Constraining clouds and convective parameterizations in a climate model using paleoclimate data

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Key Points:

- Paleoclimate simulations show greater sensitivity to parameter perturbations, allowing for an evaluation of uncertainties over a wider range of climate states
- Certain simulations reproduced the $\delta^{18}O$ of precipitation from paleoclimate proxies better than the default parameterization
- Not a single set of parameters works well in all climate states likely due to varying boundary conditions influencing cloud feedbacks

Abstract

Cloud and convective parameterizations strongly influence uncertainties in equilibrium climate sensitivity (ECS). We provide a proof-of-concept study to constrain these parameterizations in a perturbed parameter ensemble of the atmosphere-only version of the Goddard Institute for Space Studies (GISS) Model E2.1 simulations by evaluating model biases in the present-day runs using multiple satellite climatologies and by comparing simulated $\delta^{18}O$ of precipitation ($\delta^{18}O_p$), known to be sensitive to parameterization schemes, with a global database of speleothem $\delta^{18}O$ records covering the Last Glacial Maximum (LGM), mid-Holocene (MH) and pre-industrial (PI) periods. Relative to modern, paleoclimate simulations show greater sensitivity to parameter changes, allowing for an evaluation of model uncertainties over a broader range of climate forcing and the identification of parts of the world that are parameter sensitive. Certain simulations reproduced absolute $\delta^{18}O_p$ values across all time periods and LGM and MH $\delta^{18}O_p$ anomalies relative to the PI better than the default parameterization. Not a single set of parameterizations worked well in all climate states, likely due to the non-stationarity of cloud feedbacks under varying boundary conditions.

Plain Language Summary

Equilibrium climate sensitivity (ECS) is a key climate metric that quantifies the rise in global mean surface temperature in response to doubling of atmospheric CO_2 relative to pre-industrial levels. Changes in hydroclimate, temperature extremes, and other aspects of the climate system in future projections, as well as mitigation and adaptation decisions, are closely tied to a model's ECS. For decades, estimates of ECS have remained wide despite improvements from using multiple lines of evidence. One persistent source of this spread is related to cloud and convective processes, which occur at scales too small to be explicitly resolved, and thus require parameterizations to be represented in climate models. These parameterizations directly influence water isotopes by modulating simulated cloud cover, rainfall and atmospheric circulation, and thus can be used to constrain model processes and identify model biases. In this study, we first demonstrate that paleoclimate simulations including the Last Glacial Maximum (LGM), mid-Holocene (MH) and pre-industrial (PI) periods are more parameter sensitive than the modern, covering wider regions of the world that can discriminate among perturbed parameter ensemble members, thus, highlighting the potential of paleo-simulations in better constraining cloud and convective parameterizations. We then identified the top performing parameterization using multiple satellite climatologies and proxy-model comparisons using the oxygen isotope of precipitation where we considered the sensitivity of a proxy site to parameter changes. Our proxy-model comparisons (i.e., absolute values) show an excellent agreement in all runs and time periods but two parameterizations, also supported by the satellite analysis, emerged to perform better than the default GISS parameterization. We also find that simulations are able to capture broad scale LGM-PI and MH-PI oxygen isotope of precipitation patterns, with the latter showing reduced model skill. Similar to the absolute value comparisons, the best parameterization differ for each time period likely due to varying cloud feedbacks under diverse climatic forcing. Overall, our results provides a framework for fine-tuning model representations using paleoclimate data which provides a unique opportunity to assess model uncertainties over a broader range of climate variability than is afforded by the instrumental period and identifying target regions where future archive and proxy development may be most valuable.

1 Introduction

Cloud and convective processes vary at scales significantly smaller than a general circulation model (GCM) grid box, requiring them to be parameterized on simulated grid-scale variables (Boucher *et al.*, 2013). Such parameterizations employ different assumptions (Lopez, 2007) and thus representation of cloud and convective effects in climate models inherently hold large uncertainties. Cloud and convective parameterizations, aside from aerosol schemes and aerosol-cloud interactions (Meehl *et al.*, 2020), are considered the leading source of inter-model spread in equilibrium climate sensitivity (ECS) estimates (Dufresne and Bony, 2008; Sherwood *et al.*, 2014; Webb *et al.*, 2015; Zelinka *et al.*, 2020) and consequently, the broad range of future climate projections (Flato *et al.*, 2013; Sherwood *et al.*, 2014). The latest generation of climate models participating in Coupled Model Intercomparison Project Phase 6 (CMIP6) have an average ECS value of 3.9°C and range from 1.8°C to 5.6°C (Zelinka *et al.*, 2020), which is higher and more variable than the CMIP5 models (i.e., mean of 3.3°C and range of 1.5°C to 4.5°C (Flato *et al.*, 2013; Knutti *et al.*, 2017)) and estimates from Intergovernmental Panel on Climate Change Assessment Report 6 (i.e., mean of 3°C with a very likely range of 2°C to 5 °C, (IPCC, In Press)). Constraining cloud and convective parameterizations may potentially help narrow ECS uncertainties.

A perturbed parameter ensembles (PPE) experiment, which creates different versions of a climate model by systematically changing a parameter value within a reasonable range, is particularly useful in assessing how much of the uncertainties are explained by parameter choices. Typically, clouds and convective parameterizations are chosen based on the bias score between the climate model and an observational dataset, usually from satellite remote sensing which dates back to 1994 (Mauritsen *et al.*, 2012; Galewsky *et al.*, 2016). However, in the context of future climate change, these observational datasets only offer a fraction of the range of climate change projected over the next 100 years. Finding ways to constrain these choices on a broader variety of climates in thus desirable. Moreover, in a traditional PPE approach, models are not typically re-tuned into radiative balance after altering a single tuning parameter (Schmidt *et al.*, 2017), which may have important implications in resolving or revealing biases from previous compensating errors (Collins *et al.*, 2011). However, not much is known whether this tuning approach after each parameter change is preferable especially when considering a broader range of climate states.

