We would like to thank both reviewers for their comments that helped improve our manuscript. Please see below replies to all comments. The reviewers' (RC1) comments are in black, our replies in blue, and any updated or new text from the revised manuscript in "*quoted blue italics*". All line numbers mentioned below are from the submitted manuscript.

Reviewer 1

Singh et al. "Modelling framework for asynchronous land-atmosphere coupling using NASA GISS ModelE and LPJ-LMfire: Design, Application and Evaluation for the 2.5ka period"

GENERAL

This study simulates the climate of the 2.5 ka period using the NASA GISS ModelE, which is asynchronously coupled to the dynamic vegetation model LPJ-LMfire. The authors conducted several sensitivity experiments to assess the impacts of initial land cover and bias correction on paleoclimate and ancient vegetation. Additionally, they used multiple proxy datasets to validate the simulation results. While this study represents a considerable effort in developing a modeling framework and conducting numerical simulations, the robustness of the main results is questionable, and the study's novelty remains unclear.

First, the study lacks sufficient novelty. The primary focus is on asynchronous land-atmosphere coupling between a climate model and a vegetation model. However, it is unclear why this coupling approach warrants extensive application, as it does not appear to enhance the simulated paleoclimate. As shown in Fig. 12, temperature anomalies exhibited the lowest biases in the 2.5k_PI_ctrl simulation, which did not include asynchronous land-atmosphere coupling. This finding suggests that vegetation coupling has a minimal impact on improving model performance, thereby weakening the study's novelty.

The novelty of this modeling framework is that this methodology represents a pragmatic approach for simulating the past climate conditions using the climate models without having the dynamic vegetation components, which is different from what we and other such models are currently following under PMIP4. In this study, we applied this methodology for the 2.5ka period, which is not among the standard periods selected for paleoclimate simulations under PMIP4, but crucial for the emergence of several complex societies and their climate interactions. Testing this for the 2.5ka period explicitly demonstrated a very broad and generic applicability of this framework, which can be used either by us for another period, or other modelers, since we describe in detail the steps to be taken and the metrics to be used to objectively quantify when equilibrium has been achieved. Along with highlighting the novelty at several places, a sentence is added into the abstract:

"*This study also presents a framework for incorporating biogeophysical responses into climate models without dynamic vegetation, for simulating past climates, in line with the recommendations of the Paleoclimate Modelling Intercomparison Project (PMIP)*."

The explanation for figure 12 was incomplete, and that might have created confusion, we apologise for that. We modified the figure and the discussion around it, so that the reader will not miss the main points behind it. Please see the detailed changes we made below, where we replied to the specific question about the figure 12 (figure 6 in revised, as per reviewer2's suggestion to move this section earlier). The key point that the reviewer missed because of our presentation of that figure is that the runs with the updated vegetation are actually better than the standard preindustrial one (lowest biases) when compared against reconstructions.

Second, the key sources of discrepancies remain unexplored. While the authors compared results from multiple experiments, they primarily noted that bias correction led to a warmer and more stabilized climate, without further investigating the underlying causes of climate variations across different simulations. In particular, the influence of initial vegetation cover, climate variability, and climate-vegetation interactions on the simulated paleoclimate should be explicitly quantified and explained.

We thank the reviewer for highlighting the need for greater clarity in presenting the results. Accordingly, we have revised the paragraph (L626–L635) by adding the following sentence at its beginning.

"It shows that the 2.5 ka control simulation with present-day vegetation is comparable to pre-industrial conditions, exhibiting a slightly cooler climate. In contrast, proxy-based surface temperature reconstructions (Kaufman et al., 2020) indicate slightly warmer conditions at global mean as well as across most latitude bands, except the far south (60S-90S). Applying bias correction allows the model to reproduce the same anomaly sign as the reconstruction, with minimal global (90N-90S) mean bias relative to the proxy data (2.5k_PI_BC_LPJ and 2.5k_GS_BC_GISS). Although the magnitude of warming remains higher at the northern hemisphere high latitudes, this framework demonstrates improved capability for incorporating biogeophysical effects of past vegetation by adopting bias correction."

Furthermore, the δ18O validations revealed similar biases across different experimental configurations (Fig. 15), raising the question: what is the added value of employing different model configurations?

