinear relation between PC 1 and PC 3 (fig. ??c and d). Therefore the third axis should be regarded mostly as binary variable that introduces snow cover, the other information that is usually associated with albedo is already contained in the first two axes.

5.0.25 Figure 2:

1. Reason: PC 3
2. Change: Added subfigures to show trajectories in all combinations of PC 1–3

5.0.26 Caption Figure 2:

1. Reason: PC 3; Changes to figure 2.
2. From: Trajectories of some points (colored lines) and the area weighted density over principal components one and two (the gray background shading shows the density) for (a) the raw trajectories and (b) the mean seasonal cycle. The trajectories were chosen to fill a large area in the space of the first two principal components. Some of the trajectories in (b) have an arrow indicating the direction. The numbers illustrate the value of some variables, for units, see tab. ??. Description of the points: Red: Tropical Rainforest, 67.625°W, 2.625°S; Blue: Maritime

climate, 7.375°E, 52.375°N; Green: Monsoon climate, 82.375°E, 22.375°N; Purple: Subtropical, 117.625°W, 34.875°N; Orange: Continental climate, 44.875°E, 52.375°N; Yellow: Arctic climate, 119.875°E, 72.375°N;

3. To: Trajectories of some points (colored lines) and the area weighted density over principal components one and two (the gray background shading shows the density) for (left column) the raw trajectories and (right column) the mean seasonal cycle. The trajectories are shown in the space of PC 1–PC 2 (first row), PC 1–PC 3 (second row), and PC 2–PC 3 (third row). The trajectories were chosen to fill a large area in the space of the first two principal components. Some of the trajectories have an arrow indicating the direction. The numbers illustrate the value of some variables, for units, see tab. **??**. Description of the points: Red: Tropical Rainforest, 67.625°W, 2.625°S; Blue: Maritime climate, 7.375°E, 52.375°N; Green: Monsoon climate, 82.375°E, 22.375°N; Purple: Subtropical, 117.625°W, 34.875°N; Orange: Continental climate, 44.875°E, 52.375°N; Yellow: Arctic climate, 119.875°E, 72.375°N;

5.0.27 L201:

1. Reason: Typos
2. From: We can see that the bowen ratio embedds well into the space spanned by the first two PCs.
3. To: We can see that the Bowen ratio embeds well into the space spanned by the first two PCs.

5.0.28 L210:

1. Reason: Fix references

2. From: The principal components may be used to summarize the movement of a spatiotemporal pixel in variable space, so that they represent the current state of the ecosystem at a certain location in space and time (fig. **??**a) or time of year of the mean seasonal cycle of the pixel (fig. **??**b).
3. To: The principal components may be used to summarize the movement of a spatiotemporal pixel in variable space, so that they represent the current state of the ecosystem at a certain location in space and time (fig. **??** left column) or time of year of the mean seasonal cycle of the pixel (fig. **??** right column).

5.0.29 L219:

1. Reason: PC 3
2. Added: The third components shows a different picture. Due to a consistent winter snow cover in higher latitudes the albedo is much higher and the amplitude of the mean seasonal cycle is much larger than in other ecosystems. Other areas show comparatively little variance on the third axis and their relation to productivity and moisture content is even positively correlated to the third axis, which is the opposite of what is expected from an albedo axis.

5.0.30 Figure 3:

1. Reason: PC 3
2. Change: Added the MSC of component 3.

5.0.31 Caption Figure 3:

1. Reason: PC 3

2. From: Mean seasonal cycle of the first principal component during the year. Left column: first principal component. Right column: second Principal Component. Rows from top to bottom: equally spaced intervals during the year.
3. To: Mean seasonal cycle of the first principal component during the year. Left column: first principal component. Middle column: second principal component. Right column: third principal component. Rows from top to bottom: equally spaced intervals during the year.

5.0.32 L228:

1. Reason: PC 3; changes to Figure 3.
2. From: The second principal component (fig. **??**, right column) tracks water deficiency:
3. To: The second principal component (fig. **??**, middle column) tracks water deficiency:

5.0.33 Caption Figure C1:

1. Reason: Typo
2. From: (c) $\log_{10}\left(\frac{LatentHeat}{SensibleHeat}\right)$, the $\log_{10}$ of the Bowen Ratio.
3. To: (c) $\log_{10}\left(\frac{SensibleHeat}{LatentHeat}\right)$, the $\log_{10}$ of the Bowen Ratio.