Widely observed through satellites and preserved on various paleoclimate archives, water isotopes provide a common means to understand present and past climates. Water isotopes serve as integrative tracers of the hydrologic cycle due to molecular differences in mass that drive fractionation during water phase changes. In the atmosphere, the variability in the oxygen isotopic composition of precipitation ($\delta^{18}O_p$) is driven by several local and non-local processes including the origin and initial isotopic composition of the water vapor in an air parcel, amount of rainout, evaporation of rainfall, seasonality and temperature history, and mixing with other air parcels (Dansgaard, 1964; Galewsky *et al.*, 2016; Gat, 1996; Noone, 2008). Increasingly incorporating water isotopes in model simulations has significantly advanced our understanding of the mechanisms that govern their variability in broader spatiotemporal scales (Galewsky *et al.*, 2016).

Previous studies have demonstrated the sensitivity of water isotope ratios to perturbations in cloud and convective parameterizations in isotope enabled GCMs, signifying their utility in evaluating model performance and potentially identifying model biases (Bolot *et al.*, 2013; Bony *et al.*, 2008; Field *et al.*, 2014; Lee *et al.*, 2009; Schmidt *et al.*, 2005; Nusbaumer *et al.*, 2017).

For example, excessive diffusive advection and high convection frequency were shown to cause significant model biases in the isotope enabled Laboratoire de Météorologie Dynamique Zoomed version 4 (LMDZ4, (Risi *et al.*, 2012)) and Community Atmosphere Model version 5 (CAM5, (Nusbaumer *et al.*, 2017)) models, respectively. In the atmosphere-only version of Goddard Institute for Space Studies (GISS) Model E2, water isotopes were found to be more sensitive to parameter changes than traditional diagnostics such as precipitation and temperature, likely related to cumulus entrainment strength (Field *et al.*, 2014). These models were compared against modern water isotope observations from satellites (e.g., Aura Tropospheric Emission Spectrometer (TES), (Worden *et al.*, 2007)); Scanning Imaging Absorption Spectrometer for Atmospheric Cartography (SCIAMACHY), (Frankenberg *et al.*, 2009)), providing a spatially robust means of constraining model results.

Variability in water isotopes may also be obtained from various paleoclimate archives that are not only spatially well-distributed but are also available across timescales drastically different from today, such as the Last Glacial Maximum (LGM; 21 ka, or kilo-years before present) and mid-Holocene (MH; 6 ka) periods. The LGM corresponds to a time when global ice volume was at its maximum and greenhouse gas concentrations were lower than today, both driving major changes in the atmosphere compared to present conditions (Pausata *et al.*, 2011; Kageyama *et al.*, 2021; Tierney *et al.*, 2020b). During the MH, insolation is seasonally amplified in the Northern Hemisphere, with larger winter-to-summer temperature differences and associated changes in the hydrological cycle (Brierley *et al.*, 2020; Otto-Bliesner *et al.*, 2006). Performing proxy-model comparison across these contrasting time periods thus allows for evaluating model performance over the full range of hydroclimatic variability in the Earth system.

One excellent source of past hydroclimatic information are speleothems. Speleothems are secondary cave deposits that form from dissolution of carbonate bedrock through water action. While their geographical distribution is largely constrained by the geology of a region, speleothems form under a broad range of hydroclimatic regimes ideal for investigating predominant regional patterns. Variations in speleothem $\delta^{18}O$ largely reflects the $\delta^{18}O$ of soil ($\delta^{18}O_s$) and groundwater percolation, which in turn is heavily influenced by $\delta^{18}O_p$ above the cave and other processes within the karst system (Fairchild and Baker, 2012; Lachniet, 2009). Early speleothem $\delta^{18}O$ compilations and the more recently available Speleothem Isotope Synthesis and Analysis (SISAL) database (Atsawawaranunt *et al.*, 2018; Comas-Bru *et al.*, 2020, 2019), a large global compilation of speleothem isotope records since the last glacial, have aided in evaluating GCM performance across the LGM and MH time periods (Caley *et al.*, 2014; Cauquoin *et al.*, 2019; Comas-Bru *et al.*, 2019; Werner *et al.*, 2016) and have served as an independent validation check in reconstructions of glacial temperature fields (Tierney *et al.*, 2020a), demonstrating their usefulness in benchmarking isotope enabled paleoclimate simulations. However, not all parts of the world are equally influenced by cloud and convective parameter changes, implying that proxy record locations may be more or less constraining against simulations. This has not been fully quantified in existing paleoproxy-model comparisons and/or analyses of model-satellite discrepancies both globally and restricted to proxy sites only.

In this study, we explore cloud and convective parameterizations (Table 1) in the GISS-E2.1 climate model (Kelley *et al.*, 2020) that likely have a significant impact on water isotope distribution and ECS. We use two sets of atmosphere-only simulations: one that has been re-tuned into radiative equilibrium in the pre-industrial (hereafter referred to as the balanced version) and another which only changes the parameters (hereafter referred to as the unbalanced version), to evaluate whether this approach is preferable in simulations of past climates with large differences in radiative forcing. We investigate the variability and sensitivity of key climate variables to cloud and convective changes and identify parameter-sensitive sites in the present-day (PD, year 2000) and paleoclimate simulations covering the pre-industrial (PI, 0 ka), MH and LGM periods. We also compare and evaluate the model simulations against multiple satellite climatologies and assess the agreement between simulated $\delta^{18}O_p$ and speleothem $\delta^{18}O$ from the SISAL version 2 (SISALv2, Comas-Bru *et al.*, 2020) database. This proof-of-concept study presents a basis to which we determine the best suite of parameters representing clouds and convective processes across distinct time periods, critical in improving isotope-enabled models and thus, ECS and climate projections.

