Keery et al., Sensitivity of the Eocene Climate to CO2 and Orbital Variability

Response to M. Crucifix (Referee)

Referee comments in black
Author responses in red

We are very grateful for this thorough review.

1 Summary

Keery et al. present a sensitivity analysis of the Eocene climate to four factors: CO_2 concentration, eccentricity, obliquity, and precession angle. They use, to this end, the PLASIM-GENIE model (details in their section 3) with suitable palaeogeography. The methodology relies on a 50-member hyper-cube sample of a 5-d space (one extra dummy variable was added), and linear modelling with a Information Criteria for model selection. Experiment output are summarised using fit-for-purpose summaries like "tropical-polar temperature difference" and monsoon indices, as well as principal components obtained from a singular value decomposition. The authors conclude on the importance of CO_2 for global mean temperature, and of the orbital elements for the spatial distribution and regional weather systems such as monsoons.

2 Main comments

1. The paper is in the line of a number of recent studies attempting to estimate the relative sensitivity of the climate system to CO_2 and orbital forcing, using a methodology founded on ensemble of experiments. This includes, in addition to the Holden et al. (2015) and Bounceur et al. (2015) cited, Araya-Melo et al. (2015) and Lord et al. (2017). Keery et al. is the only article to focus on the Eocene, which makes it an original contribution. It also uses a much simpler methodology than Araya-Melo et al. (2015), Bounceur et al. (2015), and Lord et al. (2017) because it uses linear regression instead of a Gaussian process emulator. In fact, the authors reference to the word "emulator" is slightly unusual because emulation is, in the climate literature, often used to designate statistical meta-modelling with a focus on uncertainty quantification. Claiming (p. 8) that a "similar emulator approach has been applied by Bounceur et al. 2015" is therefore somewhat misleading. Bounceur et al. and Araya-Melo et al. applied the developments of Oakley and O'Hagan (2004) with, in the case of Bounceur, the additional complication of the PCA emulator.

We agree that the comparison of our emulator to the emulators developed by Araya-Melo et al. (2015) and Bounceur et al. (2015) was misleading, and we will amend this section:

> Our emulator approach uses linear regression, rather than a Gaussian process, and is therefore simpler than the methods applied by Bounceur et al. (2015) in a study of the response of the climate-vegetation system in interglacial conditions to astronomical forcing, and by Araya-Melo et al. (2015) in their study of the Indian monsoon in the Pleistocene.

In spite of its simplicity, we are confident that our approach may be correctly described as an emulator, as it fulfills the criteria described by O'Hagan (2006), and cited by Araya-Melo et al. (2015):

- it is derived from a small number of model runs filling the entire multidimensional input space
- once the emulator is built, it is not necessary to perform any additional runs with the model

In passing, Araya-Melo et Lord used HadCM3 which shows that ensemble-based sensitivity analysis to orbital forcing is doable with GCMs (this qualifies the author's comment on line 15, p.2).

We will amend this paragraph to acknowledge recent ensemble studies using GCMs:

> Climate simulations with high temporal and spatial resolution can be obtained from General Circulation Models (GCMs), but the requirement of GCMs for powerful computers and long run-times makes them difficult to deploy for large ensembles of model simulations and restricts their ability to investigate the large uncertainties in forcings and model parameterisations. Such ensembles are more practical with more heavily parameterised and hence more computationally efficient Earth system Models of Intermediate Complexity (EMICs), (Weber, 2010), although we note that Araya-Melo et al. (2015) and Lord et al. (2017) have deployed the GCM HadCM3 in ensemble-based studies of orbital forcing effects on climates of the Pleistocene and late Pliocene respectively.

Of course, the fact that other authors have adopted a more sophisticated methodology invalidates by no means the approach used by Keery et al.: there may be no need to use a sledgehammer to crack a nut. It remains that the methodological set up used here is a step backwards compared to recent studies, and this arguably requires some justification. How much do we lose with the linearity assumption, and which impact does it have on the uncertainties of the quantification of main effects? (see comment 3. more specifically on main effects).

As we have noted in our methods section, we have demonstrated that the linear models can be used to emulate PC scores with very high correlations to the PC scores derived directly through SVD, with examples from temperature and precipitation shown in Table 3. We can therefore be confident that main effects derived from the linear models are robust. We will amend the text:

> Unlike linear models, GP models are intrinsically stochastic and give a more accurate quantification of their own error in emulating the input data. However, GP models can become computationally demanding in high dimensional space, and their results can be more difficult to interpret.