5.0.34 L232:

1. Reason: PC 3

2. Added: The third principal compontent (fig. **??**, right column) tracks surface reflectance. Therefore we can see the highest values in the arctic region during winter, other areas vary much less in their reflectance throughout the year. Again, the third component shows a counterintuitive behavior in midlatitudes, as it is positively correlated with productivity and therefore shows the oposite behaviour of what would be expected from an indicator tracking albedo.

5.0.35 Figure 4:

1. Reason: PC 3. Error in calculation
2. Change: Added hysteresis for all combination of PC 1–3. There was an error in the calculation of the previous version.

5.0.36 Caption Figure 4:

1. Reason: PC 3; Changes to Figure 4.
2. From:
3. To:

5.0.37 L235:

1. Reason: Rewrite of the hysteresis section due to adding more combination of indicators and a calculation error in the original version of the manuscript
2. From: Hysteresis in ecology means that the pathways $A \rightarrow B$ and $B \rightarrow A$ between stable states A and B can be different (**?**. These alternative paths arise

from the ecosystem tracking seasonal changes in the environmental condition, e.g. summer–winter or dry–rainy seasons (fig. ??b)).

Hysteresis is a common occurrence in ecological systems, e.g. in community ecology it is often cited as the reason why communities may not recover after a disturbance, it is usually attributed to memory and lag effects (???). For instance, a hysteresis loop can be found when plotting soil respiration against soil temperature (?). The sensitivity of soil respiration to soil temperature changes seasonally due to changing soil moisture and photosynthesis (by supplying carbon to rhyzosphere) producing a seasonally changing hysteresis effect ({?)gaumont-guayinterpreting2006, richardsoncomparing2006, zhangchanges2018}. Biological variables also show a hysteresis effect in their relations with atmospheric variables, e.g. ? found a hysteresis effect between seasonal NEE, temperature, and a number of other ecosystem and climate related variables.

Looking at some mean seasonal cycles of trajectories, e.g. the orange trajectory (area close to Moscow) in fig. ??b shows that the paths between maximum and minimum productivity can be very different, in contrast to the blue trajectory located in the north west of Germany which also has a very pronounced yearly cycle but shows no such effect. The trajectories that show a more pronounced hysteresis effect seem to have pronounced growing, dry, and wet seasons and therefore shift their limitations more strongly during the year, i.e. the moisture reserves deplete during growing season and therefore the return path has higher values on the second principal component. We can also see that most trajectories that show hysteresis turn counterclockwise for the same reason (see fig. ??). Usually plant growth starts when there is enough water available (low values on component 2), leading to increasing values on the first component. At the end of the growing season water resources deplete (increasing values on component 2) and productivity decreases (decreasing values on component 1).

3. To: Hysteresis in ecology means that the pathways $A \rightarrow B$ and $B \rightarrow A$ be-

tween states A and B can be different (?. These alternative paths arise from the ecosystem tracking seasonal changes in the environmental condition, e.g. summer–winter or dry–rainy seasons (fig. ??b)).

Hysteresis is a common occurrence in ecology, e.g. in community ecology it is often cited as the reason why communities may not recover after a disturbance, it is usually attributed to memory and lag effects (???). For instance, a hysteresis loop can be found when plotting soil respiration against soil temperature (?). The sensitivity of soil respiration to soil temperature changes seasonally due to changing soil moisture and photosynthesis (by supplying carbon to rhyzosphere) producing a seasonally changing hysteresis effect ({?)gaumont-guayinterpreting2006, richardsoncomparing2006, zhangchanges2018}. Biological variables also show a hysteresis effect in their relations with atmospheric variables, e.g. ? found a hysteresis effect between seasonal NEE, temperature, and a number of other ecosystem and climate related variables. Here we look at the mean seasonal cycles of pairs of indicators and the area they enclose.