Table 1. Parameter space exploration of GISS-E2.1.

Short Name	Parameter	GISS-E2.1 default	New Value	Mean Surface Air Temperature, °C (global, NH, SH)	Mean Precipitation, mm/day (global, NH, SH)	Radiation balance at TOA, W/m^2 (PI, MH, LGM)
std	standard	----	----	13.99,14.31,13.67	2.96,2.88,3.03	0.098,0.663,-1.92
rev	rain re-evaporation above cloud base	On (1)	Off (0)	13.80,14.04,13.53	0.63,0.63,0.62	0.013,0.094,1.46
entr50-50	entrainment rate for plume (1 & 2)	0.4; 0.6	0.5; 0.5	13.98.14.29,13.66	2.98,2.90,3.06	0.168,-0.04,-2.00
entr60-40			0.6; 0.4	14.02,14.33,13.70	2.95,2.87,3.02	-0.156,-0.304,-2.20
entr20-80			0.2; 0.8	14.00,14.28,13.72	2.91,2.82,3.01	0.134,0.018,-1.80
tconvadjX2	convection adjustment time	1	2	14.00,14.28,13.72	2.97,2.86,3.06	0.107,-0.062,-2.08
trigger1.1	convective trigger	2	1.1	13.96,14.29,13.63	2.98,2.90,3.06	0.289,0.061,-1.98
trigger1.2			1.2	13.96,14.29,13.62	2.98,2.90,3.06	0.289,0.162,-1.98
trigger0.99			0.99	13.98,14.30,13.66	2.98,2.89,3.06	0.046,-0.101,-2.11
trigger1.3			1.3	13.97,14.28,13.66	2.98,2.91,3.05	0.289,0.162,-1.98
trigger1.0			1.0	13.98,14.30,13.66	2.98,2.90,3.06	0.047,-0.101,-2.11
droprad50-50	cloud droplet radius (liquid- ice)	1; 1	0.5; 0.5	13.87,14.11,13.62	2.87,2.76,2.98	-0.194,-0.52,-2.92
droprad50-130			0.5; 1.3	14.17,14.52,13.82	2.91,2.81,3.00	0.249,0.067,-1.54
droprad130-50			1.3; 0.5	13.76,14.00,13.53	2.97,2.89,3.05	-0.164,-0.475,-2.96
droprad30-130			1.3; 1.3	14.01,14.36,13.67	2.99,2.91,3.06	0.032,-0.625,-1.80

critQ2-2	critical cloud water content (liquid & ice)	2; 1	2; 2	14.00,14.32,13.68	2.96,2.86,3.05	0.085,-0.153,-2.12
critQ1-0.5			1; 0.5	14.00,14.34,13.67	2.99,2.90,3.08	0.181,0.135,-1.92
critQ1-4			1; 4	13.95,14.26,13.64	2.96,2.87,3.06	-0.020,-0.168,1.13
critQ2-4			2; 4	13.96,14.30,13.63	2.95,2.85,3.05	0.142,-0.04,-2.23

2 Materials and Methods

2.1 NASA GISS E2.1

Simulations were conducted using the atmosphere-only GISS-E2.1, a CMIP6 submission described in length in Kelley et al. (2020). Relative to GISS-E2 (Schmidt *et al.*, 2014), the default E2.1 configuration has an improved treatment of mixed-phase clouds, improvements in the planetary boundary layer parameterization, and systematic increases in convective entrainment rates (Kelley *et al.*, 2020), though these rates are perturbed as part of this study as detailed below.

Water tracers ($^{1}H_2{}^{16}O$, “normal” water; $^{2}H^{1}H^{16}O$, δD; and $^{1}H_2{}^{18}O$, $\delta^{18}O$; where permil (‰) $\delta \equiv 1000 * [(R_{std}/R_{smow})-1]$) were included in the land surface, sea ice, sea surface, and atmosphere. These isotopes are tracked through all stages of the water cycle and are advected like water through the model with appropriate fractionation during each phase change (LeGrande and Schmidt, 2009; Schmidt *et al.*, 2005, 2007).

2.2 Time slice experiments

We performed three paleo-time slice experiments as described for the LGM (Kageyama *et al.*, 2021, 2017), MH (Otto-Bliesner *et al.*, 2017) and PI (Eyring *et al.*, 2016). These followed the Paleoclimate Modelling and Intercomparison Project (PMIP4) and CMIP6 protocols (Kageyama *et al.*, 2017; Otto-Bliesner *et al.*, 2017). For each time slice, appropriate changes to topography, bathymetry, and land-ocean-ice mask (LGM: Glac1D, Abe-Ouchi *et al.*, 2013;

Briggs *et al.*, 2014; Tarasov and Peltier, 2002; Tarasov *et al.*, 2012); river routing (Licciardi *et al.*, 1998, 1999; Peltier, 2004); vegetation cover (Ray and Adams, 2001); orbital changes (Berger and Loutre, 1991); greenhouse gases (Indermühle *et al.*, 1999); standard mean ocean water, salinity and water isotopes (Fairbanks, 1989) were made (Table 2). All these runs were completed to surface equilibrium in GISS-E2.1-G (Kelley *et al.*, 2020); the surface sea ice fraction, sea ice thickness, and sea surface temperatures were then recorded. Coupled simulations are computationally expensive, and thus, surface conditions were used in this proof-of-concept study to drive a new suite of GISS-E2.1 simulation (CMIP6) in atmosphere-only mode with the same forcing conditions to create the LGM, MH and PI runs. We conduct one further present-day (PD) experiment to facilitate comparison with the satellite products, using year 2000 atmospheric constituents and a climatological mean from Hadley for 2000-2015 for ocean surface conditions (Table 2).