Figure 15 (figure 9 after revisions) illustrates that, despite the high sensitivity of the modeling framework to various factors, The model successfully captures key regional climate features across different areas. This highlights the need for additional paleoclimate proxy reconstructions to enable a more robust evaluation of the model's skill in simulating past regional climates. (See the conclusion section, lines 731–743.)

SPECIFIC

Line 40: "The coupled model system is sensitive to the representation of shrubs." What is the underlying reason for this particular sensitivity? Is this a characteristic of this specific model, or is it a general feature of all coupled models?

This is one of key sensitivity features noticed from the NASA-GISS ModelE-LPJ-LMfire coupling framework and reported as an abstract point of this study. The underlying reason is that the alteration of arid shrubs (over Northern African Region) and cold shrubs (Northern hemisphere high latitudes) with bare soil and trees, respectively, changed the surface albedo, and, consequently, the vegetation-albedo feedback substantially modifies the regional climate (Charney et al., 1977; Charney, 1975; Doughty et al., 2012; Stocker et al., 2013).

We found this being a characteristic of the particular coupling between GISS ModelE and LPJ-LMfire, and it is a feature of ModelE. We cannot generalize this conclusion to other models.

We modified the sentence as given below:

"The NASA GISS ModelE found to be particularly sensitive to the representation of shrubs, implying that this land cover type requires particular attention as a potentially important driver of climate in regions where shrubs are abundant."

Lines 176-177: How well does the LPJ model perform in simulating present-day vegetation? It would be more appropriate to validate the LPJ model using observed meteorological data and vegetation parameters rather than relying solely on PI simulations.

These lines in the text do not refer to an LPJ simulation but rather the boundary conditions used to force the initial (0th order; 2.5ka) simulation of ModelE. Nevertheless, LPJ has been shown to simulate realistic global distributions or present-day biogeography (Sitch et al., 2003) and wildfire (Pfeiffer et al., 2013; Thonicke et al., 2010). In the description of LPJ-LMfire (section 2.1.2) we added a few words to emphasize that the model has been evaluated in the context of contemporary observations.

"LPJ-LMfire has been successfully validated for simulating present-day biogeography and fire regime characteristics, and its outputs have been compared against contemporary observations (Sitch et al., 2003; Thonicke et al., 2010; Pfeiffer et al., 2013)."

Line 207: What observational datasets could be used to validate the derived 'wet days? Additionally, models tend to overestimate the frequency of small rainfall events, which suggests that the nonlinear relationship derived from observations may not be directly applicable to model outputs.

We thank the reviewer for this insightful comment. It is precisely because climate models tend to overestimate the frequency of small rainfall events (positive drizzle bias) that instead of using daily (or 6-hourly) precipitation from the ModelE output to provide the wet days variable required by LPJ-LMfire, we use a dataset based on daily observations of precipitation (CRU TS). Since this observational dataset is not available for periods in the past, we use the local regression model as an empirical, observation-based way of estimating wet days under paleoclimate conditions. This simple relationship does not capture non-linearities, but in the absence of past precipitation data we can't know the extent of such non-linearities, let alone include them in our calculations.

Line 220: "Adding interannual variability"—why is this an important consideration? How do simulations differ with and without interannual variability?

We added the following in the text in section 2.3.3:

"*LPJ requires climate input data with interannual variability because fires and other disturbance events occur only in years with anomalous climate, for example hot or dry years Sitch et al. (2003). Driving the model with a climatological mean climate will result in disturbance frequencies that are lower than the expected mean, that in some regions would lead to an overabundance of tree cover when we would expect herbaceous vegetation*."

Also, since the ModelE simulations presented here include a dynamic ocean, and interannual variability such as the El Niño–Southern Oscillation has a significant impact on global temperature and precipitation, excluding this variability would bias and distort our results.

Line 235: What is the connection between plant functional types (PFTs) and fire frequency? Please clarify the underlying mechanism.

High fire return interval will favor early successional plant functional types because the elapsed time since the last disturbance would not have been long enough for the establishment and/or dominance of late successional plant functional types. By definition, late-successional plant functional types require long periods of low disturbance to be present in ecosystems.