2. Experiment design. The authors do not say much about the ensemble design, except that this is a latin hypercube. There are many ways to do a latin hypercube, and it usually involves additional constraints.

We will add a detailed description of the method used to generate the latin hypercube in an appendix, include forcing factor values for the full ensumble in a new Table, and we will amend the main text:

> The present study has been designed to facilitate direct comparison between the results for specific ensemble members and their direct counterparts in a related study using the EMIC GENIE-1 (Edwards and Marsh, 2005), which will include additional forcing parameters not used by this PLASIM-GENIE study. We have applied an iterative method to generate a pair of corresponding hypercubes with five and eleven dimensions for the PLASIM-GENIE and GENIE-1 studies respectively, in which the minimum Euclidean distance between any two points is maximised, and linear correlation between any two parameters is minimised. Details of the steps taken to generate the hypercubes are provided in Appendix A. The absolute value of the correlation coefficient r did not exceed 0.1 for any pair of input (forcing and dummy) parameters. Uniform ranges for each of the PLASIM-GENIE forcing parameters and the dummy parameter are shown in Table 1, and the values applied in all 50 PLASIM-GENIE ensemble members are shown in Table 2.

Table 2 Forcing factors and dummy values for each member in the ensemble. Precession = ω, the angle between the moving vernal equinox and the longitude of perihelion.

Member (-)	CO_2 (ppm)	Eccentricity (-)	Precession (°)	Obliquity (°)	Dummy (-)
1	975.6	0.0022	142.5	22.37	0.822
2	2418.7	0.0256	165.2	23.95	0.907
3	1259.4	0.0007	307.1	23.91	0.323
4	801.3	0.0163	270.4	23.50	0.276
5	1720.1	0.0559	206.7	23.82	0.402
6	327.1	0.0595	135.9	23.53	0.681
7	2937.7	0.0418	287.1	22.53	0.650
8	1200.3	0.0237	313.2	24.12	0.978
9	1420.7	0.0158	297.1	23.86	0.931
10	2157.6	0.0432	100.6	23.74	0.661
11	1791.7	0.0241	247.2	23.43	0.429
12	2369.0	0.0425	78.9	22.65	0.167
13	2502.9	0.0296	0.5	22.69	0.122
14	2149.2	0.0405	249.9	24.23	0.347
15	1061.7	0.0394	40.9	23.94	0.189
16	711.3	0.0199	274.6	22.08	0.913
17	1817.1	0.0578	291.4	23.08	0.888
18	722.1	0.0463	195.8	24.38	0.865
19	2988.5	0.0039	110.1	24.40	0.049
20	539.4	0.0251	212.5	23.29	0.234
21	450.6	0.0335	96.1	22.28	0.674
22	2700.1	0.0049	165.9	23.66	0.630
23	2025.4	0.0320	189.4	23.63	0.087
24	2268.7	0.0308	233.3	22.86	0.461
25	1447.2	0.0364	62.0	23.40	0.541
26	1168.3	0.0300	147.4	22.97	0.947
27	1317.6	0.0377	12.4	23.04	0.714
28	1639.5	0.0265	150.9	22.98	0.524
29	399.0	0.0589	262.7	23.46	0.028
30	2876.3	0.0411	203.0	22.05	0.608
31	2611.1	0.0170	54.3	22.84	0.746
32	2831.7	0.0564	187.2	23.72	0.696
33	1998.5	0.0372	278.8	24.19	0.805
34	1465.0	0.0439	38.9	23.50	0.376
35	1660.0	0.0109	85.3	22.88	0.896
36	2393.7	0.0587	127.9	24.27	0.191
37	286.3	0.0004	27.1	23.99	0.391
38	667.4	0.0509	116.5	22.71	0.569
39	2246.8	0.0450	317.4	22.90	0.103
40	2334.2	0.0096	294.7	23.61	0.532
41	2968.2	0.0346	329.8	22.51	0.314
42	768.2	0.0085	218.3	23.00	0.000
43	925.8	0.0450	327.2	24.32	0.753
44	384.5	0.0081	60.6	22.59	0.436
45	850.7	0.0551	322.9	23.21	0.459
46	1112.8	0.0150	356.7	23.27	0.579
47	1255.8	0.0116	212.2	22.31	0.487
48	1124.1	0.0530	343.7	22.40	0.065
49	2113.9	0.0276	9.9	22.19	0.856
50	1681.0	0.0354	175.5	22.45	0.287

In fact this experiment design raises some doubts. For example, why are some secondary structures (periodic up and downs) apparent in the response to obliquity, Figure 5, middle column? Is this just a subjective visual impression?