Table 2. Summary of forcing and boundary conditions for each time slice experiment. All experiments applied topography, bathymetry, land-ocean-ice mask, greenhouse gas, river routing and appropriate SMOW changes.

Time slice	**Ice sheet**	**SST/SICE**	**GHG**	**Mean salinity, psu**	**SMOW ($\delta^{18}O$, δD)**
Present Day	modern	Hadley Obs	year 2000	34.7	0‰, 0‰
PI, 0 ka	modern	CMIP6: PI	year 1850	34.7	0‰, 0‰
MH, 6 ka	modern	CMIP6: MH	6 ka	34.7	0‰, 0‰
LGM, 21 ka	Glac1D	CMIP6: LGM	21 ka	35.7	1.0‰, 8.0‰

2.3 Cloud and convective parameterizations and model tuning

GISS-E2.1 regularly uses five tuning parameters (Kelley *et al.*, 2020). Here, we re-tuned the model by altering cloud reflectivity (Schmidt *et al.*, 2017), after each parameter change to ensure that the decadal top of the atmosphere net planetary radiation is within 0.2 W/m^2 during a pre-industrial simulation (i.e., balanced version). We conduct a parallel set of experiments where this tuning was not done (i.e., unbalanced version) to check that the tuning itself is not influencing our interpretation. Ideally, this positions us to complete fully coupled simulations to explore the full range of variability imparted by these clouds and convective changes during the paleoclimate simulations. However, these experiments are computationally expensive, and beyond the scope of this proof-of-concept study (but are planned in the future). The practical consequence is that variability over the ocean especially is throttled, and the climate system during the paleoclimate runs may no longer be in radiative equilibrium (a symptom of the incomplete climate response to the strong paleoclimate forcing perturbed parameter runs); we note the net top of the atmosphere radiative balance of each simulation (Table 1).

The basic structure of the clouds and convection schemes are described in (Del Genio, 2012; Del Genio *et al.*, 2015; Kim and Kang, 2012). We have chosen here to explore six different parameters utilized in the cloud and convection schemes that likely have a substantive impact on ECS as well as water isotope distribution (Table 1). A total of 19 simulations were performed for each time period. Parameters chosen are ones not directly constrained by current in situ or satellite observing platforms.

Rain re-evaporation above the cloud base (*rev*) has been a parameter previously considered for change because it improves convection and variability (e.g., Madden-Julian Oscillation in Kim and Kang, (2012)). This parameter makes the GISSE-2.2 model distinct from the GISSE-2.1 (Rind *et al.*, 2020). Water isotopes are sensitive to changing this parameter (Field *et al.*, 2014). Increasing this parameter results in additional atmospheric moistening and a subsequent increase in precipitation over the Maritime Continent (i.e., increased bias); however, it does improve isotopic matches between GISS-E2.1 simulations and satellite observations (Worden *et al.*, 2007).

The entrainment rate (*entr*) parameters control how much environmental mass is entrained into a less- and more-entraining convective plume. At most, two updraft plumes are permitted to initiate at each model level in the GISS convective scheme, and the only requirement is that they have different entrainment rates thus allowing a representation of shallow (i.e., more entraining) and deep (i.e., less entraining) convective towers within any convective cloud ensemble in the GCM grid box.

The convective adjustment time (*tconvadj*) is a parameter that controls how quickly convective mass reaches the tropopause, and thus how quickly the environmental profile of temperature and moisture adjusts to moist convective processes.

The convective trigger (*ctrigger*) parameter determines what environmental conditions are necessary for initiating convection. Physically this parameter can be interpreted as accounting for the multi-faceted role that the planetary boundary layer plays in convective initiation (e.g., turbulent lifting of parcels, variations in near-surface stability or moisture across a grid box), the role of vertical wind shear, the role of mesoscale ascent causing local destabilization, or the role of gravity waves in the weakening of convection-inhibiting stable layers.

The radius multiplier (*droprad*) is a parameter that governs the sizes of liquid droplets and ice particles for a given condensate amount. Though there are some observational estimates of sizes at cloud tops, within-cloud estimates are largely unconstrained (and particularly within convection, where attenuation of radiometric signals are substantial). In general, smaller sizes result in clouds reflecting more shortwave radiation coincident with reduced outgoing longwave radiation.

Auto-conversion of cloud water content to precipitation is governed by a critical cloud water content scaling parameter (*critQ*). Any liquid or ice water content above the scaled critical threshold will be converted to precipitation via auto-conversion, thus affecting cloud condensate, cloud fractions, and in turn, radiation.

2.4 Satellite data

Our perturbed parameter configurations are balanced and evaluated using multiple present-day satellite climatologies provided by the Obs4MIPS project (https://esgf-node.llnl.gov/projects/obs4mips/) hosted on the Earth System Grid Federation (https://esgf.llnl.gov). Top of the atmosphere absorbed shortwave (SWabsTOA) and outgoing longwave radiation (OLR), along with cloud radiative forcing estimates (SW_CRE, and LW_CRE) are provided by the CERES EBAF Edition 4.1 product (Kato *et al.*, 2018; Loeb *et al.*, 2018, 2020). Temperature and water vapor profiles are provided by AIRS Version 6 retrievals (Tian *et al.*, 2019; Tian and Hearty, 2020) for altitudes at and below 600 hPa, and by MLS Version 4 satellite retrievals (Waters *et al.*, 2006) at and above 200 hPa. Column integrated total (cloud plus precipitating) liquid water estimates (TLWP) are provided by the MAC-LWP (Elsaesser *et al.*, 2017) and TRMM 3A12 (Kummerow *et al.*, 2001) products, while the column integrated ice counterparts (TIWP) are provided by the CloudSat 2C-Ice (Deng *et al.*, 2015) R05 and MODIS C6 (Marchant *et al.*, 2016; Platnick *et al.*, 2015; Yi *et al.*, 2017) products. Total precipitation (prec) is provided by GPCP Version 2.3 (Adler *et al.*, 2003) and TRMM TMPA (Adler *et al.*, 2009; Huffman *et al.*, 2007) Version 7 products. Convective precipitation (prec_mc) is provided by the GPM Dual-frequency Precipitation (DPR) Radar product (Iguchi *et al.*, 2012). Global total cloud cover (tcc_isccp) is provided by the ISCCP (Rossow and Schiffer,

1999) D1 total cloud fraction product, while surface wind estimates are provided by the QuikSCAT satellite and Remote Sensing Systems surface wind products (Wentz and Schabel, 2000; Wentz *et al.*, 2007).

