

Interactive comment on “Systematic Correlation Matrix Evaluation (SCoMaE) – A bottom-up, natural science-based approach to identify Indicators” by Nadine Mengis et al.

Anonymous Referee #1

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General Comments:

This paper describes a method to identify indicators of environmental change that have statistical measurability, political and societal relevance, and scientific consistency. Indicator identification follows a novel 3-step process, based on the construction of a correlation matrix and significance of the  $r$  values. They use an Earth System Model of intermediate complexity run with 3 scenarios (historical, RCP 4.5 and 8.5) and 16 sensitivity perturbations in an example of their methodology.

While this paper was interesting and the concept was of indicators being used to describe natural and forced states is sound, there were some major issues that I feel need to be addressed in the introduction and methods sections.

Thank you for your generally positive evaluation of the applied method. We hope to have addressed all of your suggestions mentioned below to your satisfaction. We feel, that your comments helped us to improve the paper.

Specific Comments:

First, what is the common way to identify/construct indicators? Why would this methodology be new, novel, different, better, etc? Their argument is one-sided and more background into other methods is needed. It is implied that expert judgment is the only criteria for indicator selection.

We added two references on indicator selection to give more back ground on this topic and point out why we think this should be improved:

"Working group II of the Intergovernmental Panel on Climate Change (IPCC) (Houghton et al., 2001) used [ global mean surface air temperature (SAT)] as the main climate change indicator, due to its predominance in the existing literature and its large scientific consistency as such." (page 2, lines 12-15)

"However, selecting one indicator, while disregarding the other is a normative choice Krellenberg et al. (2010), which can (unknowingly) be biased by e.g. technical knowledge (Rametsteiner et al., 2011). In this study we want to introduce a bottom-up indicator selection method, that uses statistical information about variables in addition to expert judgement, attempting to reduced this bias in the selection process." (page 2, lines 29-33)

This type of methodology was not compared across models, hence results are strongly model specific. Also, the methodology could only be applied if the ability to examine

model sensitivity exists through perturbation runs. This would limit applying this method to specific models or would be far too computationally expensive to pursue.

Based on your comment and also the comments from the second reviewer, we decided to add a section in which we explain in more detail the set up of the example. Here we explain that comparing our perturbed parameter simulations, is similar to comparing a multi-model ensemble. This would be a computationally doable application. However, also the application of this method to temporal correlations is possible. (See new Section 2 on page 3)

The rationale for using 11-year averages for calculating delta was not given. I can assume that because these are global averages and the model has low internal variability (referenced from page 14 line 20) that 11 years is sufficient? 10-30 year periods are more common. Also, for the calculation of the historical period deltas, what years were used? The title on Figure 3 would suggest that some linear method was used to calculate delta? I could not find specific years used.

The fact that the model has low internal variability was the reason for the 11-year averages. We identified the years in Figure 2 and 3 more clearly. Thank you for pointing this out.

Additionally, 5% significance level is extremely low. What is the rationale for using such a low significance value? Why not use an absolute threshold for  $r$  instead? Or inflate the ensemble used for the correlation calculation by using more than 1 realization from each perturbation? Indicators from the historical period are interesting in that there are likely very few variables that have a clear signal or significant trend. Is this why the very low 5% significance level was used?

Using a 95% confidence that a correlation is significant, is a standard value often used in scientific studies, and was in our opinion appropriate for the assessment of all three scenarios, where varying signal strengths are present. Given that we only have 16 simulations, this is a quite strict criteria. However, we wanted to make sure that there is a real signal in the correlation between the variables reaction to our parameter perturbations.

Cluster analysis: Why would this method be preferred over more standard methods of PCA/EOF analysis or step-wise regression to group variables? Can the results be compared? The emphasis seems to be on non-redundancy of variables, but what is the value of non-redundant groupings?

The point we wanted to make here is that we might be able to obtain very similar information from the variables within one cluster, e.g. sea ice and temperature, these are then redundant and there is more value in regarding variables from another cluster, which we would possibly have neglected due to our possibly unknown bias (see page 2, lines 29-31). The value of non-redundancy is also within not un-proportionally stressing one result while reading multiple correlated indicators.

We agree with the reviewer that our method should be compared to other ones.

However, we feel that such a comparison is too much for this publication and we are currently working on a follow-up study in which we compare our results to a PCA, to see how similar the results obtained by those methods are.

In the discussion section (Page 12, line 27-28), it is stated that “our results do suggest that a comprehensive assessment of future climatic states needs a re-evaluation of the ad-hoc chosen indicators, due to changes in prevailing climatic responses.” This is an interesting statement in that it implies that the historical indicators are often used to determine future states. Are there previous studies to compare this to? If there were more details in the introduction, this statement would make more sense and have a stronger impact.

The study by Rametsteiner et al., (2011) points a little bit into the direction, that a reassessment of sustainability indicators with time is important, in case new knowledge is obtained about the Earth system, but in their case also in case of changes in societal preferences. We point to their study in the introduction now (see page 2, line 30), but we think, that the finding of changed correlations in future high CO<sub>2</sub> and temperature scenarios and the according implications for indicator selection, is one of the novel points in our study.

Minor comments:

Page 2, line 23: The citation uses “respectively” but it is not needed.

Removed.

Page 3, line 2. Is there a reference for this model? There are many references in the appendix section, but there should be one here as well.

We added a reference.

The correlation matrix is constructed by taking correlation coefficient of 2 variable deltas under 16 perturbation experiments. I am assuming you are using Pearson correlation coefficient (r). This should be stated at least once in the methods.

We added a cleared explanation of the calculation of the correlations.

The caption of Figure 1 could use more detail, and the figure itself could be generalized. If this paper is about the method (and not the model) it should be much cleaner and clearer. For example, if the 16 perturbation runs are not discussed in the methods section, why are they shown in the figure? This critique also applies to Figure 2.

We hope to have addressed these issues by adding a new section 2, which explains the experimental set up as well as the single parameter perturbation, before these figures appear.

The naming structure of the data was confusing. Prefixes A, O, F, and L were used. I am assuming that A was either atmosphere or absolute, F was flux, and O was ocean? There were also suffixes of O or L, which are ocean and land, and N or S (North and South?). While I understand that these variables were used to showcase the method and as such the naming conventions were not important, it was hard to interpret the results based on variable names.

We added an explanation of the prefixes at least in Figure 2 and 3. Hoping that this improves the basic understanding, otherwise we made sure to have the explanation of

the variables names, when ever they are mentioned in the text. Also we added table S1 to the appendix now.

In the abstract, there are 3 non-optional steps, but in the manuscript Step 3 is listed as “optional”.

In fact, we already regard step 3 as optional, so we changed the text accordingly.

Page 5 line 25, should there be forward slashes in the variable names?

We changed the text to make it more clear that we we referring to two variables here.

Figure 5, the title of the x-y correlation ‘quilt’ has the word “periods”. Should this be changed to scenarios instead? It is not clear what is meant here. This isn’t a plot of the significance of the changes in periods, but more of the significance of the r values between variable deltas?

We changed the heading to read scenarios now, thank you for pointing this out. Also we edited the figure caption hoping this makes it more clear now.

Page 15, line 16: what is meant by “natural science-based assessments”? “Natural” is used throughout the manuscript, but I am not sure it is needed.

This was referring to a natural science versus social science assessment. We changed the phasing now to science-led assessment, following the phrasing used in Rametsteiner et al., 2011.

The discussion in the Supplementary section is very interesting, but I would argue that it doesn’t belong in this paper. However, it could and should be used in a follow-up paper. Thank you, we removed everything that is not directly referred to in the main article and may publish some of it later.

#### References:

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- Krellenberg, K., Kopfmüller, J., and Barton, J. R.: How sustainable is Santiago de Chile? Current performance, future trends, potential measures. Synthesis report of the risk habitat megacity research initiative (2007-2011), Tech. rep., UFZ-Bericht, Helmholtz-Zentrum für Umweltforschung, 2010.
- Rametsteiner, E., Pülzl, H., Alkan-Olsson, J., and Frederiksen, P.: Sustainability indicator development—Science or political negotiation?, *Ecological indicators*, 11, 61–70, 2011.

Interactive comment on “Systematic Correlation Matrix Evaluation (SCoMaE) – A bottom-up, natural science-based approach to identify Indicators” by Nadine Mengis et al.

Anonymous Referee #2

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General Comments:

This paper introduces a bottom-up approach (SCoMaE) to select a climate indicator for certain climate related question, and illustrates that to answer the same question, climate indicator under different climate scenarios may be different, and common correlation matrix could be used to assess multi-scenarios question. This topic is suitable for the journal, but clarification and improvement are needed.

The paper used one example to demonstrate SCoMaE. However, the example is not clearly described. What is the scientific question to answer? How are those variables selected? It might be better to include an experiment setting section instead of appendix, since all Figures are based on the model experiments.

Please clarify the meaning of ‘correlation’, as shown in Figure 1, the correlation is not simply correlation between two variables, but correlation of two variable correlations under different input parameter scenarios. It is misleading through the whole text when discussing ‘correlation of variable A and variable B’. Please modify the whole result and discussion.

Thank you for your constructive comments. We have added a section on the experimental design of our example and moved some of the appendix to the methods section. We hope this clarifies what exactly we are aiming in the example. Also we have added a definition of the term correlation to this section. What we are referring to is the correlation of changes in different variables induced by the parameter perturbations. Note, that if a parameter is causing higher global mean temperatures, the physical response in the model in turn is to reduce the sea ice extent. So there is a physical meaning behind these correlation between changes in variables. We have changed the text, wherever we talk about the example to be more explicit on which correlations we are referring to.

Specific Comments:

Page 2, Line 14: a comprehensive assessment of what?

As now more clearly stated in the new Section 2 (page 3) later on, we are here referring to an assessment of the sensitivity of changes in the climate system. We added that also in the text at this position, although here it is still a general point not referring to the example case.

"Which ones should we select for a fully comprehensive assessment of changes in the climate system, ideally, without providing redundant information?" (page 2, lines 16-17)

Page 2, last paragraph: Although there are more details on this topic on Page 3, line 12-21, it is not clear here whether the authors mean to use all variables from output of an Earth System Model or only certain selected variables? If variables are selected, how to select the variables regarding to certain scientific question? In addition, how about output of different time frequencies?

Page 3, Line 2: What are those selected indicators presenting in this paper? What is the question to answer here?

As discusses in Section 3.1.2 "Limitations of the analysis from the example", we are here not considering any temporal correlations apart from total changes between two points in time. This is clearly a limitation, but considering the low internal variability in the model, temporal correlations would have been un-proportionally overestimated. Looking at different time frequencies would, for other experiments, be a very interesting question, we elaborate on this now in the new Section 2 (page 3). We explain the variable selection as follows:

"In our example we applied the SCoMaE method to the correlation matrix concerning 46 commonly used variables for the assessment of climatic changes in the historical forcing scenario as simulated by the UVic ESCM". (page 9, lines 16-17)

Page 3, Line 16-21: This method is bottom-up, but the selection of variables is still expert judgment, as well as how to process the variable (e.g. monthly average or seasonal average?). And as the author mentioned "The selection...is very important for the outcome of the study". Please comment more on this.

Thank you for pointing this out again. Yes, the preselection as well as the processing of the variables still requires expert knowledge about the possibly relevant processes and time scales that might be important to answer the research question. To strengthen this point we added a sentence. We hope that we have also made this point clearer by adding section 2.