We have created an additional plot of the two forcing factors obliquity and CO_2, for discussion, but not for inclusion in the paper, and this shows a very similar pattern to the obliquity-MAT subplot in Figure 5, with corresponding clusters and the same slight impression of periodicity. We can therefore be confident that the apparent periodicity noted by the reviewer in the model output is an artefact of randomly generated structure in the model input.

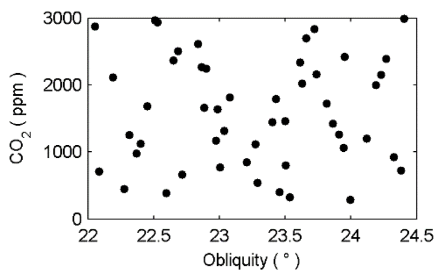

Figure R1 Obliquity plotted against CO_2.

One potentially problematic element is the definition of the sampled astronomical space. It seems that latin hypercube sampling is made on axes along e, ω (longitude of perihelion) and ε. If this is what the authors have been doing then this is non-physical. We know that the astronomical forcing generates effects through seasonal and daily insolation, which are very well approximated by linear functions of e sinω (which the authors call the precession index on Fig. 6) and e cosω. This is the reason why several authors have chosen to sample the astronomical space following the axes e sinω and e cosω and regress against these components. Presumably the regression analysis by Keery is indeed done against these indices but the text is not always clear. Lines 1-2 p. 8. rather suggest that the explanatory variables where sinω and cosω (instead of their multiplication by e) and the lines 4-5 p. 11 are quite confusing. Hopefully the choice of regression variables is mainly matter of text clarification, but the design of the latin hypercube may have a more fundamental problem.

We have indeed constructed our hypercube by sampling independently on e, ω (longitude of perihelion) and ε, but we do not agree that this is non-physical, as there are no combinations of these parameters which can be excluded for the early Eocene period. If we have ignored any information which would imply that some combinations are less likely to have occurred than others (we are not aware of any), then this would only result in a minor reduction in the efficiency with which we fill our state space. We note that precessional effects are well approximated by $e\sin\omega$ and $e\cos\omega$, and that several authors have chosen to sample and regress against these components, but we have chosen not to take this approach, as it would not allow any climatic effects of eccentricity which may exist independently of precession to be identified.

We will amend our description of the forcing factors:

> In order to investigate the sensitivity of the Eocene climate to variation in atmospheric CO_2 and orbital parameters, we have constructed an ensemble of 50 model configurations, each with a unique set of forcing parameters comprising atmospheric CO_2, eccentricity (e), obliquity (ε) and precession (ω), the angle on the Earth's orbit around the Sun between the moving vernal equinox and the longitude of perihelion (Berger et al., 1993). When e is zero, the Earth's distance from the Sun is constant at all points

on the orbit, so there is no precessional effect. The magnitude of precessional effects is controlled by e, while phase is controlled by ω, so precessional effects are commonly described by the precession index given by $e\sin\omega$. The only orbital parameter which alters the total annual solar radiation received by the Earth is e, although the range of variation is very small. We include e and ω as separate and independent forcing parameters, rather than combined as the precession index, or in the form $e\cos\omega$. This approach does not make the assumption that the only effect of eccentricity on the Earth's climate is through its effect on the amplitude of the precession cycle, but allows experimental results to be examined for effects of e and ω either separately or in combination. An additional dummy parameter is included to test for possible overfitting of relationships between forcing parameters and model output fields.

We will also amend our description of our preparation of the forcing factors for linear modelling:

> Values of the forcing parameters CO_2, e and ε (with its very small angular range considered to be approximately linear) were normalised to the range [-1, 1] and combined with $\sin\omega$ and $\cos\omega$ to form 50-element column vectors representing the forcing factors.