We compared these multiple satellite climatologies to the perturbed parameter simulations and computed both global and proxy site-averaged root mean square error (RMSE) scores.

2.5 Paleoclimate data

To evaluate the atmosphere-only $\delta^{18}O_p$ simulations, we used land-based paleoclimate constraints which are less impacted by the lack of surface ocean and ice feedbacks in these runs, minimizing proxy-model mismatches that may be expected from including ice core records. We use the latest Speleothem Isotope Synthesis and Analysis (SISAL) version 2 database (Comas-Bru *et al.*, 2020) and extracted 378 speleothem records from a total of 224 unique sites. In this version, multiple age models for most cave sites were generated but we used the original published chronologies in obtaining mean $\delta^{18}O$ over the following time periods: LGM (21 ± 1 ka), MH (6 ± 1 ka) and PI (last 2 ka). Depending on the mineralogy (i.e., calcite or aragonite), mean $\delta^{18}O$ values (VPDB) were converted to their drip water equivalents analogous to $\delta^{18}O_p$ (VSMOW) (Comas-Bru *et al.*, 2019). We used model-generated mean annual SAT extracted at the grid points nearest the cave sites as representative for cave temperatures required in the drip water conversion. Records where mineralogy is unknown or mixed were excluded. Multiple records in a single site and model grid box were then averaged except for those that report large dating errors (e. g., Kesang Cave, (Cai *et al.*, 2017)). A total of 257, 195 and 81 records were obtained for the PI, MH and LGM periods, respectively.

2.6 Sensitivity to perturbations and proxy-model comparison

To assess the spatial sensitivity of $\delta^{18}O_p$ to perturbations in cloud and convective parameterizations, we derived z-scores for each experiment, $z = \frac{(x-\mu)}{\sigma}$; where x is the mean $\delta^{18}O_p$ of an ensemble member, μ is the PPE mean and σ is the standard deviation greater than the mean decadal variability of each experiment per grid box. We counted the number of ensembles per grid box where the absolute value of the z-score is greater than 1 and then normalized the total against the number of PPE runs to derive a sensitivity score. A maximum score of 1 indicates that all 19 ensemble members show significant difference from the PPE mean, and thus the highest sensitivity to parameter changes. We similarly evaluated the spatial sensitivity of PREC and SAT to parameter changes.

Simulated $\delta^{18}O_p$ were extracted from the nearest grid points to the cave sites and compared with that of the proxy for each period, and time slice anomalies with PI as the baseline. Skill statistics were calculated over each time period using a weighted least square regression. The weights applied to the extracted grid points were from the derived sensitivity scores of a $\delta^{18}O_p$ grid box to changes in cloud and convective parameterizations to highlight the strength of a proxy site in discriminating among perturbations.

3 Results

3.1 Spatial sensitivity to perturbations in clouds and convective parameterizations

Based on the resultant spatial variability of precipitation (PREC), surface air temperature (SAT), and $\delta^{18}O_p$ (Text S1 in the supporting information), we derived scores that represent the number of ensembles per grid box showing significant difference from the PPE mean (see

Section 2.6) to highlight spatial sensitivity to parameterization choices. Using the simulations from the balanced version, PREC and $\delta^{18}O_p$ are more sensitive to parameter changes, with nearly 50% of the overall land surface showing significant difference from the mean across all time periods (Figure 1). SAT, on the other hand, show less sensitivity, covering less than 30% of the total land surface.