The orange trajectory (area close to Moscow) in fig. ??b shows that the paths between maximum and minimum productivity can be very different, in contrast to the blue trajectory located in the north west of Germany which also has a very pronounced yearly cycle but shows no such effect. Fig. ?? also indicates that the area inside the means seasonal cycles of PC1–PC2 and PC1–PC3 show important characteristics while hysteresis in PC2–PC3 is a much less pronounced feature, i.e. we can only see a pronounced area inside the yellow curve in fig. ??f.

The description of climatic zones in this section are taken from the Köppen–Geiger classification (?). The trajectories that show a more pronounced anticlockwise hysteresis effect in PC1–PC2 (fig. ??a) are areas with a warm and temperate climate and partially those that have a Snow climate with warm summers, i.e. areas that have pronounced growing, dry, and wet seasons and therefore shift their limitations more strongly during the year, i.e. the moisture reserves deplete during growing season and therefore the return path has higher values on the second principal component. We can also see that areas with dry winters tend to have a clockwise hysteresis effect, e.g. many areas in East Asia, due to the humid summers there is no increasing water limitation during the summer months which causes a decrease on PC2 instead on an increase. Other areas with with clockwise hysteresis can be found in winter dry areas in the Andes and the winter dry areas north and south of the African rainforests. Tropical rainforests do not show any hysteresis effect due to their low seasonality. In general we can say that the area inside the mean seasonal cycle trajectory of PC1–PC2 depends mostly on water availability in the growing and non-growing season, i.e. the contrast of wet summer and dry winter vs. dry summer and wet winter.

The hysteresis effect on PC1–PC3 (fig. ??b) shows a pronounced counterclockwise MSC trajectory mostly in warm temperate climates with dry summers, while it shows a clockwise MSC trajectory in most other areas, again tropical rainforests are an exception due to their low seasonality. The most pronounced clockwise MSC trajectories are are found tundra climates in arctic latitudes, where there is a consistent winter snow cover and a very short growing period. The lower end of PC3 is positively correlated with ecosystem productivity, but there are still enough differences to PC1 to distinguish the start and the end of the growing season and show different trajectories. A counterclockwise rotation can be found in summer dry areas, such as the Mediterranean and and California, but also some more more humid areas, such as the south east United States and the south east coast of Australia. In these areas we can find a decrease on PC3 in during the non-growing phase which probably corresponds to a drying out of the vegetation and soils.

The hysteresis effect on PC2–PC3 (fig. ??c) mostly depends on latitude, there is a large counterclockwise effect in the very northern parts, due to the large ampli-

tude of PC3, the amplitude gets smaller further south until the rotation reverses in winter dry areas at the the northern and southern extremes of the tropics and disappears on the equatorial humid rain forests.

We can see that the hysteresis of pairs of indicators represents large scale properties of climatic zones. Not only the area enclosed gives interesting information, but also the direction of the rotation. Hysteresis can give information on the seasonal availability of water, seasonal dry periods or snowfall. With the method presented here, we can not observe intersecting trajectories, which would probably give even more interesting insights (e.g. the green trajectory in fig. ??b).

5.0.38 Figure 5:

1. Reason: PC 3
2. Change: added panes for PC 3

5.0.39 Caption Figure 5:

1. Reason: PC 3, changes to Figure 5
2. From: Anomalies of the first three principal components; Brown-green contrast shows the anomalies on PC1, a relative low productivity or greening respectively. Blue-green contrast shows the anomalies on PC2, a relative wetness or dryness respectively. (a) Map showing the PC1 anomalies on the 1/1/2001. (b) and (c) show longitudinal cuts of PC1 and PC2 at the red vertical line in sub-figure (a) respectively. The effects of of the drought on the Horn of Africa (2006) and the Russian heatwave (2010) are highlighted by circles. (d) Map showing the PC2 anomalies on the 1/1/2001. (e) and (f) show longitudinal cuts of PC1 and PC2 at the red vertical line in sub-figure (d) respectively. Strong droughts in the Amazon

during 2005 and 2010 can be observed as large red spots on the fringes of the Amazon basin (highlighted by circles).