"Note, that for this preselection of the possibly relevant variables to answer the given question, as well as for the construction of the correlation information in the matrix, a certain level of expert judgement is needed." (page 7, lines 27-28)

Page 3, line 23-32: Please clarify the example question here, if it is "the correlation between global mean 'surface air temperature' (A\_sat) and 'northern hemisphere sea ice area' (O\_iceareaN)", then the correlation should be between time series of A\_sat and O\_iceareaN. If it is "the correlation between model output variables, given their reaction to varying model input parameters", then should compare correlations between time series of A\_sat and O\_iceareaN under different scenarios (different input parameters).

Sorry for the confusion, we hope to have addressed these issues in the new section 2, that we added following your suggestions.

Page 3, Line 30: should mention Appendix A before Appendix B. Otherwise switch the order of A and B.

In the original manuscript, Appendix A was called at page 3 line 4, and appendix B at the same page line 30. However, this changed, since we moved the appendix to the

section 2. We have made sure that during the revision process the Appendices appear chronologically.

Page 4, Figure 1: please don't overlap the labels, as well as in other Figures. Sorry for the subpar figure. We have changed the figure accordingly.

Page 5, line 1: what does the 'negative correlation' indicate to? If it indicates to the locations of all crosses in the top right panel in Figure 1 (positive SAT change associated with negative sea ice change), it is correct. If it indicates '-0.955', the negative correlation of correlations in different input scenarios, it is wrong. The location of the crosses in Figure 1, do give us a -0.955 correlation between the positive SAT change associated with negative sea ice change. So the negative correlation we mention here does refer to the correlation between changes in the two variables. We attempted to make this more clear in section 2.

Page 5, Line 5: Figure 3 should show after Figure 2. Or change the order of figures. We removed this figure reference. The order of the figures are following the logical order of the method and should now be correct.

Page 5, Line 21: precipitation over ocean areas is the first indicator of what? The new section explaining the set up for the example hopefully clarifies this, but we also added text here.  
"We find that the first indicator for our research question in the historical period is precipitation over ocean areas (F\_precipO)" (page 10, lines 10-11).

Page 5, Line 20-30: Do Figure 2 and Figure 3 also use the same way to calculate correlation as in Figure 1 ( $r=-0.955$ )? If so, then those correlations are not correlations between variables, but the correlations of correlations under different input scenarios. If Figure 3 is showing the correlations between variables, I strongly doubt that A\_sat (global surface temperature) and F\_uplwr (surface upwelling longwave radiation) show no correlation. It is impossible, higher surface temperature results stronger surface upwelling longwave radiation according to black body radiation. If Figure 3 is showing correlations among different input scenarios, it makes sense, as in all input parameter scenarios, black body radiation should be the same. In that way, please change the way of description through the whole text: the colorbar is not indicating the correlations of variables.

Sorry for the confusion, we have improved figure 1, hoping to make more clear, which information is taken to construct the correlation matrix in the example. We have also corrected the phrasing of the correlation information throughout the text.

On Page 5, lines 20-23 in the original text we just wanted to point out, that the output variable surface net upwelling long wave radiation in our model is influenced not only by the global mean surface air temperature, but also by processes like evaporative cooling. These two processes are in turn influenced differently by our chosen parameter perturbations than global mean temperature. Therefore we find a significant correlation e.g. between changes in net upward long wave radiation (F\_uplwr) and changes in

evaporation over land ( $F_{\text{evapL}}$ ), but not to changes in temperature. A fact that we learned about during these analysis, and which we might have overlooked, if we had assumed a perfect correlation between those two variables. This is exactly the kind of learning process the correlation matrix analysis enables.

Figure 2: not clear how many model output variables are tested until Figure 3. Instead of “clustered variables”, it might be better to list all variable names. How are those variables selected to answer the question of what is “the correlation between global mean ‘surface air temperature’ ( $A_{\text{sat}}$ ) and ‘northern hemisphere sea ice area’”? Or other questions? Please clarify.

The correlation between the  $A_{\text{sat}}$  and  $O_{\text{iceareaN}}$ , is supposed to be one example to explain how the correlations in the matrix have been calculated in this exemplary case study. We edited Figures 1 and 2 to make it more clear.

Why Figure S5-S10 are after reference and tables?

Thank you for pointing this out. We changed this.

Figure 3: need to explain all the variables.

This is done in the text, whenever we actually refer to the variables, apart from that we provided a table in the appendix and point to it in the figure label.

Page 8, 2.3: please clarify the meaning of correlation first, if the correlation is based on different input parameter scenarios, then the text needs to be modified.

Yes, we have edited the text, defining the correlation more clearly. See also the new section 2 and the edited Figure 1 for more details on the correlations.

Page 13, Line 27: RCP4.5 and RCP8.5 has more CO<sub>2</sub> emission than historical scenarios and higher sea temperature will contain less CO<sub>2</sub> gas in the ocean. Therefore according to Henry’s Law, larger CO<sub>2</sub> gradient over the atmosphere and the ocean will enhance the air to sea carbon flux. In addition, under RCP4.5 and RCP8.5, soil respiration enhanced also due to higher temperature.

Yes, these two physical processes are acting here, we added a statement on this to the text. But the fact that the correlation between changes in the variables is changing sign between the two regarded time periods is linked to the imposed parameter perturbations, as stated in the text.

Page 14, 3.1.2: The method assumed that two time periods have the same climate sensitivity regarding to the input parameter change. But it is not true. For example, CO<sub>2</sub> fertilization effect is different under different temperatures. In addition, how to select the variables for analysis will make a big difference in the result.

The parameter perturbations are now described in the section 2.3, and not novel, since we applied previously used parameter perturbations that have been studied for this model. The preselection of the variables for our example is also explained now.

“In our example, we applied the SCoMaE method to the correlation matrix concerning 46 commonly used variables for the assessment of climatic changes in the historical



forcing scenario, simulated by the UVic ESCM (See Section 2.1 for details on the simulations).” (page 10, lines 12-13).

# Systematic Correlation Matrix Evaluation (SCoMaE) - A bottom-up, ~~natural science-based~~ science-led approach to identify Indicators

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**Abstract.** This study introduces the Systematic Correlation Matrix Evaluation (SCoMaE) method, a bottom-up approach which combines expert judgment and statistical information to systematically select transparent, non redundant indicators for a comprehensive assessment of the state of the Earth system. The methods consists of ~~three~~-two basic steps: 1) Calculation of a correlation matrix among variables relevant for a given research question, and 2) Systematic evaluation of the matrix, to identify clusters of variables with similar behavior and respective mutually independent indicators, ~~and~~. Optional further analysis steps include: 3) Interpretation of the identified clusters, enabling a learning effect from the selection of indicators. ~~Optional further analysis steps include:~~ 4) Testing the robustness of identified clusters with respect to changes in forcing or boundary conditions, 5) Enabling a comparative assessment of varying scenarios by constructing and evaluating a common correlation matrix, or 6) Inclusion of expert judgment such as to prescribe indicators, to allow for considerations other than statistical consistency. The exemplary application of the SCoMaE method to Earth system model output forced by different CO<sub>2</sub> emission scenarios reveals the necessity of re-evaluating indicators identified in a historical scenario simulation for an accurate assessment of an intermediate-high, as well as a business-as-usual, climate change scenario simulation, ~~which~~. This arises from changes in prevailing correlations in the Earth system under varying climate forcing. For a comparative assessment of the three climate change scenarios, we construct and evaluate a common correlation matrix, in which we identify robust correlations between variables across the three considered scenarios.

## 1 Introduction

An indicator is a quantitative value, measured or calculated, that describes relevant aspects of the state of a defined system. A useful indicator should fulfill certain characteristics that depend on the purpose of the indicator (Gallopín, 1996). Environmental indicators are developed based on quantitative measurements or statistics of environmental conditions in order to allow for a comparison of states of the environment across time or space (Ebert and Welsch, 2004). For environmental indicators of climate change Radermacher (2005) defined statistical measurability, political and societal relevance and scientific consistency, i.e. a scientifically meaningful link between indicator and the state to be described, as three main characteristics that should be

considered as important during the indicator selection process. Moreover, other characteristics can be defined as desirable for such indicators, such as a high signal-to-noise ratio of the measurement, the relevance for ethical considerations, or the fact that the chosen indicators should not provide redundant information.

For the assessment of ongoing climate change, models representing the physical and biogeochemical processes of the Earth system, so called Earth system models (ESMs), are one of the essential tools, because the inertia of the climate system to (carbon) perturbations requires projections of future climate states. Early climate models applied simple zero to two dimensional calculations to assess the effect of atmospheric CO<sub>2</sub> on the climate by using global mean surface air temperature (SAT) as an indicator (e.g., Arrhenius, 1896; Callendar, 1938; Sellers, 1969). This commonly used climate change indicator, SAT, fulfills all three above mentioned characteristics: Several long term temperature records as well as proxies for assessing SAT exist, which makes this indicator well measured (Statistical measurability). SAT is closely linked to other climate variables, e.g. evaporation, sea level rise, or biological productivity. Although SAT may not be the most relevant variable for society, using this indicator as a proxy for climate impacts is scientifically consistent (Seneviratne et al., 2016). Its political, economical and ethical relevance evolved over time and is now evident in discussions concerning e.g. global warming (Ott et al., 2004) or the 2-degree temperature increase target, which was endorsed by the Conference of the Parties in 2015 (UNFCCC, 2015). Working group II of the Intergovernmental Panel on Climate Change (IPCC) (Houghton et al., 2001) used SAT as the main climate change indicator, due to its predominance in the existing literature and its large scientific consistency as such.

~~As~~ But as Earth system models and observational data sets continuously increase in complexity there are more and more ~~output~~ variables available that could potentially serve as indicators for the state of the climate system. Which ones should we ~~regard for a comprehensive assessment~~ select for a fully comprehensive assessment of changes in the climate system, ideally, without providing redundant information? A common bottom-up approach for measuring ~~such~~ complex systems is to start from a broad set of (Earth system) variables and consecutively select more appropriate ones depending on the research question (e.g. Pintér et al. (2005); Kopfmüller et al. (2012)). For ~~natural-science-based science-led~~ climate change assessments reports, such as published by Working Group I of the ~~Intergovernmental Panel on Climate Change (IPCC), the task of selecting scientifically consistent indicators to inform policy and the general public is a highly non-trivial task. In IPCC,~~ in addition to SAT, nowadays ~~many additional~~ more indicators are selected to evaluate changes in different components of the Earth system, e.g., precipitation, or often precipitation extremes, the Arctic summer sea ice or the rate of ocean acidification etc. As such they are discussed in e.g. the IPCC's summary for policy makers of the recent assessment report of climate change (Stocker et al., 2013).

~~However, given a certain data set, already the selection of an indicator is a normative choice and there~~ The selection of a limited number of indicators that support scientific, or political decision making is a major challenge for experts, who in this case have to decide on the relative importance of a variable in relation to others (Rametsteiner et al., 2011). There exist no unambiguous rules for the selection process (~~Krellenberg et al. (2010) and Böhringer and Jochem (2007), respectively). Any selection process of indicators and construction process of metrics~~ Böhringer and Jochem (2007). Any indicator selection or metrics construction from Earth system variables, implies a value and weighting decision, and is applying a weight of zero on any disregarded variable. While the value judgment ideally requires the inclusion of potential end-users or stakeholders, the weighting requires a well-informed and broad participation of scientific disciplines, i.e., expert judgment (Radermacher, 2005). However,

selecting one indicator, while disregarding the other is a normative choice (Krellenberg et al., 2010), which can (unknowingly) be biased by e.g. technical knowledge (Rametsteiner et al., 2011). Furthermore, Rametsteiner et al. (2011) point out, that the ad-hoc defined indicators should be subject to reevaluation over time.