We have added a sentence to section 2.3.3 to clarify this point.

"High fire frequency favors early-successional PFTs because the time between disturbances is shorter than that required for establishment. By definition, late-successional PFTs require extended periods of low disturbance to persist within the ecosystem"

Line 243: "A predefined threshold"—Is this threshold applied uniformly at the global scale, or do different grid cells use varied thresholds? How was this threshold determined?

Yes, this classification is applied uniformly over the global scale. We modified this sentence: "A *globally-uniform* predefined threshold".

Tree growth is one of fundamental and widely adopted criteria for vegetation models to distinguish different PFT types (forest trees, shrubs, herbs) (DeFries et al., 1995; Kim et al., 2015)(DeFries et al., 1995; Kim et al., 2015). Thus, we designed and evaluated a set of thresholds here as detailed in table S1, which is already cited in the manuscript.

Line 272: "climate vegetation models"—this phrase is missing an "and" (should be "climate and vegetation models").

It is corrected as "*climate and vegetation models*".

Line 285: "Linearly interpolating"—Are there any proxy datasets available to constrain vegetation cover for the 2.5 ka period? How would different initial conditions affect the final simulated vegetation cover? Additionally, how can the derived paleo-vegetation be evaluated?

No, we don't have any proxy dataset to constrain the vegetation for 2.5ka.

As mentioned in the text, we interpolated linearly for 2.5ka from the mid-Holocene (6ka) vegetation proposed to reproduce the green Sahara conditions under PMIP4 protocol (Otto-Bliesner et al., 2017). The model simulation using this linearly interpolated vegetation, represented as shrubs and grass over North Africa and boreal forest over the northern high latitudes, substantially modified the surface albedo in the Northern Hemisphere. This vegetation–albedo feedback increased the pole-equator thermal gradient, shifting the ITCZ northward and consequently strengthening the African and South Asian monsoons (Singh et al., 2023).

The derived paleo vegetation represents the global climate response to the slowly varying orbital forcing which is, for time periods much shorter than the various cycles, effectively linear. Precessional cycles are 20 kyr. Obliquity cycles are 40 kyr. Eccentricity is 100 kyr. We have interpolated over 3 kyr.

Table 2: The reasoning behind the different simulation lengths across various experiments is unclear. What criteria were used to determine the duration of each experiment?

The varying simulation length across experiments primarily results from differences in the number of iterations performed for each setup. Based on the analysis, we used the following criteria to evaluate the model equilibrium during any iteration and convergence across the various iteration

1.) Model equilibrium: We evaluate the model equilibrium based on the condition that the absolute value of the decadal-mean planetary radiative imbalance should be < 0.2 W m^{-2}. We also evaluate the trend in global surface temperature, which (in absolute value terms) should be <0.1 ^{o}C/50 years within a 20-year moving window, and should change sign more than once across the last 100 years of equilibrium, which demonstrates oscillation around zero, rather than a small positive or negative bias.
2.) Convergence across each iteration: We evaluated model convergence across iterations by comparing the mean climate of the equilibrated model run with that of the previous iteration. For example, the plot below shows a comparison of the simulated annual surface temperature between iterations 4 and 3 of the experiment "2.5k_GS_BC_GISS". We performed similar evaluations for other diagnostics, such as ground albedo and net planetary radiation, as well as the spatial vegetation distributions, with each corresponding previous iteration.