3. To: Anomalies of the first two principal components; Brown–green contrast shows the anomalies on PC1, a relative low productivity or greening respectively. Blue–red contrast shows the anomalies on PC2, a relative wetness or dryness respectively. Brown–purple contrast shows the anomaly on PC3, a relative deviation in albedo. (a), (e), and (i) are map showing the anomalies of PC1–3 on the 1/1/2001 respectively. (b), (c), and (d) show longitudinal cuts of PC1–3 at the red vertical line in sub-figure (a) respectively. The effects of of the drought on the Horn of Africa (2006) and the Russian heatwave (2010) are highlighted by circles. (f), (g), and (h) show longitudinal cuts of PC1–3 at the red vertical line in sub-figure (e) respectively. Strong droughts in the Amazon during 2005 and 2010 can be observed as large red spots on the fringes of the Amazon basin (highlighted by circles). (j), (k), and (l) show longitudinal cuts of PC1–3 at the red vertical line in sub-figure (i) respectively. A strong snowfall event affecting Central and Southern China is marked in circles.

5.0.40 L257:

1. Reason: Language
2. From: These anomalies have a directional component and can be therefore be interpreted the same way as the original PCs which contain information of the underlying variables that were affected. In this sense, one can infer the state of the ecosystem during an anomalous state.
3. To: These anomalies have a directional component and can be therefore be interpreted the same way as the original PCs which contain information of the

underlying variables that were affected, therefore one can infer the state of the ecosystem during an anomaly.

5.0.41 L272:

1. Reason: PC 3
2. Added: Another extreme event that can be seen is the extreme snow and cold event affecting Central and South China in January 2008, causing the temporary displacement of 1.7 million people and economic losses of approximately US $ 21 billion (**?**). This event shows up clearly on PC2 and PC3 as cold and light anomalies respectively (see fig. **??**k and f).

5.0.42 Figure 7:

1. Reason: PC 3
2. Change: Added PC3 trend. Split up the bivariate color map. Added Bivariate trends for all combinations of PC1–3

5.0.43 Caption Figure 7:

1. Reason: Changes Figure 7
2. From: Trends in PC1 and PC2 indicators. Trends were calculated using the Theil-Sen estimator. (a) The spatial distribution of slopes, only significant slopes are shown ($p < 0.05$, Benjamini-Hochberg adjusted). The maximum cutoff for the legend limits was set symmetrically around zero to the maximum absolute value of the 0.1 and 0.9 quantiles. (b) Distribution of spatial points in the space of the first two PCs. The colors correspond to the ones used in (a).

3. To: (a), (c), (e) Trends in PC1–3 respectively. (b), (d), (f) Bivariate distribution of trends. Trends were calculated using the Theil-Sen estimator, (a), (c), and (e) show significant trends only ($p < 0.05$, Benjamini–Hochberg adjusted).

5.0.44 L308:

1. Reason: large -> larger, is more correct
2. From: The accumulation of CO2 in the atmosphere should cause an increase in global productivity of plants due to CO2 fertilization, while large and more frequent droughts and other extremes may counteract this trend.
3. To: The accumulation of CO2 in the atmosphere should cause an increase in global productivity of plants due to CO2 fertilization, while larger and more frequent droughts and other extremes may counteract this trend.

5.0.45 L313:

1. Reason: PC 3
2. From: To find local trends, we used the Theil-Sen estimator to calculate robust slopes on the trajectories. Figure **??** shows positive and negative trends of the principal components over time. General patterns that can be observed are a positive trend (higher productivity) on the first principal component in the arctic regions and higher temperatures. A large scale dryness trend can be observed across large parts of western Russia. Increasing productivity can also be observed on almost the entire Indian subcontinent and eastern Australia.
3. To: To find local trends, we used the Theil–Sen estimator to calculate robust slopes on the trajectories. Figure **??** shows positive and negative trends of the

principal components over time. General patterns that can be observed are a positive trend (higher productivity) on the first principal component in many arctic regions, may of these regions show also show a wetness trend, with the notable exception of the western parts of Alaska which have become dryer, this is important, because wildfires play a major role in these ecosystems (**??**), these changes are also accompanied by a decrease on PC3 due to a loss in snow cover. A large scale dryness trend can also be observed across large parts of western Russia. Increasing productivity can also be observed on large parts of the the Indian subcontinent and eastern Australia.