In this study we ~~go beyond the usual scientific approach of applying expert judgment to select indicators for addressing a given research hypothesis, and want to~~ introduce a bottom-up ~~method that combines expert judgment with statistical information on the data set to systematically select scientifically consistent indicators~~ indicator selection method, that uses statistical information about variables in addition to expert judgement, thereby attempting to reduced bias in the selection process. Systematic Correlation Matrix Evaluation (SCoMaE) uses information on correlations between variables to identify "clusters" of variables that show similar behavior, ~~and hence can be represented by one key indicator.~~ We then systematically select scientifically  
10 consistent indicators to represent these clusters. The identified indicators are independent and do not provide redundant information. A set of independent indicators hence allows for a more comprehensive ~~natural-science-based~~ science-led assessment of the system under consideration, than a set of correlated indicators. Furthermore, SCoMaE allows for a learning process by providing new information about correlations between the given variables, and hence ~~can help to increase the process~~ increases  
15 the system understanding.

To illustrate the SCoMaE method, we ~~apply it to the output of an Earth system model of intermediate complexity, the University of Victoria Earth system climate model (UVic-ESCM). We select indicators from Earth system variables for a comprehensive assessment of our simulated climate system, given three forcing scenarios, namely a historical scenario, an intermediate-high CO<sub>2</sub> emission scenario, and a business as usual emission scenarios (see Appendix 2.1)~~ exemplarily select indicators to answer the following defined research question: 'How are changes in the climate system influenced by the sensitivity of the marine and  
20 terrestrial biological system to temperature and CO<sub>2</sub>?'. This example enables us to 1) illustrate how a correlation matrix can be constructed given a specific research question, 2) identify a comprehensive indicator set ~~for the historical forcing scenario,~~  
3) show that an indicator set derived from a ~~historical-one~~ historical forcing scenario is not necessarily appropriate to ~~describe future states of the climate system under global warming~~ a changed forcing scenario, 4) identify a common indicator set valid for ~~all three~~ multiple forcing scenarios, and finally 5) illustrate how the method could be used in an iterative process including expert  
25 judgment or previous knowledge of the given system. These steps will serve as the guideline of this paper.

## 2 Defining the research question for the SCoMaE example case

To illustrate the SCoMaE method, we exemplarily select indicators to answer the research question: 'How are changes in the climate system influenced by the sensitivity of the marine and terrestrial biological system to temperature and CO<sub>2</sub>?'. While for this question we chose to evaluate perturbed parameter simulations of an intermediate complex Earth system model (see  
30 section 2.1 and 2.3 for details), it is possible to apply this method to other data sets to answer different questions. Here are a few exemplary alternative ways to define research questions and use the SCoMaE method to investigate.

1) Our application is comparable with a multi-model ensemble, where each of the perturbed parameters is a slightly different version of the default model. We could hence do the very same analysis as described in Section 3, with e.g. the different models

and scenarios simulated in the Coupled Model Intercomparison Project 5 (CMIP5). The research question 'How are simulated changes in the climate system influenced by multi-model model variability under climate change?' could be answered by this setting.

2) To select indicators to answer the research question 'Which changes in the simulated Earth system are robust throughout state-of-the-art Earth system models?', we again could use the CMIP5 datasets. Here, one would probably want to calculate correlations between time series of different variables. This would give information about similar frequencies of those variables, which in turn hints to similar underlying processes. One could compare Correlation Matrices of one model during different forcing scenarios, as described in sections 3.3 and 3.4, or check the robustness of the correlations in one time period across models.

3) In that sense SCoMaE could also be applied to calculate correlations of observational time series. Since there is a much higher signal to noise ratio within this data, it is possible to concentrate the research question on pre-defined time scales and filter the time series of the variables before applying the SCoMaE method to the time series of the varying observed time series. The indicators would accordingly be selected to answer the underlying research question 'Which are the independent processes that I need to study for a comprehensive assessment of changes in the climate system of a given frequency band?'.

Coming back to our exemplary application of the SCoMaE method, we now want to shortly explain the model set up and simulations.

## 2.1 Model description

This paper illustrates the SCoMaE method for the example of model simulations performed with version 2.9 of the University of Victoria Earth System Climate Model (UVic ESCM), an Earth system model of intermediate complexity (Eby et al., 2013).

It includes schemes for ocean physics based on the Modular Ocean Model Version 2 (MOM2) (Pacanowski, 1995), ocean biogeochemistry (Keller et al., 2012), and a terrestrial component including soil and vegetation dynamics (Meissner et al., 2003). It is coupled to a thermodynamic sea-ice model (Bitz et al., 2001) with elastic visco-plastic rheology (Hunke and Dukowicz, 1997). The atmosphere is represented by a two dimensional atmospheric energy moisture balance model (Fanning and Weaver, 1996). All model components have a common horizontal resolution of 3.6 ° longitude and 1.8 ° latitude and the oceanic component has a vertical resolution of 19 levels, with vertical thickness varying between 50 m near the surface to 500 m in the deep ocean. Wind velocities used to calculate advection of atmospheric heat and moisture as well as the air-sea-ice fluxes of surface momentum, heat and water fluxes, are prescribed as monthly climatological wind fields from NCAR/NCEP reanalysis data (Eby et al., 2013). Wind anomalies, which are determined from surface pressure anomalies with respect to pre-industrial surface air temperature, are added to the prescribed wind fields.

A list of the globally aggregated output variables is given in Table A1.

## 2.2 Spin-up and Scenario Forcing

For the default model simulation, the UVic ESCM was spun up with pre-industrial (year 1765) seasonal forcing for over ten thousand years. All simulations were integrated from 850 until 2005 using historical fossil-fuel emissions and land-use changes.

**Table 1.** List of perturbed model input parameters

| <u>Abbreviation</u>                     | <u>short explanation of parameter perturbation</u>                              |
|---|---|
| <u>Kv low</u>                           | <u>lower bound of vertical ocean diffusivity</u>                                |
| <u>Kv high</u>                          | <u>higher bound of vertical ocean diffusivity</u>                               |
| <u>no marine T sens</u>                 | <u>no marine biological sensitivity to temperature</u>                          |
| <u>no terr. T sens</u>                  | <u>no terrestrial vegetation sensitivity to temperature</u>                     |
| <u>veg q10 low</u>                      | <u>lower bound of the vegetation Q10 sensitivity</u>                            |
| <u>veg q10 high</u>                     | <u>higher bound of the vegetation Q10 sensitivity</u>                           |
| <u>soil q10 low</u>                     | <u>lower bound of the soil Q10 sensitivity</u>                                  |
| <u>soil q10 high</u>                    | <u>higher bound of the soil Q10 sensitivity</u>                                 |
| <u>CO<sub>2</sub> fert. zero</u>        | <u>no CO<sub>2</sub> fertilization effect</u>                                   |
| <u>CO<sub>2</sub> fert. low</u>         | <u>lower bound of CO<sub>2</sub> fertilization effect</u>                       |
| <u>CO<sub>2</sub> fert. high</u>        | <u>higher bound of CO<sub>2</sub> fertilization effect</u>                      |
| <u>transp. CO<sub>2</sub> sens zero</u> | <u>no CO<sub>2</sub> sensitivity of transpiration</u>                           |
| <u>transp. CO<sub>2</sub> sens low</u>  | <u>lower bound of CO<sub>2</sub> sensitivity of transpiration</u>               |
| <u>transp. CO<sub>2</sub> sens high</u> | <u>higher bound of CO<sub>2</sub> sensitivity of transpiration</u>              |
| <u>CN CO<sub>2</sub> sens</u>           | <u>stoichiometric changes in response to changing ocean carbonate chemistry</u> |

as well as radiative forcing from solar variability and volcanic activity following Eby et al. (2013). Following Keller et al. (2014), continental ice sheets were held constant to facilitate the experimental setting and analyses. Warming from black carbon, indirect ozone effects, and cooling from indirect sulphate aerosol effects were not included. From 2005 onward until 2100 the Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios from Meinshausen et al. (2011) were implemented as an intermediate and high CO<sub>2</sub> emissions driven scenario, respectively.

For the sensitivity analysis performed with the UVic ESCM different model input parameters and parameterizations were perturbed, and for some of them it was necessary to do a new model spin-up to again reach steady-state conditions, apart from that the forcing was the same for all simulations.

### **2.3 Parameter Perturbations**

In the following sections the single parameter perturbation experiments, which are used in the example and shown in Figure 1 are explained in detail. We chose these parameters to explore the sensitivity of the UVic ESCM to uncertainties in terrestrial and marine biological productivity with respect to temperature and CO<sub>2</sub>, since these processes will influence the future carbon cycle. In addition, we perturbed ocean vertical diffusivity, since this is a physical process influencing marine carbon uptake. All parameters were perturbed within physically meaningful ranges, which was evaluated based on their agreement with the time series of the historical global mean air temperature (Figure S5). See Table 1 for a quick overview of the simulations.

### Vertical Ocean Diffusivity

Small-scale physical mixing (vertical diffusivity or diapycnal mixing) in the ocean is parameterized in all global models because of their resolution. Thus, this important process, which plays a key role in determining ocean circulation and biogeochemical cycles as well as ocean to atmosphere heat and carbon fluxes, is set by necessity as a single global, or several regional, values that falls within the range of observational estimates of vertical diffusivity. To test how this affects all model results we varied this parameterization by increasing and decreasing it by 50% (Kv low and Kv high), which is within the range of observational estimates (Duteil and Oschlies, 2011). For these sensitivity analysis the model was spun-up with the corresponding setting for 10000 years, until a new equilibrium climate state was reached.

### 10 Lower Bounds of Biological Temperature Sensitivity

Although biological processes are known to be sensitive to temperature, there is a significant amount of uncertainty in how biology will respond to warming caused by climate change (Friedlingstein et al., 2006; Taucher and Oschlies, 2011). Furthermore, there are many different ways to model the effects of temperature on biology and it is unknown which is best for Earth system model applications. To investigate the lower bounds of the sensitivity of biological processes to direct temperature effects we conduct simulations where direct temperature effects on biology are not included. In order to ensure that global biogeochemical fluxes are as close to present-day ones as possible, flux-weighted global averages for temperature-dependent rates were set for all temperature-dependent functions (see Taucher and Oschlies (2011) for details). This approach was applied separately to marine and terrestrial ecosystems:

a) No marine biological sensitivity to temperature: The results of this analysis can be used to estimate a lower boundary for how marine plankton and how their effect on biogeochemical cycles will respond directly to global warming (no marine T sens). For this sensitivity analysis the model was spun-up with the corresponding setting for 10000 years, until a new equilibrium climate state was reached.

b) No terrestrial vegetation sensitivity to temperature: The results of this analysis can be used to estimate a lower boundary for how terrestrial vegetation and its effect on the carbon cycle will respond directly to global warming (no terr. T sens). For this sensitivity analysis the model was spun-up with the corresponding setting for 10000 years, until a new equilibrium climate state was reached.

### Vegetation and Soil Sensitivity to Temperature

To further investigate the sensitivity of terrestrial biology to temperature we varied the vegetation and soil Q10 values, which are observationally-derived coefficients that are used to model the biological system rate of change in response to a 10 °C temperature increase. Low and high Q10 values of 1.5 and 3.0 (model default is 2.0), which are within the range of observational estimates (Lloyd and Taylor, 1994), were set to investigate how different terrestrial biological sensitivities to temperature affects the model results (veg q10 low/high and soil q10 low/high). For this sensitivity analysis the model was spun-up with the corresponding setting for 10000 years, until a new equilibrium climate state was reached.