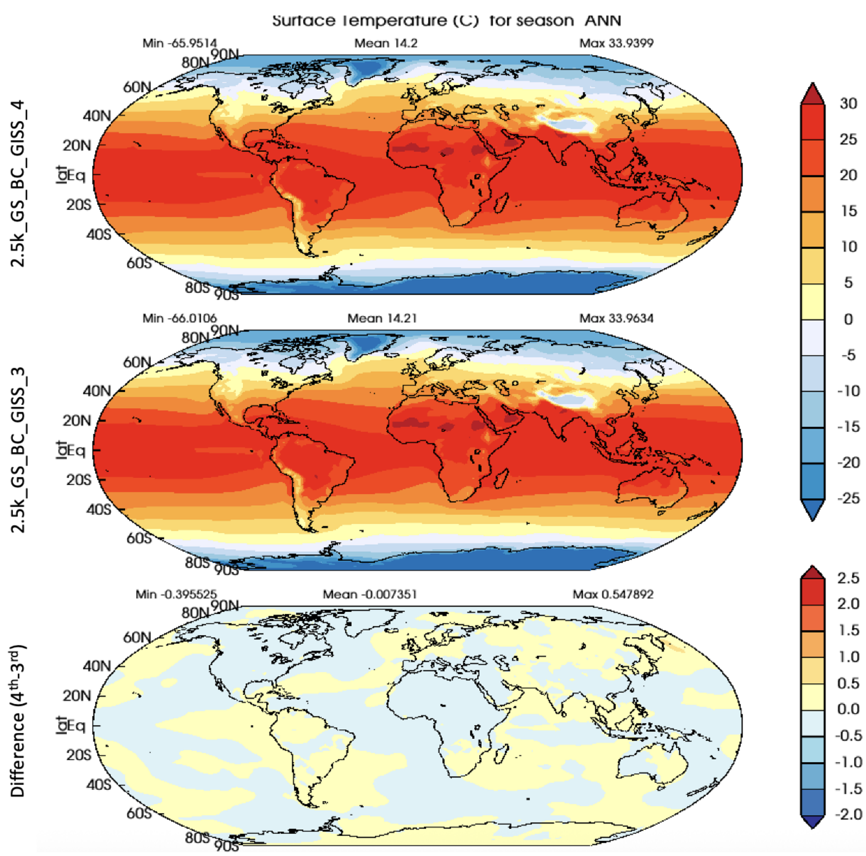

Figure Mean surface temperature for iterations 4 (top) and 3 (middle) for the 2.5k_GS_BC_GISS simulation, and difference between the two iterations (bottom).

We added the following sentences in section 3.0:

"Model equilibrium is determined using the threshold that the absolute value of the decadal-mean planetary radiative imbalance must be < 0.2 W m^{-2}, along with the surface temperature trend (absolute value <0.1 C/50 years). Convergence across iterations is evaluated by comparing the annual mean climate state and vegetation distributions between successive iterations."

Figure 3: Is it reasonable to use present-day satellite-derived land cover for PI simulations? Please provide justification.

The tradeoff in doing paleoclimate and even early historical climate simulations is that the forcing changes to the climate system are relatively larger, but the constraining data sparser. Thus, unfortunately, observations of the entire world are somewhat lacking in the pre-satellite era and biased heavily towards Europe and North America. Thus, the background vegetation during the vegetation in pre-industrial times is prescribed globally by combining not only the global retrieval of vegetation, but also global estimates of fraction of anthropogenic land-use. The natural vegetation fractions remain the same per grid box, but anthropogenic (crop) land-use changes with time, which suppresses natural vegetation as crops expand (Matthews, 1983).

Lines 389-391: These sentences belong in the figure captions rather than the main text.

We believe that these lines are important, as they refer to the supplementary figures in context to the discussion of land cover changes under asynchronous coupling. No changes made.

Figure 10: The differences between LPJ and GISS, as well as between PI and GS, are relatively minor. The most significant differences appear between x and BC. This conclusion should be explicitly stated and explained in the main text.

Thanks for pointing this out. It suggests that internal variability is not substantially different between the two models (LPJ and GISS), thus their consequences are not noticeable during the asynchronous coupling. Whereas, in the case of partial greening over Sahara, the GISS model initially produced an increase in precipitation over North Africa (in the initial run), but this northward propagation of ITCZ over Africa didn't sustain in subsequent iterations or at the equilibrated simulation.

Thus, we added the following sentences in the abstract.

"The asynchronously coupled model system shows strong vegetation-albedo feedback on climate and is comparatively more sensitive to the bias correction than the internal model variability and green Sahara conditions."

We also added a sentence at the end of the abstract culminating the overall objective of this study. (L42).

"This study presents a generalized framework for incorporating biogeophysical responses into climate models without dynamic vegetation, for simulating past climates, in line with the recommendations of the Paleoclimate Modelling Intercomparison Project (PMIP)"

and similar statements highlighted this outcome in the section "6.0 Discussion and Conclusion" section (see L710 and L749)

Figure 11: In some regions, differences among simulations are substantial, while in others, they are minimal. What accounts for these regional variations? What role does vegetation play in shaping these differences?