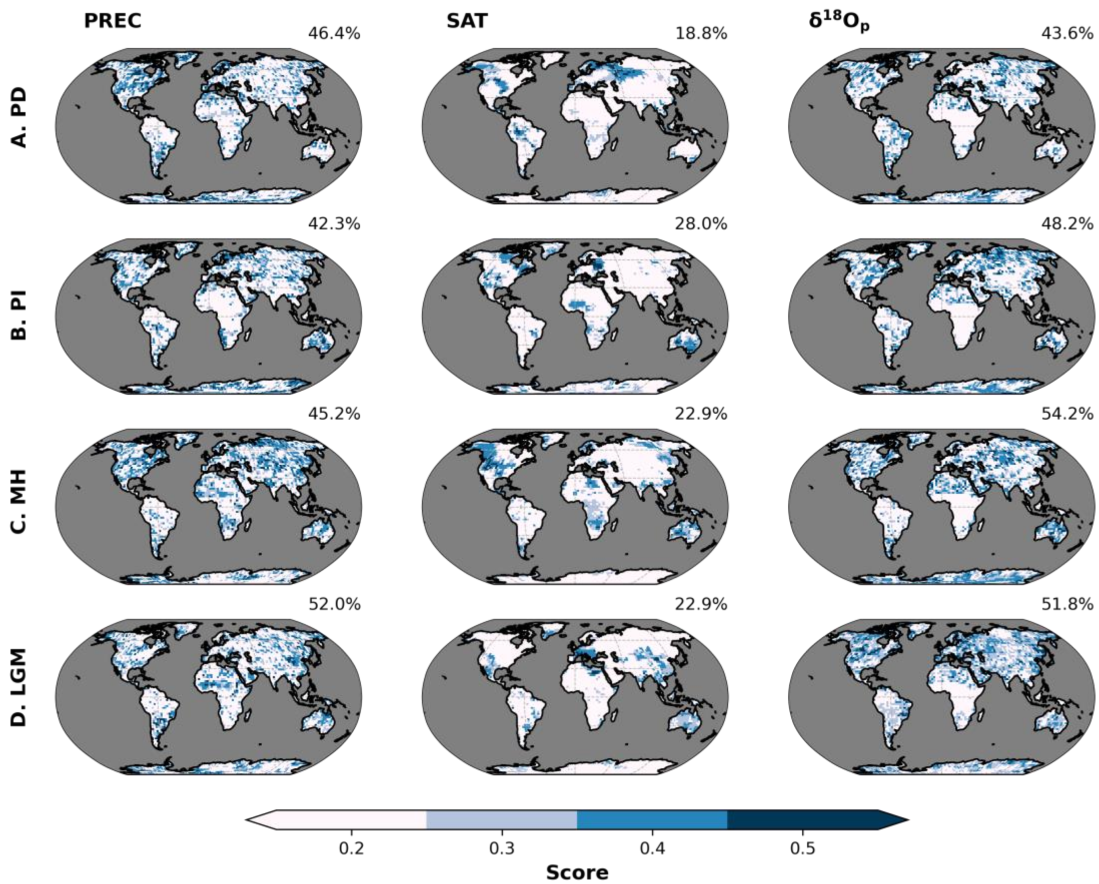

Figure. 1. Spatial sensitivity of precipitation (PREC), surface air temperature (SAT), and $\delta^{18}O_p$ to perturbed cloud and convective parameters for different time periods (a-d). Shading represents the scores or the fraction of the total number of ensembles per grid box showing significant difference from the PPE mean. The higher the score, the more sensitive a location is to parameter changes. The oceans are masked to highlight changes on land for these atmosphere-only simulations. Percentages reported at the top right of each panel indicate the fraction of land surface (using PD configuration) having a score greater than 0.2.

The regions that are *most* sensitive to clouds and convective processes in the GISS-E2.1 simulations of SAT are spatially varying across time periods while that of PREC and $\delta^{18}O_p$ are located away from deep convection zones (Figure 1). Sensitive regions consistently include North America, subtropical South America, Europe, western and northern Africa, north Asia, middle East, and Australia across time periods, forming the key sites to which model results may be principally constrained by the presence of viable paleo-proxy records.

Relative to the PI period, sensitive regions for each variable increase in extent in the MH and LGM periods (Figure 2), indicating that paleoclimate simulations are more sensitive to parameter changes relative to the modern, supporting the premise of this proof-of-concept study that paleoclimate simulations may be better at discriminating cloud and convective parameterization changes across multiple PPE members than modern.

This observation is consistent with that of the unbalanced version, however, the spatial extent of highly parameter-sensitive sites has decreased across all time periods (Text S1, Figures S3 and S4 in the supporting information), indicating that tuning can impact model sensitivity.

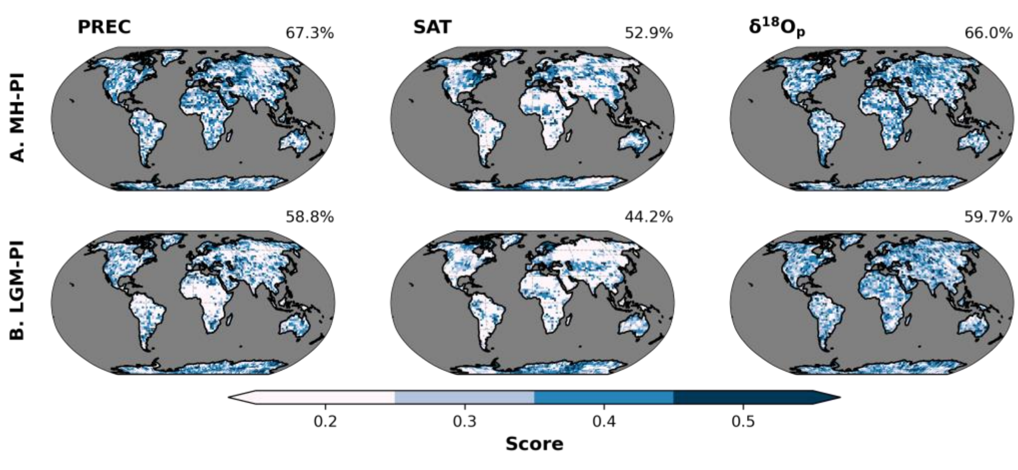

Figure 2. Spatial sensitivity of precipitation (PREC), surface air temperature (SAT), and $\delta^{18}O_p$ to perturbed cloud and convective parameters for (a) MH-PI and (b) LGM-PI. Shading represents the scores or the fraction of the total number of ensembles per grid box showing significant difference from the PPE mean. The higher the score, the more sensitive a location is to parameter changes. The oceans are masked to highlight changes on land for these atmosphere-only

simulations. Percentages reported at the top right of each panel indicate the fraction of land surface (using PD configuration) having a score greater than 0.2.

3.2 Model evaluation using multiple satellite climatologies

Radiation, cloud, and thermodynamic variables from modern PPE simulations are compared to satellite estimates provided largely from the Obs4MIPS archive (Waliser *et al.*, 2020) (see Section 2). It is often the case that inter-product differences for any cloud or thermodynamic variable exceeds published random noise or uncertainty estimates. Such differences arise due to systematic regime-dependent unknowns in satellite cloud and precipitation remote sensing (Duncan and Eriksson, 2018; Elsaesser and Kummerow, 2015; Liu *et al.*, 2017). To avoid root mean square error (RMSE) scores being dependent on any one satellite product choice, we explicitly account for satellite product systematic biases by allowing no contribution to RMSE if the model field falls within the observational range bounded by the minimum and maximum product estimates.