35

### CO<sub>2</sub> Fertilization of Vegetation

Increasing atmospheric CO<sub>2</sub> is thought to stimulate terrestrial carbon uptake, through the process of CO<sub>2</sub> fertilization (Matthews, 2007; Kee  
This negative carbon cycle feedback results in reduced atmospheric CO<sub>2</sub> concentrations, and has likely accounted for a  
substantial portion of the historical terrestrial carbon sink (Friedlingstein et al., 2006). However, the future strength of CO<sub>2</sub>  
5 fertilization in response to continued carbon emissions is highly uncertain. In order to test the impact of this uncertainty  
for future climate change simulations, we followed the approach of Matthews (2007) by scaling the CO<sub>2</sub> sensitivity of the  
terrestrial photosynthesis model. We performed a simulation with no CO<sub>2</sub> fertilization effect (CO<sub>2</sub> fert. zero), as well as two  
simulations where we varied the strength of the CO<sub>2</sub> fertilization effect by increasing and decreasing it by 50% (CO<sub>2</sub> fert.  
high/low) relative to the default model. No additional model spin-up was needed, since the simulated CO<sub>2</sub> fertilization effect  
10 only happens when the atmospheric CO<sub>2</sub> concentration begins to increase, e.g., from the preindustrial period onward.

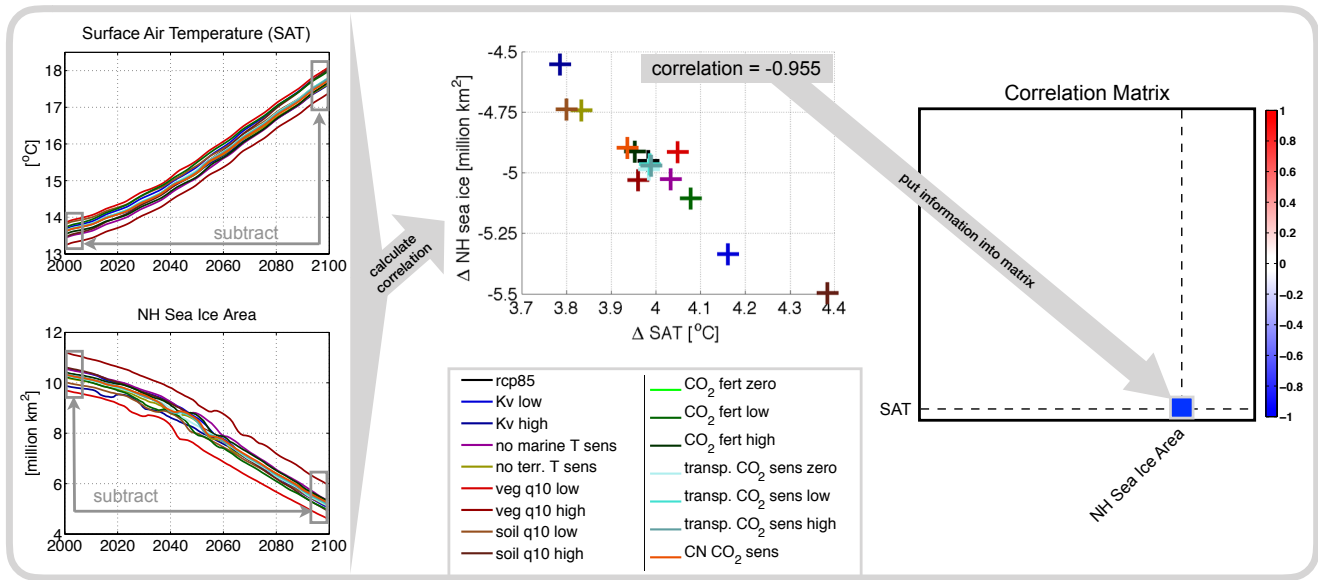
### CO<sub>2</sub> Sensitivity of Transpiration

Transpiration by plants is highly sensitive to increases in atmospheric CO<sub>2</sub>, since plants tend to open their stomata less often in  
higher CO<sub>2</sub> environments, in order to reduce water loss to the atmosphere. The strength of this effect and its impacts on climate  
15 are highly uncertain and has been studied both observation and model based (Keenan et al., 2013; Van Der Sleen et al., 2014; Mengis et al.,  
To test how strongly this affects simulations of future climate, the amount of transpiration for all plant functional types  
was scaled after Mengis et al. (2015). In this approach the CO<sub>2</sub> fertilization effect is not changed. Three simulations were  
performed: For the first simulation, transpiration did not change relative to the preindustrial level (transp. CO<sub>2</sub> sens zero). For  
the other two simulations, the scaled transpiration was increased and decreased by 50% of the amount that the model would  
20 simulate with the default setting (transp. CO<sub>2</sub> sens high/low) as CO<sub>2</sub> changes. No additional model spin-up was needed, since  
the effect of changing CO<sub>2</sub> on transpiration only becomes evident when the atmospheric CO<sub>2</sub> concentration begins to increase,  
e.g., from the preindustrial period onward.

### Stoichiometric Changes in Response to Changing Ocean Carbonate Chemistry

25 Mesocosm studies that artificially increase the amount of CO<sub>2</sub> in seawater (e.g., climate change experiments) have suggested  
that the C:N content of marine plankton may be sensitive to changes in carbonate chemistry. The mesocosm study of Riebesell et al. (2007) s  
that as CO<sub>2</sub> increases the C:N content of phytoplankton may increase, which is a change that would affect the amount of carbon  
exported to the deep ocean by biological processes and have an effect on other marine biogeochemical cycles. To test how this  
affects all model results we implemented the mesocosm-derived relationship between the atmospheric CO<sub>2</sub> concentration and  
30 the C:N content of plankton as in Oschlies et al. (2008) (CN CO<sub>2</sub> sens). No additional model spin-up was needed, since the  
effect of changing CO<sub>2</sub> on plankton stoichiometry only becomes evident when the atmospheric CO<sub>2</sub> concentration begins to  
increase, e.g., from the preindustrial period onward.





**Figure 1.** Illustration of the Correlation Matrix Construction for the example of exemplary case study, and the model output variables surface air temperature (SAT) and northern hemisphere (NH) sea ice area. Temporal In the first step, temporal differences of the simulations are calculated between 2005-2015 and 2090-2100. These Second, changes in the variables induced by the parameter perturbations are then correlated and. Last, this correlation information is used for the entry as one of many entries in the correlation matrix.

### 3 The Systematic Correlation Matrix Evaluation (SCoMaE) method

#### 3.1 Step 1: Calculate the Correlation Matrix

Throughout this study, a variable is defined as a model output or observational time series, whereas we refer to it as an indicator if a variable was selected to represent a certain aspect of the considered system. To obtain a comprehensive, non redundant set of indicators to describe a given system, the first step is to construct a correlation matrix, i.e. a matrix including the correlation information of all the relevant Earth system variables to each other. The construction of the correlation matrix strongly depends on the research question and needs to be adjusted accordingly. The selection of which variables are the relevant variables for the given research question and hence should be included in the matrix, as well as the choice on how the correlations should be calculated is very important for the outcome of the study. Correlations could for example be calculated between time series of variables or their derivatives, absolute temporal changes, or spatial patterns. Alternatively, output from ensemble simulations could be used to calculate correlations between variables changes variables due to the different ensemble members. The matrix is then evaluated based on the significance information of these correlations (see Step 2). Note, that for this preselection of the possibly relevant variables to answer the given question, as well as for the construction of the correlation information in the matrix, a certain level of expert judgement is needed.

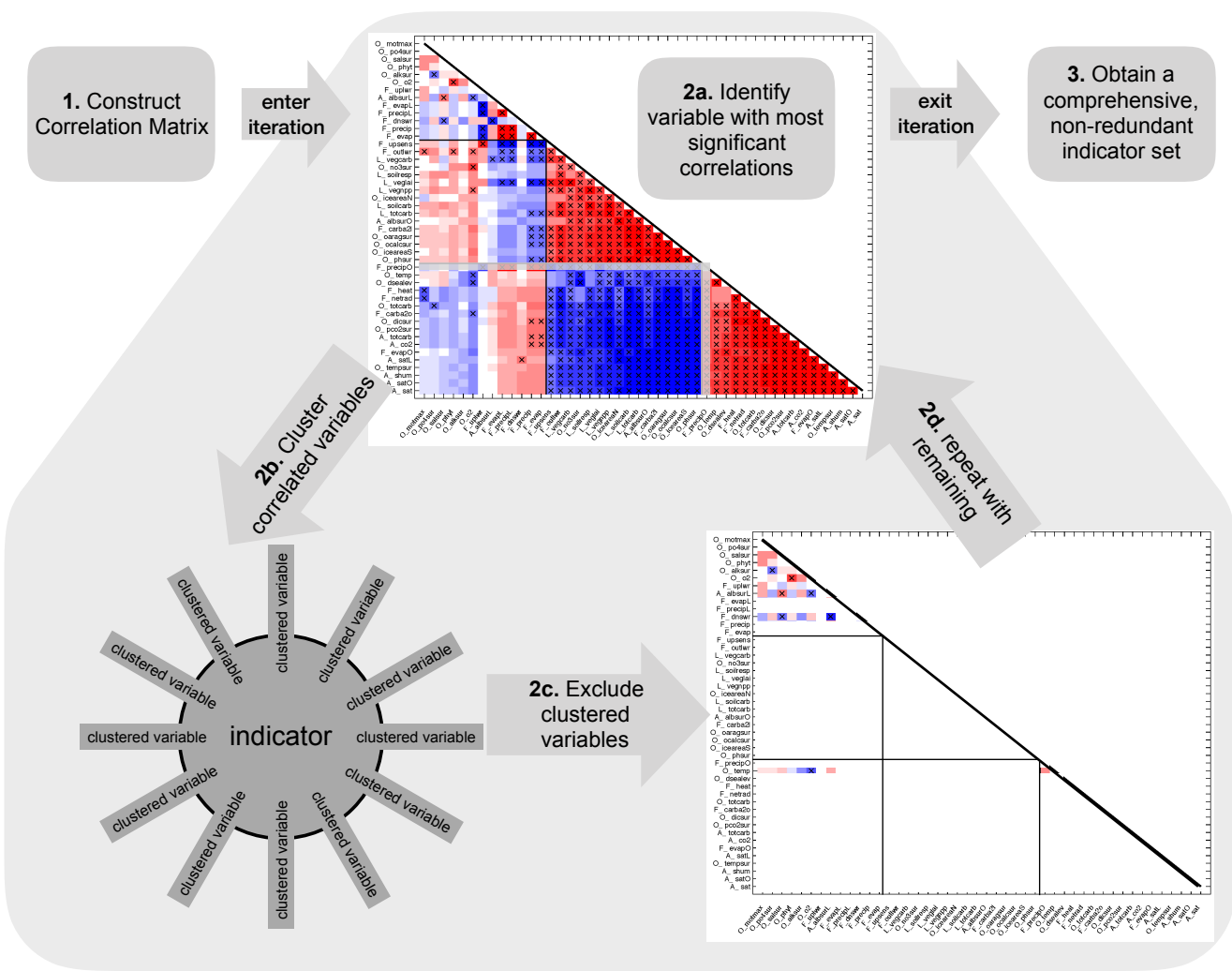
To illustrate the construction of the matrix based on our example simulations, we show how the correlation between changes in global mean 'surface air temperature' (A\_sat) and 'northern hemisphere sea ice area' (O\_iceareaN) in the Representative Concentration Pathway (RCP) 8.5 emission scenario (Meinshausen et al., 2011) due to the parameter perturbations translates to the corresponding correlation matrix entry (Figure 1). In our example we want to study the correlations between changes of model output variables, given their reaction to varying induced by varying poorly constrained model input parameters concerning ~~poorly constrained parameter processes in the model impacting the simulated the~~ carbon cycle. In the following we will refer to these as 'correlation of variable changes'.