The annual cycle of precipitation broadly shows an increase over the Indian subcontinent during the summer months and North American region during all peak precipitation months, and a decrease over the European regions during the summer months. The increase in precipitation over North America and India is more intense when bias correction is applied. This might be due to an increase in the equator-to-pole thermal gradient coupled with the vegetation-albedo feedback. In the case of partial greening over Sahara, the model initially produced an increase in precipitation over North Africa, but this northward propagation of ITCZ over Africa didn't sustain in subsequent iterations.

On the other hand, the intense decrease in summer precipitation over the European region is common among all experiments. This suggests the loss of needleleaf and cold deciduous broadleaf trees and increase of c3-grass might have contributed to the regional drying, instead of the increased warming the bias correction imposed. The loss of needleaf trees is stronger in the absence of bias correction, resulting in a stronger decrease in European regional precipitation.

We added these sentences in the corresponding

"Overall, the changes in annual precipitation cycle (increases or decreases) over the regions are primarily driven by both the pole-equator thermal gradients in the various experiments, as well as the biogeophysical effects associated with regional vegetation changes over these regions (e.g. Indian Summer monsoon, North American and European region) (Pausata et al., 2014; Tiwari et al., 2023; Singh et al., 2023)"

Section 5: This section should be positioned before the analysis for better logical flow.

We moved Section 5 before the analysis; this is now named as section 4.

Figure 12: Proxy data appear to be more consistent with PI simulations than with the 2.5 ka simulation. What is the purpose of bias correction or climate-vegetation coupling if it does not improve the agreement with proxy data?

We apologize for the poor annotation in the submitted version of this figure, which caused the misconception that the PI simulations are better than the 2.5K ones. In Fig 12 (Figure 6 after revision), the 2.5k_PI_ctrl simulation which follows the PMIP4 protocol and uses present-day vegetation, it aligns right on top of the PI control line (1850_PI_ctrl; horizontal line in the submitted figure, and cyan-colored symbols in the modified figure below and the revised manuscript). That simulation does not compare as well with Kaufman's multi-proxy estimates for 2.5ka, whereas the experiments with the bias corrections (2.5k_PI_BC_LPJ and 2.5k_GS_BC_GISS; dark green and orange symbols) more closely match with Kaufman's estimates of mean difference from pre-industrial period for global (90S-90N) as well as over the tropical (0-30N and 0-30S) latitude bands.

We enhanced Figure 12 by adding the "1850_PI_ctrl" in the plot, and also modified the text under section 5.1 (section 4.1 after revisions) as given below.