5.0.46 L321:

1. Reason: Wording
2. From: In the Amazon basin, we find a dryness trend accompanied by a decrease in productivity;
3. To: In the Amazon basin, we find a dryness trend accompanied by a decrease in productivity and a slight increase in PC3;

5.0.47 L331:

1. Reason: Wording
2. From: In the Arctic, a general trend towards higher productivity can be observed, vegetation models attribute this general increase in productivity to CO2 fertilization and climate change. The changes also cause changes to the characteristics of the seasonal cycles (**?**).

3. To: A very notable greening and wetness trend can be observed in Myanmar due to an increase in intense rainfall events and storms, although the central part experienced some strong droughts at the same time ?. In Myanmar we also find one of the strongest trends in PC3 outside of the arctic.

   In large parts of the Arctic, a trend towards higher productivity can be observed, vegetation models attribute this general increase in productivity to CO2 fertilization and climate change. The changes also cause changes to the characteristics of the seasonal cycles (?).

5.0.48 L343:

1. Reason: PC3
2. From: The first emerging indicator represents carbon exchange, while the second indicator shows the availability of water in the ecosystem.
3. To: The first emerging indicator represents carbon exchange, while the second indicator shows the availability of water in the ecosystem, the third indicator represents mostly a binary variable that indicates the presence of snow cover.

5.0.49 L347:

1. Reason: PC3
2. From: The first two indicators can detect many well-known phenomena without analyzing variables separately due to their compound nature.
3. To: The first three indicators can detect many well-known phenomena without analyzing variables separately due to their compound nature.

5.0.50 L350:

1. Reason: PC3
2. From: Deviations from the mean seasonal cycle of the trajectories indicate extreme events such as the large scale droughts in the Amazon during 2005 and 2010 and the Russian heat wave of 2010. The events are detected ina a similar fashion as with classical multivariate anomaly detection methods while directly providing information on the underlying variables.
3. To: Deviations from the mean seasonal cycle of the trajectories indicate extreme events such as the large scale droughts in the Amazon during 2005 and 2010 and the Russian heat wave of 2010. The events are detected in a similar fashion as with classical multivariate anomaly detection methods while directly providing information on the underlying variables.

5.0.51 Figure A1:

1. Reason: Added PC3
2. Change: Added 3rd pane with breakpoints of PC3.

5.0.52 Caption Figure A1:

1. Reason: Added PC3
2. From: Breakpoint detection, (a) on PC1, (b) on PC2, the color indicates the year of the biggest breakpoint if a significant breakpoint was found, grey if there was no significant breakpoint found.

3. To: Breakpoint detection, (a) on PC1, (b) on PC2, and (c) on PC3, the color indicates the year of the biggest breakpoint if a significant breakpoint was found, grey if there was no significant breakpoint found.

5.0.53 Figure B1:

1. Reason: Added PC3
2. Change: Added 3rd pane with the reconstruction error of PC1–3.

5.0.54 Caption Figure B1:

1. Reason: Added PC3
2. From: The reconstruction error of the first two pca dimensions aggregated over variables an time by the mean of the square error. The right plot shows the mean reconstruction error aggregated over latitudes.
3. To: The reconstruction error of the first until the first three PCA dimensions aggregated over variables an time by the mean of the square error. The right plot shows the mean reconstruction error aggregated over latitudes.

5.0.55 L370:

1. Reason: Added PC3, language
2. From: In order to find ecosystems that do no fit well your model of two indicators, we calculated the reconstruction error of the first two PCA axes. Ecosystems that do not fit our model well show a higher reconstruction error, see fig. **??**.

Higher reconstruction errors appear in extreme latitudes, areas with especially high reconstruction error are at the southern part of the Hudson Bay area. Very limited regions in central and eastern Russia and northern Siberia.

3. To: In order to find ecosystems that do no fit well your model of 1–3 indicators, we calculated the reconstruction error of the first up to the first three PCA axes. Ecosystems that do not fit our model well show a higher reconstruction error, see fig. **??**. Higher reconstruction errors appear in extreme latitudes but decrease strongly if the third component is included, areas with especially high reconstruction error lie at the southern part of the Hudson Bay area and very limited regions in central and eastern Russia and northern Siberia.