Assuming that the signal of interest is of a similar kind as the state differences between the start and the end of a climate change simulation, we start by calculating the temporal differences between 2005–2015 and 2090–2100 from a number of parameter perturbation simulations that serve as our ensemble in this example (see Appendix-Section 2.3 for explanations of the parameter perturbations). This enables us to learn whether the different output variables show a similar behavior for the respective parameter perturbation. Then the ~~correlation~~ Pearson correlation coefficients between these changes are calculated and tested by performing a two sided test on a 5% significance level, with  $N = 16$ , the number of perturbed parameter simulations, and accordingly  $t_{crit} = 2.145$ .

In our example, there is a negative correlation ~~evident between temporal changes in~~ of variable changes evident between 'surface air temperature' (A\_sat) and 'northern hemisphere sea ice area' (O\_iceareaN). This illustrates that these model output variables show consistent opposite reactions towards the parameter perturbations, i.e. if the perturbation causes surface air temperatures to increase, it also causes northern hemispheric sea ice to decrease. This information is then written into the correlation matrix. By studying the constructed correlation matrix (see Figure 3), and studying single correlations of changes between model output variables, we can learn about basic ~~correlations~~ processes within the simulated climate system, and test if these agree with our expectations. To simplify the visual analysis of our example we sorted the variables in the matrices according to their strength in correlation towards of variable changes relative to changes in the commonly used climate change indicator, surface air temperature, ~~(A\_sat in our model, in)~~ in the historical scenario.

### 3.2 Step 2: Cluster identification and indicator selection

To obtain a set of indicators for the assessment of changes in the regarded system, we systematically evaluate the previously constructed correlation matrix (see Figure 2 for an illustration of this procedure). To obtain a comprehensive, non-redundant indicator set, we follow these steps: 1) The first indicator is the variable with the highest number of significant correlations towards other variables. 2) All variables with a significant correlation are clustered under this indicator. 3) These clustered variables are then excluded from the selection of the next indicator. 4) The next indicators is again the variable with the highest number of significant correlations towards all the remaining variables. 5) This indicator selection procedure is repeated until all variables are clustered and are represented by an indicator. If a variable is not significantly correlated to any of the remaining variables, this variable is considered to be a single indicator. These single indicators are needed for a fully comprehensive assessment, since they show a different behavior from all previously selected indicators and hence provide additional information.



**Figure 2.** Illustration of the indicator selection process, on the example of the correlation matrix for the historical scenario (see Figure 3 for a more detailed display of the correlation matrix). The correlation matrix, was constructed as explained in Figure 1, but for the temporal differences between 1850-1860 and 1995-2005. See Section 3.2 for a detailed step-by-step description of the evaluation process. Prefixes A, O, L and F, stand for atmosphere, ocean, land and fluxes, respectively, for detail description of the model output variables see Table A1

In our example we applied this procedure, we applied the SCoMaE method to the correlation matrix of concerning 46 commonly used variables for the assessment of climatic changes in the historical forcing scenarios, simulated by the UVic ESCM (See Appendix Section 2.1 for details on the simulations). We find that the first indicator for our research question in the historical period is precipitation over ocean areas (F\_precipO) (Figure 3 and S5). By following the respective column of F\_precipO (17th from the right) in the correlation matrix we can see that changes in this model output variable is are significantly correlated to changes in all variables that are also significantly correlated to changes in 'surface air temperature' A\_sat

(1st from the bottom), with the exception of 'mean ocean temperature' (O\_temp, 16th from the bottom), but in addition also links [changes in](#) global and terrestrial precipitation and evapotranspiration (F\_precipA, F\_precipL and F\_evapA, F\_evapL, respectively, and 35th and 37th from the bottom) as well as [the changes in](#) 'surface net upward longwave radiation' (F\_uplwr, 40th from the bottom). ~~These variables~~ [The changes of these variables due to parameter perturbations](#) are not significantly correlated to [changes in](#) 'surface air temperature' (A\_sat). Hence based on purely statistical considerations, using 'precipitation over ocean' (F\_precipO) as an indicator for the [research question in the](#) historical period, would be preferable to global mean 'surface air temperature' (A\_sat), the main [ad-hoc](#) indicator for historical climate change, since it potentially holds more information.

'Surface albedo on land' (A\_albsurL) is identified as the second indicator. ~~It is~~ [Its changes due to the parameter perturbations](#) are, after excluding all variables correlated to [changes in](#) 'precipitation over ocean' (F\_precipO), significantly correlated to [changes in](#) 'net surface downward shortwave radiation' (F\_dnswr), 'ocean oxygen' (O\_o2) and 'sea surface salinity' (O\_salsur). The third indicator is 'ocean surface alkalinity' (O\_alksur), which shows the same response to the parameter perturbations as 'ocean surface phosphate concentrations' (O\_po4sur). When excluding all variables that are ~~correlated to either~~ [clustered under the](#) one of the three above mentioned indicators, three variables remain unclustered: 'Mean ocean temperature' (O\_temp), 'maximum meridional overturning' (O\_motmax), and 'ocean phytoplankton' (O\_phyt). These variables are hence single indicators, which are needed for a comprehensive assessment of the system under consideration (Figure 3b).

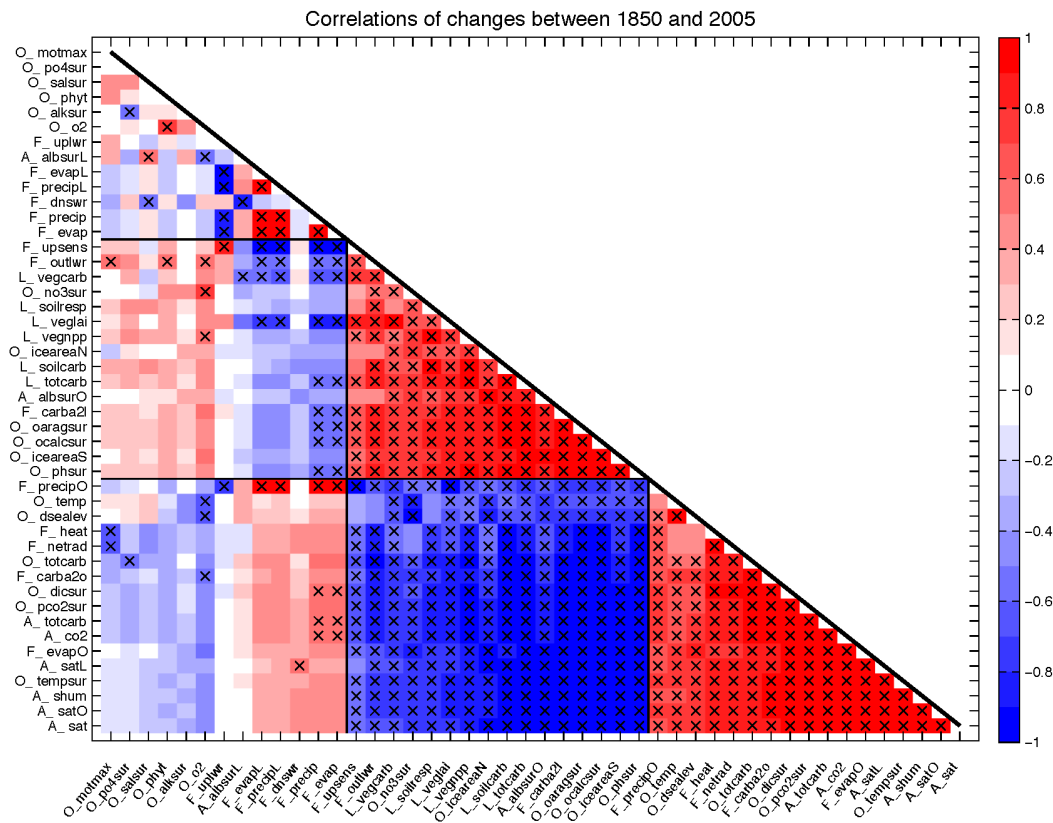
(See Section 1 and Figures S1 and S2 in the supplementary material, for the results of these analyses for the intermediate-high (RCP4.5) and the business as usual (RCP8.5) scenarios, respectively. ↪)

### 3.3 Step 3 (optional): Comparison of indicators for the different forcing scenarios

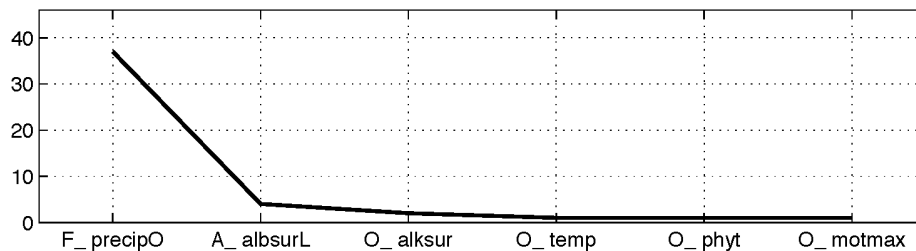
20 In order to learn how well the previously identified indicators for one scenario explain a different scenario with changed forcing, we prescribe the use of the previously identified indicator set. The SCoMaE accordingly first uses these indicators and then analyses if and which additional indicators are needed for a fully comprehensive assessment of the new scenario.

25 For the example we prescribed the indicators identified for the historical scenario to assess the intermediate-high (RCP4.5) and the business as usual (RCP8.5) emission scenarios (Figure 4). The results show, that if we were to only utilize the indicators from the historical scenario for the assessment of the two RCP scenarios, we would not be able to assess all changes in the climate system as represented by our model: For the RCP4.5 scenario, we would obtain additional information by considering the variables 'net top of atmosphere radiation' (F\_netrad) and 'ocean surface heat flux' (F\_heat), which are clustered together, 30 and 'net upward longwave radiation' (F\_uplwr) and 'ocean surface salinity' (O\_salsur), which form another indicator cluster (Figure 4).

Note, that Earth system variables clustered under the prescribed indicators differ among the different scenarios (compare Figure 3 and S1): In the historical scenario the indicator 'precipitation over ocean' (F\_precipO) includes the output variables 'net top of atmosphere radiation' (F\_netrad), 'ocean surface heat flux' (F\_heat), 'ocean surface nitrate' (O\_no3sur), 'top of atmosphere