RMSE derived for global, as well as for grid boxes co-located only with proxy sites, are shown in Figure 3. Across the board, RMSE is lower with a more muted response across PPE members for proxy site locations, where on average, both total and convective rainfall are a factor of ~2 less than most convectively active tropical regions. Less convection implies a smaller reliance on convective and cloud parameterizations, and a less complex atmosphere to simulate. Both *entr60-40* and *tconvadjX2* are most skillful for proxy site PREC, with a 5-10% reduction in RMSE compared to *std*, the default mode for GISS-E2.1; *entr60-40* was the configuration exhibiting subtle improvement across more diagnostics than other PPE members. The top performer changes when considering global scores to *droprad50-50* and *droprad130-50,* with both exhibiting the lowest global RMSE for PREC.

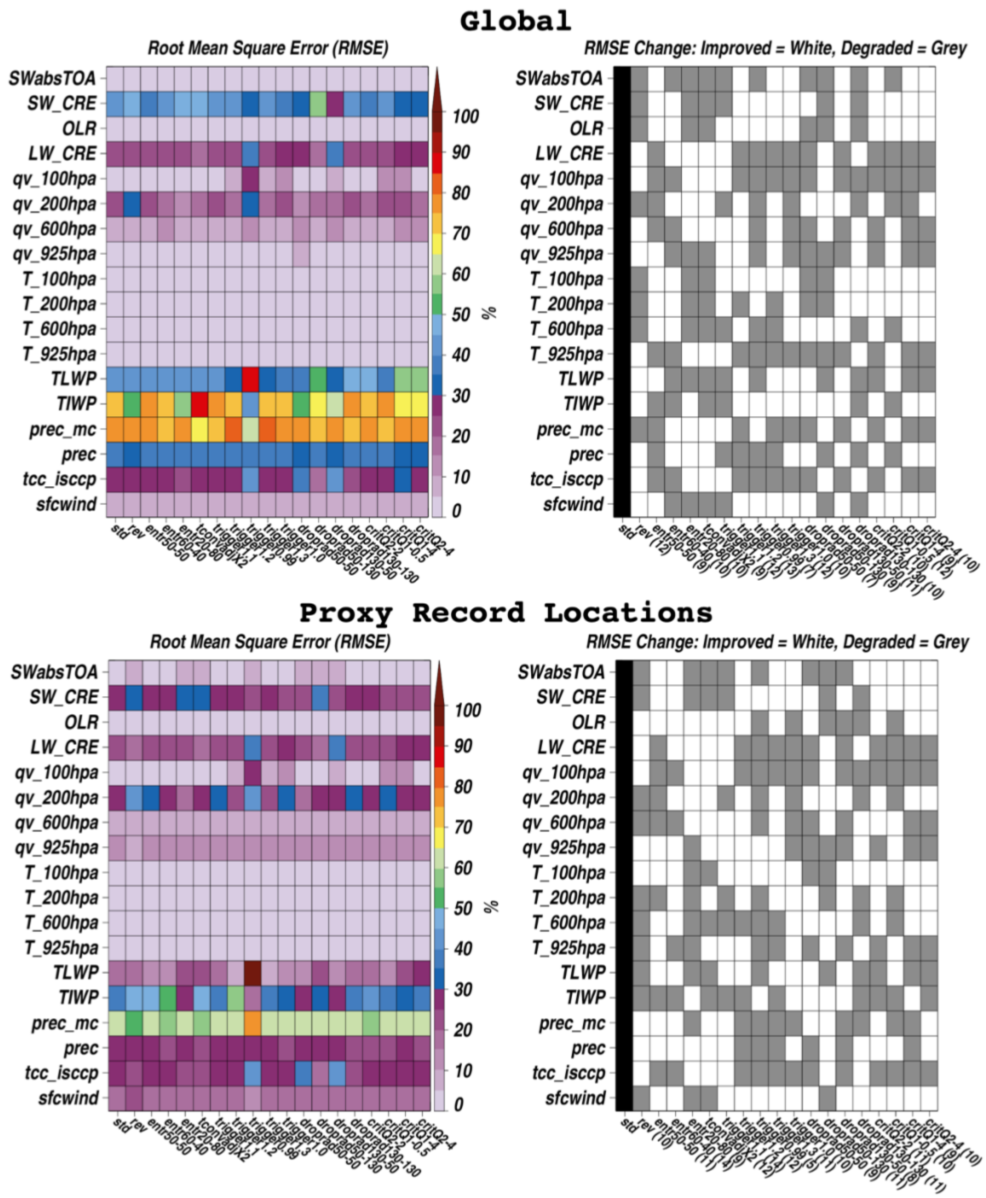

Figure 3. Comparison of model with satellite data. (top left) Global model-satellite RMSE scores for absorbed shortwave (SW) radiation at the top of the atmosphere (SWabsTOA), SW cloud radiative effects (SW_CRE), outgoing longwave radiation (OLR), longwave (LW)_CRE, water vapor (qv) and temperature (T) at various levels, total (cloud+precipitating) liquid and ice water paths (TLWP, TIWP), convective and total precipitation (prec_mc, prec), ISCCP satellite cloud cover (tcc_isccp), and 10-meter surface wind speeds (sfcwind). (top right) binary white-gray shading indicating if RMSE scores improved for a given ensemble member relative to *std*, with numbers indicating the number of metrics exhibiting improvement. (bottom row) As in the top row, but only for model and satellite grid boxes co-located with paleo-proxy sites.