5.0.56 Figure C1:

1. Reason: Typo
2. From: The background shading show the distribution of the mean seasonal cycle of the spatial points (see fig. **??**). The contour lines represent the reconstruction of the variables from the first two principal components. The reconstructed variables are (a) Latent Heat, (b) Sensible heat, and (c) $\log_{10}\left(\frac{LatentHeat}{SensibleHeat}\right)$, the $\log_{10}$ of the Bowen Ratio.
3. To: The background shading show the distribution of the mean seasonal cycle of the spatial points (see fig. **??**). The contour lines represent the reconstruction of the variables from the first two principal components. The reconstructed variables are (a) Latent Heat, (b) Sensible heat, and (c) $\log_{10}\left(\frac{SensibleHeat}{LatentHeat}\right)$, the $\log_{10}$ of the Bowen Ratio.

5.0.57 Figure E1:

1. Reason: PC3
2. Change: Added subfigure with amplitude trends for PC3

5.0.58 Caption Figure E1:

1. Reason: PC3
2. From: Trends in the amplitude of the yearly cycle, Theil-Sen estimators only significant slopes ($p < 0.05$), *unadjusted*, are shown. Because there is only a single amplitude per year and therefore only 11 data points per time series, the adjusted significances are not significant.
3. To: Trends in the amplitude of the yearly cycle, Theil–Sen estimators only significant slopes ($p < 0.05$, *unadjusted*) are shown. Because there is only a single amplitude per year and therefore only 11 data points per time series, the adjusted p-values are not significant.

5.0.59 L339:

1. Reason: Referencing the figures and results in the appendix (breakpoints)
2. Added: Another way to detect changes to the biosphere consists in the detection of breakpoints, which has been applied successfully to detect changes in global NDVI time series (**??**), or generally to detect changes in timeseries (**?**). A proof of concept analysis can be found in fig. **??**, we hope that applying this method to indicators instead of variables can detect a wider range of breakpoints analyzing a single time series.

5.0.60 L183:

1. Reason: Referencing the figures and results in the appendix (reconstruction error)
2. Added: On a global scale, effects on PC3 are dominated by snow cover because they represent the highest absolute change in albedo, this can also be seen from the reconstruction error that increases strongly towards the poles for the first two principal components but evens out if the third component is added (see fig. **??**).

5.0.61 L146:

1. Reason: Add example figure for areas of polygon.
2. From: If the vertices run clockwise, the area is negative. If the polygon is shaped as an 8, the clockwise and counterclockwise parts will cancel each other (partially) out, e.g. the green trajectory in fig. **??**b. Trajectories that cover a larger range will also tend to have larger areas.
3. To: If the vertices run clockwise, the area is negative. If the polygon is shaped as an 8, the clockwise and counterclockwise parts will cancel each other (partially) out. Trajectories that cover a larger range will also tend to have larger areas. For some example polygons, see fig. **??**.

5.0.62 L142:

1. Reason: New Figure 1 and caption.
2. Added: Example polygons and their areas, A (Eq. **??**), the arrows indicate the directionality. (a) Clockwise polygon, has a negative area. (b) Counterclockwise

polygon, has a positive area. (c) Chaotic polygon, has a very low area. (d) Polygon with a single intersection, has both a clockwise and counterclockwise portion. The clockwise portion is slightly larger than the counterclockwise portion, therefore the area is slightly negative.

5.0.63 Appendix F:

1. Reason: Add data sources

2. From: **Black Sky Albedo** is the reflected fraction of total incoming radiation under direct hermispherical reflectance, i.e. direct illumination (?).

   White Sky Albedo is the reflected fraction of total incoming radiation under bi-hemispherical reflectance, i.e. diffuse illumination (?). Together with black sky albedo it can be used to estimate the albedo under different illumination conditions.

   Evaporation $[\mathsf{mm/day}]$ is the amount of water evaporated per day (?), depends on the amount of available water and energy.

   Evaporative Stress modeled water stress for plants, zero means that the vegetation has no water available for transpiration and one means that transpiration equals potential transpiration (?).

   fAPAR the fraction of absorbed photosynthetically active radiation, a proxy for plant productivity (?).

   Gross Primary Productivity (GPP) {[gC m^{-2} day^{-1}]} the total amount of carbon fixed by photosynthesis (?).