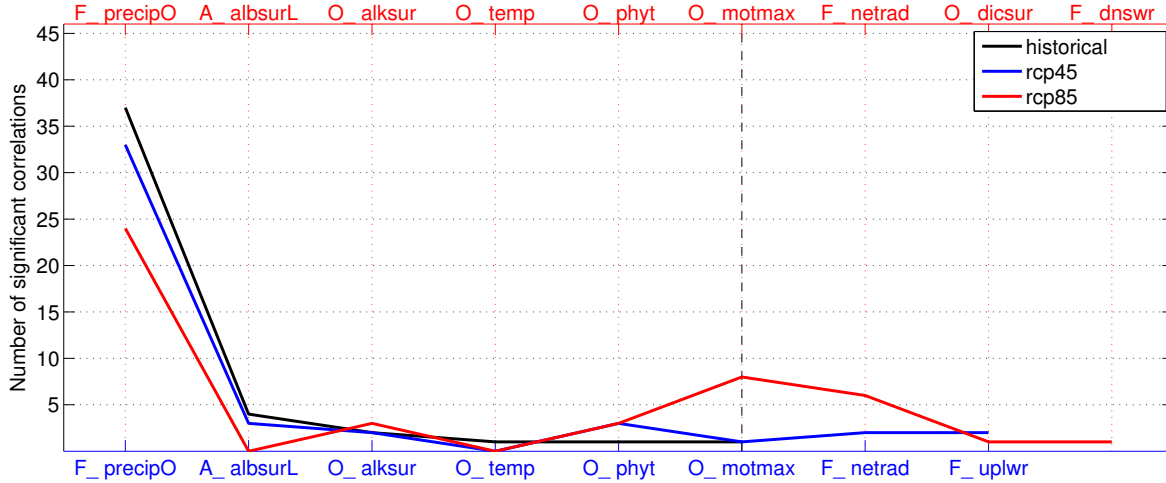


Number of significant correlations for the historical scenario



**Figure 3.** top: Correlation matrix for the historical **simulation** scenario. The correlations are calculated **according to** [between changes in the example of Figure 1 46 model output variables for temporal differences between 1850-1860 and 1995-2005](#) from the results of the perturbed parameter simulations **for each of the 46 model output variables, respectively** [\(as in Figure 1\)](#). Correlations significant on a 5% significance level are marked with 'x'. The order of the variables was determined based on their correlation strength to surface air temperature (A\_sat) in the historical scenario. **For details on** [Prefixes A, O, L and F, stand for atmosphere, ocean, land and fluxes, respectively, for detail description of the regarded model output variables see Table S1A1.](#)

bottom: Indicators as identified from **our the SCoMaE analysis based on** [of the correlation matrix above as illustrated in Figure 2](#), ranked by the amount of significant correlations. [The indicators are as follows: precipitation over ocean \(F\\_precipO\), land surface albedo \(A\\_albsurL\), ocean surface alkalinity \(O\\_alksur\), mean ocean temperature \(O\\_temp\), ocean phytoplankton \(O\\_phyt\) and ocean overturning \(O\\_motmax\).](#)



**Figure 4.** Indicators identified from the analysis of the RCP4.5 (blue) and RCP8.5 (red) correlation matrices with the precondition to use the historical indicators first. The indicators are as follows: precipitation over ocean (F\_precipO), land surface albedo (A\_albsurL), ocean surface alkalinity (O\_alksur), mean ocean temperature (O\_temp), ocean phytoplankton (O\_phyt), ocean overturning (O\_motmax), net radiation at the top of the atmosphere (F\_netrad), ocean surface dissolved inorganic carbon (O\_dicsur) and downward shortwave radiation (F\_dnswr).

outgoing longwave radiation' (F\_outlwr), and 'net upward longwave radiation' (F\_uplwr), all of which are not included in the 'precipitation over ocean' (F\_precipO) indicator for the RCP4.5 scenario. Instead, the indicator 'precipitation over ocean' (F\_precipO) for the RCP4.5 scenario includes 'mean ocean temperature' (O\_temp), which it is not included for the historical scenario.

- 5 The differences between the correlation matrices for the RCP8.5 scenario compared to the historical scenario are even larger (compare Figure 3 and S2). For the RCP 8.5 scenario eight out of 46 considered variables would not be included if we applied the indicators identified for the historical scenario. Instead we need three additional indicators for the assessment of the system under consideration, namely 'net top of atmosphere radiation' (F\_netrad), 'ocean surface dissolved inorganic carbon' (O\_dicsur), and 'net surface downward shortwave radiation' (F\_dnswr) (Figure 4). Note that six of the eight remaining variables that were initially included in the first indicator cluster for the historical scenario, namely 'precipitation over ocean' (F\_precipO), are no longer significantly correlated to it for the RCP8.5 scenario.

These differences in the correlation matrices for the different forcing scenarios indicate changes in prevailing correlations between Earth system variables with ~~climate state~~ the imposed climate forcing. This illustrates that ~~it~~ a reevaluation of the chosen indicators may be needed for a comprehensive assessment of different climate strategies yielding different climate states.

- 15 ~~Indicators identified from the analysis of the RCP4.5 (blue) and RCP8.5 (red) correlation matrices with the precondition to use the historical indicators first.~~

### 3.4 Step 4 (optional): Evaluation of a common correlation matrix

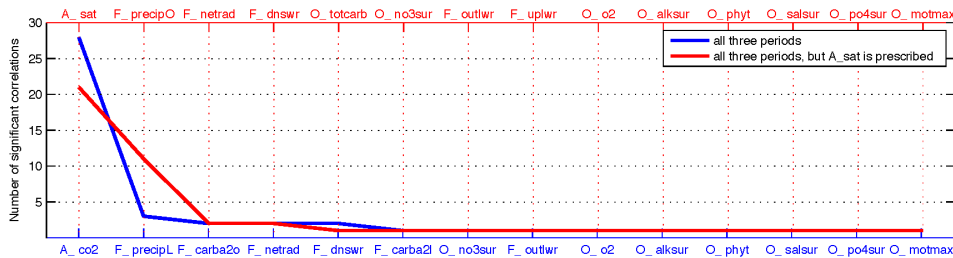
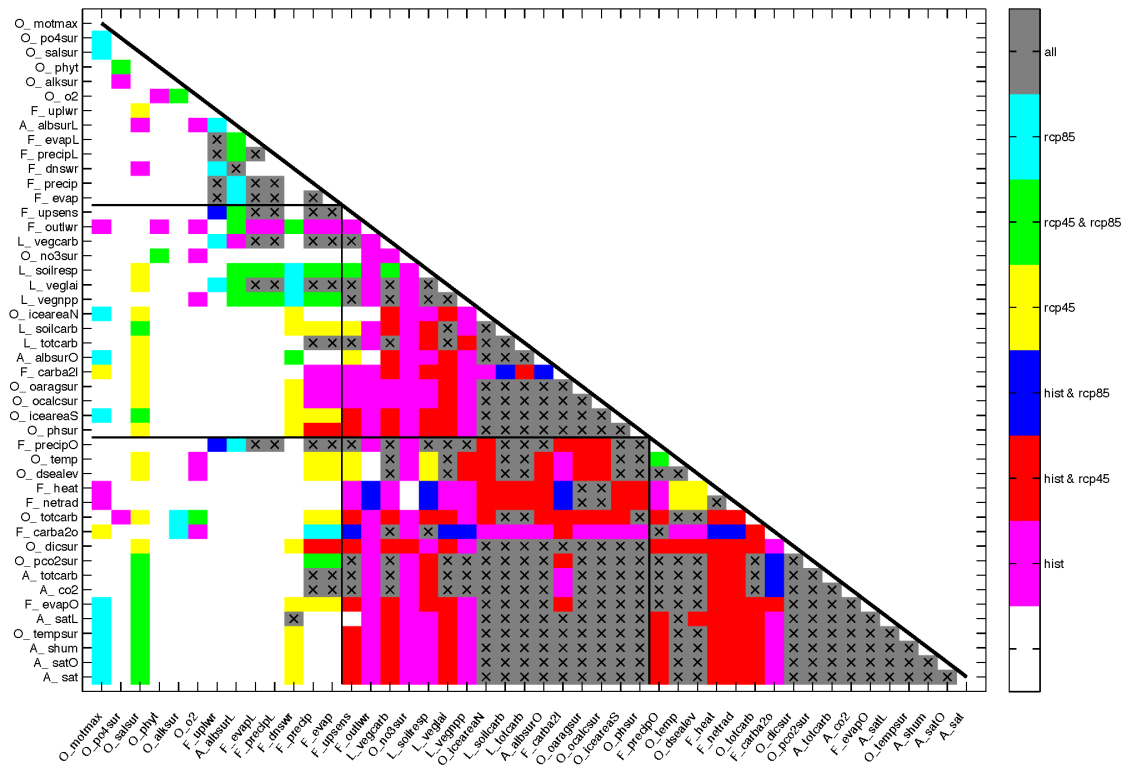
To advance this analysis such that changes in correlation matrices from different forcing scenarios can be taken into account, it is possible to create a correlation matrix representing only those correlations that are significant in all forcing scenarios, a so-called common correlation matrix. Applying the SCoMaE method to such a common correlation matrix identifies an indicator set that can be used to assess and also compare multiple scenarios, and hence differs from the previously identified sets for the individual correlation matrices.

To obtain a common indicator set for the three exemplary forcing scenarios (historical, RCP4.5 and RCP8.5), we construct a correlation matrix in which only correlations of variable changes that are significant in all these scenarios are considered (Figure 5). Furthermore the color shading indicates in which scenario the correlations between variable changes were found to be significant.

A first visual evaluation of the common correlation matrix shows more reddish than bluish shading, which indicates that the correlation patterns for the historical and RCP4.5 scenarios are more similar, than for the historical and RCP8.5 scenarios (Figure 5). This means that for a lower future emission scenario, the indicators from the historical scenario are more suitable than for a higher future emission scenario. This is true with the exception of the terrestrial and oceanic carbon fluxes (F\_carba2l and F\_carba2o, respectively), which are perturbed more by the land-use scheme implemented in the RCP4.5 scenario, since this scenario includes a high amount of afforestation and reforestation. Furthermore, greenish shading shows correlations of variable changes that are significant only in the RCP scenarios, indicating that those correlations of variable changes depend on the increasing anthropogenic (mainly CO<sub>2</sub>) forcing, included only in these scenarios.

The first indicator obtained from the common SCoMaE analysis is 'atmospheric CO<sub>2</sub>' (A\_co2), which was also found to be the first indicator in the RCP8.5 scenario (Figures S7 and S8). ~~It is~~ Its changes are significantly correlated to changes in 27 other output variables in all three scenarios, indicating that these correlations of variable changes are robust and independent of the different strength of CO<sub>2</sub> forcing in the different scenarios. The fact that 'atmospheric CO<sub>2</sub>' (A\_co2) is the first indicator with a large number of correlated variables, hints at its importance in determining the reaction of other Earth system variables during climate change e.g. changes in temperatures, carbon fluxes and moisture fluxes over the ocean.

The second indicator is 'precipitation over land' (F\_precipL), which is clustered with 'terrestrial evapotranspiration' (F\_evapL) and 'net upward longwave radiation' (F\_uplwr) (Figure S8S6). This cluster accordingly represents changes in terrestrial moisture fluxes and the resulting surface upward fluxes of longwave radiation. The latter relates to the surface air temperature, which on land is strongly influenced by the amount of evapotranspiration, and the resulting evaporative cooling. Note, that the fact that terrestrial moisture fluxes are clustered under a separate indicator, hints at a different sensitivity of these variables to climate change and the perturbed parameters. Since these three variables show significant correlations of variable changes to each other in all three scenarios, one could use any of them as the indicator for this cluster. The same is true for the next indicators and their clusters, which are 'air to sea carbon flux' (F\_carba2o) and 'soil respiration' (L\_soilresp); 'net top of atmosphere radiation' (F\_netrad) and the 'ocean surface heat flux' (F\_heat); and 'net surface downward shortwave radiation' (F\_dnswr)



**Figure 5.** a) Correlation matrix for all three scenarios, merging the colors significance information from all three scenarios. Colors indicate in which scenarios scenario the corresponding changes of variables show due to parameter perturbations showed a significant correlation, see colorbar for explanation. The 'x's mark combinations of variables, where the correlation of variable changes is significant on a 5% significance level in all three scenarios. For details on the regarded model output variables see Table S1A1.

b) indicators as identified from the analysis based on the correlation matrix above against the number of significant correlations (blue) and with the condition, that surface air temperature ( $A_{sat}$ ) is prescribed as the first indicator (red). The indicators are as follows: atmospheric carbon content ( $A_{co2}$ ), precipitation over land ( $F_{precipL}$ ), atmosphere to ocean carbon flux ( $F_{carba2o}$ ), net top of atmosphere radiation ( $F_{netrad}$ ), net surface downward shortwave radiation ( $F_{dnswr}$ ), atmosphere to land carbon flux ( $F_{carba2l}$ ), ocean surface nitrate ( $O_{no3sur}$ ), top of atmosphere outgoing longwave radiation ( $F_{outlwr}$ ), ocean oxygen ( $O_{o2}$ ), ocean surface alkalinity ( $O_{alksur}$ ), ocean phytoplankton ( $O_{phyt}$ ), ocean surface salinity ( $O_{salsur}$ ), sea surface phosphate ( $O_{po4sur}$ ), ocean overturning ( $O_{motmax}$ ), precipitation over ocean ( $F_{precipO}$ ), ocean carbon ( $O_{totcarb}$ ), and surface net upward longwave radiation ( $F_{uplwr}$ ).



and the 'land surface albedo' (A\_albsurL).