3. There may be some confusion about the meaning of the main effects. Saltelli does not use the phrase “first order” to mean linear approximation. In a case where only one factor would matter (be the relationship linear on not), the main and total effects would match (Saltelli et al. (2004), ch. 1 states clearly the definitions; or refer again to Oakley and O’Hagan (2004)). More generally, computing main and total effects is not trivial and always involves some approximations.More details on their computation would be welcome.

We will amend the text to provide more details on the computation of the main effects and total effects:

> In order to analyse the results of each of our linear models, we apply the method described in detail by Holden et al. (2015) to derive the main effects (Oakley and O'Hagan, 2004), which provide a measure of the variation in the linear model output due to each of the terms (first order, second order and cross products), derived from their coefficients, and total effects (Homma and Saltelli, 1996), which separate the effect of each forcing parameter on the variation in the model output. Since the forcing factors are scaled within the range [-1, 1], the variances of the first order, second order and cross product terms can be approximated as $1/3$, $1/9$ and $4/45$ respectively, and we have applied these values as scaling factors in calculating the main effects and total effects.

4. Singular value decomposition is a great dimensionality reduction methodology, but how much is learned by analysing the behaviour of principal components separately is a more contentious subject. Identification of principal components can be fragile to some implementation details, such as, e.g. grid area weighting and experiment design, and the physical phenomena which give rise to climate variability need not be orthogonal. In fact physical modes may project poorly on the orthogonal vectors (Monahan and Fyfe, 2006). These caveats implicitly acknowledged by the authors (p. 11, ll. 20-21) but this state-of-affairs poses some questions about the emphasis on principal components in this article.

We will amend the text to acknowledge these caveats:

> We perform a singular value decomposition to identify the PCs and empirical orthogonal functions (EOFs) of temperature and precipitation fields in the full ensemble, although we note that climate variability may not be due to physical processes which vary orthogonally, and identification of PCs can be influenced by aspects of the experimental design.

3 Minor (scientific) comments

• How Fig. 2 should be interpreted is not entirely clear since the ensemble was not explicitly designed so that the ensemble mean is an estimate of the Eocene climate mean.

Figures 2 and 4 are included to provide an illustrative summary of the spatial distribution and variation of temperature and precipitation in the full ensemble output, without implying that the ensemble mean is an estimate of the Eocene climate mean. We will amend the text:

> Analysis of the model results has focused on variation in surface air temperature and precipitation in both winter and summer in each hemisphere, although it should be noted that our experiment has not been designed such that mean values in our ensemble output represent direct estimates of the Eocene climate mean.

4 Minor (editorial) comments

• Introduce subtitle after section 2.

We will introduce the subtitle 'Climate of the Early Eocene'

• Material about cyclostratigraphy under section 2.1.2. may possibly be considered for shortening as slightly out of scope of the article. This said this is an interesting read.

We would prefer to retain the section on cyclostratigraphy in full, as we believe it provides important details which are relevant to our experimental design, particularly our selection of independent orbital values, and the separation of e and ω.

• PLASIM-GENIE does not need a specific section: it can fall under section 3.Methods.
This section will be moved to the Methods as suggested by both reviewers.

• p. 6 reference Gough (1981) is mistakenly repeated.

The duplicated reference will be removed.

• p. 7, the sentence "We apply the linear algebraic tool SVD" sounds unnecessarily sophisticated. Why not "We perform a singular value decomposition to identifyprincipal components"

We will amend this sentence:

> We perform a singular value decomposition to identify the PCs and empirical orthogonal functions (EOFs) of temperature and precipitation fields in the full ensemble.

• p. 10, l. 27 : define the word "precession" precisely.

We will make amendments to the text to define precession (ω), and the precession index ($e\sin\omega$). See our response to an earlier comment.

• p. 12, ll. 13-17 : introducing new results so close to the closing words is usually not encouraged.

We will delete these results, as further analysis suggests it is difficult to draw any very useful conclusions from the extra experiment, and we will amend the text to include the reference to Anagnostou et al. (2016):

> If atmospheric CO_2 remained within a narrower range throughout the period, for example in the range 700 to 1800 ppm indicated for the early Eocene by Anagnostou et al. (2016) in a recent study using boron isotopes, then outside of short-lived hyperthermals, the relative influence of CO_2 and orbital inputs might have been more evenly balanced.

5 Digital material

• Relevant data of the Eocene runs (at least the summaries and experiment input data) could be provided.

We will include the values of forcing factors for the 50 member ensemble in a new Table.

References

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