   Terrestrial Ecosystem Respiration (TER) {[gC m^{-2} day^{-1}]} the total amount of carbon respired by the ecosystem, includes autotrophic and heterotropic respiration (?).

   Net Ecosystem Exchange (NEE) {[gC m^{-2} day^{-1}]} The total exchange of carbon of the ecosystem with the atmosphere $NEE = GPP - TER$ (?).

   Latent energy (LE) {[W m^{-2}]} the amount of energy lost by the surface due to evaporation (?).

   Sensible Heat (H) {[W m^{-2}]} the amount of energy lost by the surface due to radiation (?).

   Root-Zone Soil Moisture {[m^3 m^{-3}]} the moisture content of the root zone, estimated by the GLEAM model (?).

   Surface Soil Moisture {[mm^3 mm^{-3}]} the soil moisture content at the soil surface (?).

3. To: **Black Sky Albedo** is the reflected fraction of total incoming radiation under direct hermispherical reflectance, i.e. direct illumination (?). This dataset is derived from the SPOT4-VEGETATION, SPOT5-VEGETATION2, and the MERIS satellite sensors.

   White Sky Albedo is the reflected fraction of total incoming radiation under bihemispherical reflectance, i.e. diffuse illumination (?). Together with black sky albedo it can be used to estimate the albedo under different illumination conditions. This dataset is derived from the SPOT4-VEGETATION, SPOT5-VEGETATION2, and the MERIS satellite sensors.

   Evaporation $[\mathsf{mm/day}]$ is the amount of water evaporated per day, depends on the amount of available water and energy. This dataset is based on the GLEAMv3 model (?), using satellite data from ESA CCI and SMOS to derive a number of variables.

   Evaporative Stress modeled water stress for plants, zero means that the vegetation has no water available for transpiration and one means that transpiration equals potential transpiration. This dataset is based on the GLEAMv3 model (?), using satellite data from ESA CCI and SMOS to derive a number of variables.

fAPAR the fraction of absorbed photosynthetically active radiation, a proxy for plant productivity (?). This dataset is based on the GlobAlbedo dataset (http://globalbedo.org) and the MODIS fAPAR and LAI products.

Gross Primary Productivity (GPP) {[gC m^{-2} day^{-1}]} the total amount of carbon fixed by photosynthesis (?). This dataset is derived from upscaling eddy covariance tower observations to a global scale using machine learning methods.

Terrestrial Ecosystem Respiration (TER) {[gC m^{-2} day^{-1}]} the total amount of carbon respired by the ecosystem, includes autotrophic and heterotropic respiration (?). This dataset is derived from upscaling eddy covariance tower observations to a global scale using machine learning methods.

Net Ecosystem Exchange (NEE) {[gC m^{-2} day^{-1}]} The total exchange of carbon of the ecosystem with the atmosphere $NEE = GPP - TER$ (?). This dataset is derived from upscaling eddy covariance tower observations to a global scale using machine learning methods.

Latent energy (LE) {[W m^{-2}]} the amount of energy lost by the surface due to evaporation (?). This dataset is derived from upscaling eddy covariance tower observations to a global scale using machine learning methods.

Sensible Heat (H) {[W m^{-2}]} the amount of energy lost by the surface due to radiation (?). This dataset is derived from upscaling eddy covariance tower observations to a global scale using machine learning methods.

Root-Zone Soil Moisture {[m^3 m^{-3}]} the moisture content of the root zone. This dataset is based on the GLEAMv3 model (?), using satellite data from ESA CCI and SMOS to derive a number of variables.

Surface Soil Moisture {[mm^3 mm^{-3}]} the soil moisture content at the soil surface. This dataset is based on the GLEAMv3 model (?), using satellite data from ESA CCI and SMOS to derive a number of variables.

5.0.64 Whole document:

1. Reason: Typography
2. From: PCx
3. To: PCx

5.0.65 Whole document:

1. Typography
   (a) From: data set(s)
   (b) To: dataset(s)
2. Affiliation
   (a) Reason: Added the affiliation to the iDiv of the lead author due to a recent change in employment.
   (b) What: Added affiliation to the iDiv of the lead author.