The remaining single indicators are 'air to land carbon flux' (F\_carba2l), 'ocean surface nitrate' (O\_no3sur), 'top of atmosphere outgoing longwave radiation' (F\_outlwr), 'ocean oxygen' (O\_o2), 'ocean surface alkalinity' (O\_alksur), 'ocean phytoplankton' (O\_phyt), 'sea surface salinity' (O\_salsur), 'ocean surface phosphate' (O\_po4sur) and 'maximum ocean meridional overturning' (O\_motmax).

### 3.5 Step 5 (optional): Including expert judgment

If stakeholders or experts were to inform the indicator selection process, it is possible to prescribe indicators and then use the SCoMaE analysis to identify additional uncorrelated variables, that are needed to obtain a comprehensive assessment of the system. Also instead of using global mean time series, one could look at time series of regions or already processed variables, such as heat stress or cumulative emissions. This approach in combination with the SCoMaE analysis enables us to learn about variables, which have previously been disregarded but potentially provide new information about the system, or to learn which of the previously regarded indicators actually provide redundant information.

15 How would the common indicator set from our example change, if we were to include the condition that 'surface air temperature' should be the first indicator, instead of 'atmospheric CO<sub>2</sub>'?

Prescribing 'surface air temperature' (A\_sat) as the first indicator for the common correlation matrix, leads to the replacement of 'precipitation over land' (F\_precipL) by 'precipitation over ocean' (F\_precipO) as the second indicator (Figure 5, bottom), which its changes to the parameter perturbations is correlated with 12 variables that are clustered under this indicator. Almost all of these variables were initially clustered under 'atmospheric CO<sub>2</sub>' (A\_co2), but are not significantly correlated to changes in 'surface air temperature' (A\_sat). These variables mainly describe global and oceanic moisture fluxes, as well as carbon fluxes or reservoirs on land: 'precipitation over the ocean' (F\_precipO), 'global evaporation' (F\_evap), 'global precipitation' (F\_precip), 'vegetation net primary productivity' (L\_vegnpp), 'leaf area index' (L\_veglai), 'vegetation carbon' (L\_vegcarb) and the 'surface upward sensible heat flux' (F\_upsens). The only exception to this behavior is 'total ocean carbon' (O\_totcarb), which in turn becomes a single indicator. In addition the second indicator, 'precipitation over the ocean' (F\_precipO), now incorporates the previously identified clusters of the second and third indicators, namely the clusters of 'precipitation over land' (F\_precipL) and the 'air to sea carbon flux' (F\_carba2o). Only 'net upward longwave radiation' (F\_uplwr), which was also clustered under 'precipitation over land' (F\_precipL) becomes a single indicator, remaining unclustered when 'surface air temperature' (A\_sat) is prescribed as the primary indicator. In turn 'air to land carbon flux' (F\_carba2l), which was a single indicator in the default SCoMaE analysis, is now clustered under 'surface air temperature' (A\_sat).

The third and fourth indicators are 'net top of atmosphere radiation' (F\_netrad) and 'net surface downward shortwave radiation' (F\_dnswr), which were found with the same underlying clusters in the default analysis (compare Figures S8 and S9). Finally, eight of the nine previously identified single indicators, remain unclustered and hence are still single indicators.

Although the total number of indicators has not changed, the identified clusters and their meaning differ: In the default analysis

the first indicator represented changes in temperatures, carbon fluxes and global and oceanic moisture fluxes. If 'surface air temperature' (A\_sat) is prescribed the global and oceanic moisture fluxes are moved to the second cluster, which in addition incorporates some Earth system variables from the previously identified second and third indicators. This is one example showing how the SCoMaE method allows for the inclusion of expert judgment or preconditions, is able to account for changes in correlation patterns, and allows one to determine which indicators are needed for a comprehensive and non-redundant assessment. (For more discussions see Section 2 and Figure S3 in the supplemental information.)

## 4 Discussion

### 4.1 Discussion of the results from the example

#### 4.1.1 ~~What could we learn from the example?~~

#### 10 What could we learn from the example?

As illustrated above, the SCoMaE method statistically evaluates the correlations between changes of model output variables and uses this information to cluster variables, while selecting a representative indicator for each cluster. The exemplary analyses of the individual scenarios illustrates the dependence of the indicator selection on the imposed forcing scenario. These results demonstrate that for our model it is insufficient to apply the historical indicator set to the future scenarios with either higher CO<sub>2</sub> forcing such as in the RCP8.5 scenario, or more limited CO<sub>2</sub> forcing and reduced anthropogenic land use such as in the RCP4.5 scenario. Although our analysis is too limited to conclusively determine a best set of climate change indicators in a purely scientific bottom-up approach, our results do suggest that a comprehensive assessment of future climatic states needs a re-evaluation of the ad-hoc chosen indicators, due to changes in prevailing climate responses.

We demonstrate one possible approach for selecting a more comprehensive indicator set by constructing a common correlation matrix to identify indicators that can be used for the assessment of all three scenarios. For the clusters of variables of the common indicator set, the correlations of variable changes remain significant even under different atmospheric carbon or land use forcing.

However, one should always ask if the identified clusters and indicators are scientifically meaningful? For the common correlation matrix (as well as the RCP8.5 scenario), the first indicator, 'atmospheric CO<sub>2</sub>' (A\_co2), groups together variables describing changes in carbon fluxes, temperatures, and moisture fluxes over the ocean. This is scientifically meaningful, since changes in carbon fluxes will affect the atmospheric carbon content and hence atmospheric temperatures, both over land and ocean. These temperature changes in turn have an effect on the moisture fluxes over the ocean, such as the evaporation over ocean, which is physically driven by temperature changes. These categories are hence physically linked and it is to be expected that they are correlated irrespective of the chosen forcing scenario.

30 The second indicator, 'precipitation over land' (F\_precipL), represents the variability of moisture fluxes on land and the associated cooling effect. The fact that these processes are clustered under a indicator that is distinct from global and oceanic

moisture fluxes indicates different underlying processes for these moisture fluxes, namely the influence of biological transpiration. This process is directly affected by the parameter perturbations concerning the sensitivity of transpiration to CO<sub>2</sub> (Mengis et al., 2015) and the CO<sub>2</sub> fertilization effect (Matthews, 2007). Given the regarded parameter sensitivities of the model, the distinction between terrestrial and marine moisture fluxes is scientifically meaningful.

5 Another identified cluster is ‘net top of atmosphere radiation’ (F\_netrad) and ‘ocean surface heat flux’ (F\_heat), which are directly linked in the model. Furthermore ‘net surface downward shortwave radiation’ (F\_dnswr) and ‘land surface albedo’ (A\_albsurL) are clustered, since changes in vegetation on land induced by the parameter perturbations, influence both the surface albedo on land and the incoming shortwave radiation at the surface.

The ‘air to sea carbon flux’ (F\_carba2o) and ‘soil respiration’ (L\_soilresp) are clustered together for all three scenarios, but  
10 show a negative correlation [of variable changes](#) in the historical scenario and positive correlations [of variable changes](#) in the two RCP scenarios, indicating a dependency on the atmospheric carbon concentrations. The predominant parameterization for those correlations [of variable changes](#) is one that affects the CO<sub>2</sub> fertilization (Figure [S10S7](#)). Since this is not an intuitive connection, we will shortly discuss this correlation in more detail: The strength of the CO<sub>2</sub> fertilization determines the increase of plant net primary production (NPP) to increasing atmospheric CO<sub>2</sub> concentrations. For the historical scenario, in the case when  
15 the CO<sub>2</sub> fertilization parameterization is increased, soil respiration increases due to an increase in vegetation and hence the soil carbon pool. In the same case the air to sea carbon flux slightly decreases due to lower atmospheric carbon concentration in case of increasing vegetation NPP and consequently land CO<sub>2</sub> uptake. Hence the negative correlation [of variable changes](#) between the ‘air to sea carbon flux’ (F\_carba2o) and ‘soil respiration’ (L\_soilresp) for the CO<sub>2</sub> fertilization perturbation in the the historical scenario (Figure [S10aS7a](#)).

20 In contrast, in the future, [high CO<sub>2</sub> and temperature](#) scenarios both Earth system variables [are higher show larger changes](#) with increased CO<sub>2</sub> fertilization parameterization. For ‘soil respiration’ (L\_soilresp) the underlying process remains the same in this case. However, the terrestrial carbon reservoir reaches a saturation state during the high emission scenarios. With increasing CO<sub>2</sub> fertilization strength the land carbon reservoir reaches this saturation state earlier, causing more carbon to remain in the atmosphere, which [following Henry’s law](#) results in an overall higher ‘air to sea carbon flux’ (F\_carba2o) in the simulations with  
25 higher CO<sub>2</sub> fertilization, since the ocean equilibrates with the atmosphere. This explains the positive correlation [of variable changes](#) under the two RCP scenarios.

Two clusters are identified in both future emission scenarios, namely ‘ocean phytoplankton’ (O\_phyt), which is clustered with ‘ocean surface phosphate’ (O\_po4sur) and ‘ocean surface nitrate’ (O\_no3sur), and ‘ocean oxygen’ (O\_o2), which is clustered with ‘ocean surface alkalinity’ (O\_alksur) (compare Figures S6 and S7). These two clusters are only identified when  
30 atmospheric CO<sub>2</sub> concentrations are high, but do not hold for the historical scenario, where other relationships seem to be of greater importance. As a result, all of these variables are unclustered for the common indicator selection, causing the number of selected indicators for a common indicator set to increase.

#### 4.1.1 Limitation of the analyses from the example

##### Limitation of the analyses from the example

For our case study, we chose to assess the uncertainty of the biological system towards increasing temperature and CO<sub>2</sub>, which is reflected in the choice of the considered perturbed parameters. In addition to directly perturbing biological parameterizations, we also perturbed some key physical parameters that indirectly influence the biological systems. All parameter perturbations were chosen because the parameterizations are poorly constrained and under future high CO<sub>2</sub> and temperature forcing it will be become increasingly important to take this uncertainty into account. These choices, however, bias the correlation analysis of the model output variables towards their sensitivity to the selected perturbations (for a detailed discussion see Section 3 and Figure S4 in the supplemental information). For a more comprehensive assessment of uncertainties, experiments with different uncertainties in the simulated Earth system, such as cloud parameterizations or the model's climate sensitivity would need to be considered. Such experiments would accordingly change the patterns of the correlation matrix.

It is important to stress the fact that the Earth system variables used in our example are annual global integrals or means and thus, not necessarily representative of regional or temporal changes. While our approach was sufficient to demonstrate the SCoMaE method, it is important to mention that global integrals and means are not always positively correlated to regional changes and therefore, may misrepresent regional responses. Furthermore, we restricted our case study to investigate temporal changes between two fixed points in time ~~and thereby~~, which limits our analysis to this time horizon. Therefore, we miss more detailed information about the temporal development of the response of the model variables to changes in parameter values. This approach was chosen since the UVic ESCM is a model with low internal variability and would hence, likely overestimate information if we had evaluated temporal correlations. Investigating the model's sensitivity to the parameter perturbations was therefore deemed a better choice for illustrating the SCoMaE method. Any more thorough climate change assessment using the SCoMaE method would also need to investigate how variable correlations and indicator clusters might change spatially and temporally.