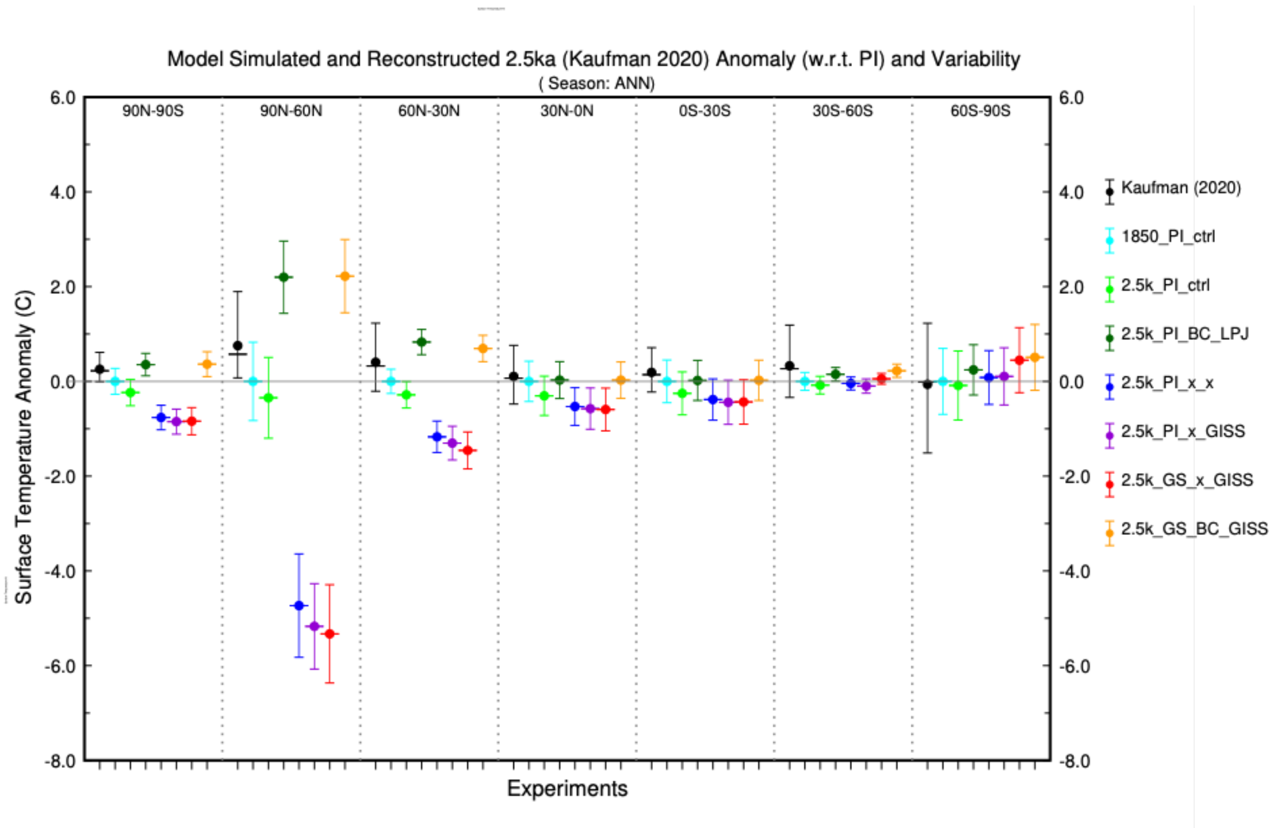

Fig 12:[Figure 6 after revision] Comparison of model-simulated annual surface temperature anomalies and interannual variability for 2.5ka (with LPJ-LMfire vegetation) against the independent proxy-based temperature reconstructions (black, Kaufman et al., 2020). Mean (circle), median (line) along with 5-95 percentile range as variability bars (whiskers) and different colors represent the final iteration of our different experiments. (AFTER Revision it is figure 6 now)

"It shows that the 2.5ka control simulation with present-day vegetation is comparable to pre-industrial conditions (1850_PI_ctrl), exhibiting a slightly cooler climate. In contrast, proxy-based surface temperature reconstructions (Kaufman et al., 2020) indicate slightly warmer conditions at global mean as well as across most latitude bands, except the far south (60S-90S). Applying bias correction allows the model to reproduce the same anomaly sign as the reconstruction, with minimal global (90N-90S) mean bias relative to the proxy data (2.5k_PI_BC_LPJ and 2.5k_GS_BC_GISS). Although the magnitude of warming remains higher at the northern hemisphere high latitudes, this framework demonstrates the improved capability of the model to reproduce reconstructions via incorporating biogeophysical effects of past vegetation by adopting a bias correction".

Line 640: How is isotopic composition represented in the model simulations? Please provide details on its setup.

We added some citations for the implementation of isotopes in ModelE: "*The details of the implementation of water isotopes are described elsewhere (Schmidt 1998; Aleinov and Schmidt 2006; LeGrande et al 2006)*". We also included the text below in section 5.2: (AFTER revision section 4.2)

"The isotopic composition of oxygen in water, expressed as the ratio of ^{18}O to ^{16}O serves as a fundamental tracer for investigating changes in the hydrological cycle. This ratio is highly sensitive to regional climate conditions and to the processes that regulate the hydrological cycle, such as temperature, precipitation, and evaporation. ModelE2.1 includes a representation of the stable water isotopologues as passive tracers and the isotopic composition of precipitation can be diagnosed from the model output (Schmidt 1998; Aleinov and Schmidt 2006; LeGrande and Schmidt 2006)".

References (Both RC1 & RC2)

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