#### 4.2 Discussion of the SCoMaE method

The construction of an individual or a common correlation matrix can be a useful tool for assessing the state of complex systems. Individual correlation matrices allow one to obtain an initial overview of relationships between the different system variables, whereas a common correlation matrix shows how changes in the state of a system, imposed by e.g. varying forcing scenarios, influences these relationships. The SCoMaE method then allows us to cluster the variables, based on statistical considerations, to obtain a non-redundant indicator set to guide more detailed analysis.

However, in order to be useful one must carefully select which information to include in the correlation matrix, which is something that strongly depends on the given research question. This can be illustrated by the implicit choices made for our exemplary case study, where we regarded correlations of variable changes of globally averaged model output variables given various parameter perturbations. The first choice in this case study was to use global aggregates of the model output. However, if the research focus would be set on, e.g., regional phenomena the correlations for the matrix could also be constructed either

between regional aggregates, or based on the correlation strength for a given spatial pattern.

The second choice we made for the case study was to regard correlations between changes in model output variables based on their reaction to a parameter perturbation. Using a model with higher internal variability, it would also be possible to regard temporal correlations of a chosen time period, or other derivatives of the model output variables such as heat stress or cumulative time series. This would, in contrast to the purely process-based parameter perturbations, hold information about the time scales of the model output variables, which again might hint at common underlying processes in the model. Additionally, if the considered time series show higher internal variability it might be conceivable to apply a specific temporal filter to the data before calculating the correlation matrix. This might allow one to distinguish important processes on different time scales from daily and seasonal to inter-annual or decadal.

10

In the following we want to discuss the contribution of the SCoMaE method to achieve the three characteristics for indicator selection as introduced by Radermacher (2005). Constructing a correlation matrix enables scientists to comprehensively identify correlations in complex systems, such as the Earth system, both simulated and real. The application of SCoMaE allows one to identify scientifically consistent sets of indicators, which are independent and do not provide redundant information, to be used in a ~~natural-science-based~~ science-led assessments. This method represents a bottom-up, natural science perspective on indicator selection. It thereby tackles one of the three characteristics as discussed by Radermacher (2005), namely that of scientific consistency.

In our example the SCoMaE method is based on model data, and hence does not account for information about the statistical measurability of the identified indicators. This makes it difficult to directly translate a model-based indicator set to a 'real world' application. This is for example the case for the first indicator in the historical scenario, 'precipitation over ocean' (F\_precipO), the lack of long term historical precipitation measurements over the ocean (New et al., 2001) would prevent this indicator from being used in a 'real world' application. It is however, noteworthy that there is value in the knowledge that this variable could hold information about other Earth system variables, and hence it might be worth improving the observational system.

25 The third characteristic mentioned by Radermacher (2005) is the political relevance of indicators. Since SCoMaE is a bottom-up, ~~natural-science-based~~ science-led approach for indicator selection, it at first disregards political, ethical and economical considerations. However, these considerations as well as measurability constraints can be included in the analysis. By prescribing a certain indicator, e.g. 'surface air temperature' (A\_sat) in Section 3.5, SCoMaE allows us to include expert judgment and enables us to identify the remaining indicators needed for a fully comprehensive assessment. An iterative learning process of which indicators are needed and useful, would hence allow SCoMaE to identify a scientifically meaningful, measurable, and politically relevant indicators set (Oschlies et al., 2016; Singh et al., 2015).

30

## 5 Conclusions

In this study we introduced a bottom-up, correlation-based approach to systematically identify indicator sets for the assessment of complex systems. To demonstrate the **power of the SCoMaE** method, we applied it to correlation matrices constructed with changes in Earth system variables of an intermediate complex Earth system model, with which we simulated three forcing scenarios. We were able to identify indicators sets for an assessment of the historical as well as for an intermediate high and a business as usual future emission scenario. The comparison of the three correlation matrices yielded the opportunity to assess changes in correlations between changes in Earth system variables introduced by the imposed forcing. These changes in the correlation patterns also motivated a re-evaluation of the selected indicator sets for the different scenarios. We show that it is not sufficient to apply the indicator set identified for the historical scenario to the intermediate high nor the business as usual future emission scenario. This result points to the fact, that the classical procedure of ad-hoc indicators, such as surface air temperature, may work well for certain environmental conditions or scenarios, but possibly not so well for others. That is, the subjective choice of indicators may lead to unintended preferences in the interpretation of different scenarios. By combining the three scenarios into a common correlation matrix, we could identify correlations between changes in Earth system variables that are robust across the three forcing scenarios. Considering these correlations only, enabled us to identify a common indicator set, which was scientifically consistent and allowed us to comparatively assess the three considered scenarios. This case study is one example out of many possible applications of the correlation matrix and SCoMaE method. The construction of the correlation matrix can be adjusted to the respective research question, which makes the SCoMaE method a generic and flexible tool. An iterative application of the SCoMaE method offers the user the chance to comprehensively assess complex systems such as the Earth system, while including political, ethical and economical considerations, as well as measurability constraints.

*Data availability.* The model data used to generate the figures will be made available at <http://thredds.geomar.de>.

*Author contributions.* N.M., A.O. and D.P.K. conceived and designed the experiments. D.P.K. and N.M. implemented and performed the experiments. N.M analyzed the data and wrote the manuscript with contributions from D.P.K. and A.O..

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

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**Table A1.** List of globally aggregated model output variables considered in this study. Part 1: Atmosphere, Fluxes, and Land

| <u>model output name</u> | <u>description</u>                                   | <u>unit</u>  |
|--------------------------|--|--|
| <u>A_albsurL</u>         | <u>land surface albedo</u>                           | [1]  |
| <u>A_albsurO</u>         | <u>sea surface albedo</u>                            | [1]  |
| <u>A_co2</u>             | <u>atmospheric CO<sub>2</sub></u>                    | [ppm]  |
| <u>A_sat</u>             | <u>air surface temperature</u>                       | [°C]   |
| <u>A_satL</u>            | <u>land air surface temperature</u>                  | [°C]   |
| <u>A_satO</u>            | <u>ocean air surface temperature</u>                 | [°C]   |
| <u>A_shum</u>            | <u>surface specific humidity</u>                     | [1]  |
| <u>A_totcarb</u>         | <u>total atmospheric carbon</u>                      | [Pg C]   |
| <u>F_carba2l</u>         | <u>air to land carbon flux</u>                       | [Pg C yr <sup>-1</sup> ]                               |
| <u>F_carba2o</u>         | <u>air to sea carbon flux</u>                        | [Pg C yr <sup>-1</sup> ]                               |
| <u>F_dnswr</u>           | <u>net surface downward shortwave radiation</u>      | [W m <sup>-2</sup> ]                                   |
| <u>F_evap</u>            | <u>global evaporation</u>                            | [kg H <sub>2</sub> O m <sup>-2</sup> s <sup>-1</sup> ] |
| <u>F_evapL</u>           | <u>evaporation over land</u>                         | [kg H <sub>2</sub> O m <sup>-2</sup> s <sup>-1</sup> ] |
| <u>F_evapO</u>           | <u>evaporation over ocean</u>                        | [kg H <sub>2</sub> O m <sup>-2</sup> s <sup>-1</sup> ] |
| <u>F_heat</u>            | <u>ocean heat flux</u>                               | [W m <sup>-2</sup> ]                                   |
| <u>F_netrad</u>          | <u>net top of atmosphere radiation</u>               | [W m <sup>-2</sup> ]                                   |
| <u>F_outlwr</u>          | <u>top of atmosphere outgoing longwave radiation</u> | [W m <sup>-2</sup> ]                                   |
| <u>F_precip</u>          | <u>global precipitation</u>                          | [kg H <sub>2</sub> O m <sup>-2</sup> s <sup>-1</sup> ] |
| <u>F_precipL</u>         | <u>precipitation over land</u>                       | [kg H <sub>2</sub> O m <sup>-2</sup> s <sup>-1</sup> ] |
| <u>F_precipO</u>         | <u>precipitation over ocean</u>                      | [kg H <sub>2</sub> O m <sup>-2</sup> s <sup>-1</sup> ] |
| <u>F_uplwr</u>           | <u>surface net upward longwave radiation</u>         | [W m <sup>-2</sup> ]                                   |
| <u>F_upsens</u>          | <u>surface upward sensible heat flux</u>             | [W m <sup>-2</sup> ]                                   |
| <u>L_soilcarb</u>        | <u>soil carbon</u>                                   | [Pg C]   |
| <u>L_soilresp</u>        | <u>soil respiration</u>                              | [Pg C yr <sup>-1</sup> ]                               |
| <u>L_totcarb</u>         | <u>total land carbon</u>                             | [Pg C]   |
| <u>L_vegcarb</u>         | <u>vegetation carbon</u>                             | [Pg C]   |
| <u>L_veglai</u>          | <u>leaf area index</u>                               | [1]  |
| <u>L_vegnpp</u>          | <u>vegetation net primary productivity</u>           | [Pg C yr <sup>-1</sup> ]                               |

**Table A1.** List of globally aggregated model output variables considered in this study.Part 2: Land and Ocean

| <u>model output name</u> | <u>description</u>                                    | <u>unit</u>                           |
|--------------------------|---|---------------------------------------|
| <u>O_alksur</u>          | <u>sea surface alkalinity</u>                         | <u>[mol m<sup>-3</sup>]</u>           |
| <u>O_dicsur</u>          | <u>sea surface dissolved inorganic carbon</u>         | <u>[mol m<sup>-3</sup>]</u>           |
| <u>O_dsealev</u>         | <u>change in sea level</u>                            | <u>[m]</u>                            |
| <u>O_iceareaN</u>        | <u>northern hemisphere sea ice area</u>               | <u>[m<sup>2</sup>]</u>                |
| <u>O_iceareaS</u>        | <u>southern hemisphere sea ice area</u>               | <u>[m<sup>2</sup>]</u>                |
| <u>O_motmax</u>          | <u>maximum meridional overturning stream function</u> | <u>[m<sup>3</sup> s<sup>-1</sup>]</u> |
| <u>O_no3sur</u>          | <u>ocean surface nitrate</u>                          | <u>[mol m<sup>-3</sup>]</u>           |
| <u>O_o2</u>              | <u>ocean oxygen</u>                                   | <u>[mol m<sup>-3</sup>]</u>           |
| <u>O_oaragsur</u>        | <u>sea surface omega aragonite</u>                    | <u>[1]</u>                            |
| <u>O_ocalcur</u>         | <u>sea surface omega calcite</u>                      | <u>[1]</u>                            |
| <u>O_pco2sur</u>         | <u>sea surface partial CO<sub>2</sub> pressure</u>    | <u>[ppmv]</u>                         |
| <u>O_phsur</u>           | <u>sea surface pH</u>                                 | <u>[1]</u>                            |
| <u>O_phyt</u>            | <u>ocean phytoplankton</u>                            | <u>[mol N m<sup>-3</sup>]</u>         |
| <u>O_po4sur</u>          | <u>sea surface phosphate</u>                          | <u>[mol m<sup>-3</sup>]</u>           |
| <u>O_salsur</u>          | <u>sea surface salinity</u>                           | <u>[1]</u>                            |
| <u>O_temp</u>            | <u>mean ocean temperature</u>                         | <u>[°C]</u>                           |
| <u>O_tempsur</u>         | <u>sea surface temperature</u>                        | <u>[°C]</u>                           |
| <u>O_totcarb</u>         | <u>total ocean carbon</u>                             | <u>[Pg C]</u>                         |

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