3.3 Model evaluation using proxy data under PI, MH and LGM conditions

Our selected proxy database comprises a total of 257, 195 and 81 records for the PI, MH and LGM periods, respectively. From each of the models, we extracted the simulated $\delta^{18}O_p$ nearest each cave site. As shown in our proxy-model comparisons (Figure 4), the mean $\delta^{18}O_p$ distribution in all runs and time periods are in excellent agreement with the proxies. In these comparisons, we prescribed weights to the simulated $\delta^{18}O_p$, based on Figure 1, which gives importance to the spatial sensitivity of a particular site to parameter changes. This significantly improved the overall proxy-model agreement compared to the unweighted calculation (Figure S6-a to -s and S7 in the supporting information).

While these first order comparisons show excellent agreement, discrepancies remain; for example, simulated $\delta^{18}O_p$ is more negative (positive) at low (mid- to high) latitude speleothem sites compared to the proxies, with those from the LGM exhibiting the largest offsets (Figure 4). These discrepancies could be due to cave specific factors and model limitations (see Discussion) that may exacerbate proxy-model mismatches. Because simulated $\delta^{18}O_s$ has the potential to better reflect processes within the karst system, we then compared the proxies with the $\delta^{18}O_s$ model results. Comparisons show high and significant correlations across all time periods (Figure S8 in the supporting information) with the enriched $\delta^{18}O_s$ values showing a better match. However, the mismatch between the depleted $\delta^{18}O_s$ values remain leading to an overall lower agreement compared from using simulated $\delta^{18}O_p$ (Figure S9 in the supporting information).

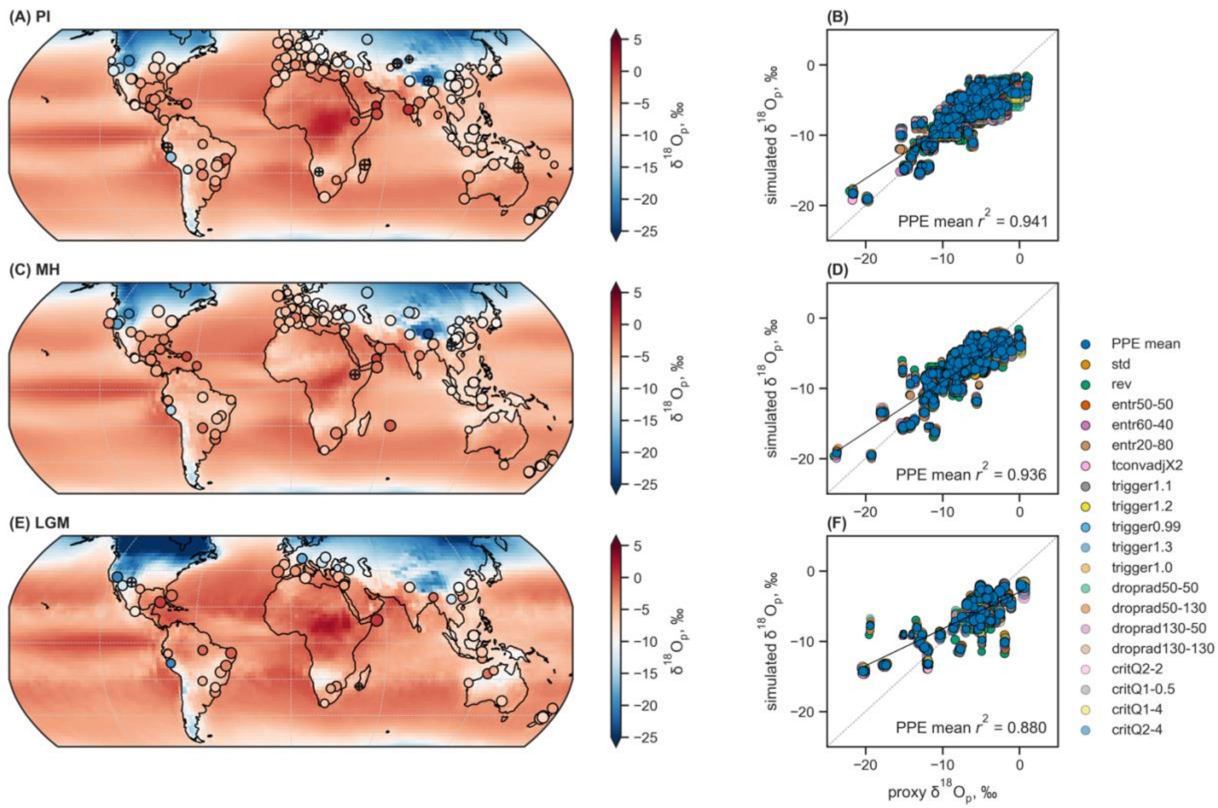

Figure 4. Comparison of simulated $\delta^{18}O_p$ with speleothem $\delta^{18}O$. Global distribution of simulated $\delta^{18}O_p$ (background) and speleothem $\delta^{18}O$, converted to their drip water equivalents (See Materials and Methods) under (a) PI (n = 257), (c) MH (n = 195) and (e) LGM (n = 81) conditions. Background and extracted data points are from the PPE mean. SISAL $\delta^{18}O$ points with standard deviation greater than 1 are marked with '+'. Scatterplots between simulated and proxy $\delta^{18}O_p$ for the respective time periods (b, d, f). PPE members are differentiated by color. Black lines represent the weighted least squares regression fits to data points while the gray dashed lines represent the 1:1 line. Weighted r^2 for the PPE mean is reported in the lower right corner of each scatterplot. The size of the circles in all plots are scaled to the sensitivity scores derived in Figure 1. Results for each ensemble member are in Figure S6-a to S6-s in the supporting information.

Spread among the weighted r^2 values in each parameterization is small (standard deviation, $\sigma < 0.05$, Figure 5), indicating that the parameterization choices do not drastically impact $\delta^{18}O_p$ simulations, consistent with the proxy site-collocated satellite results. Nonetheless, certain simulations represent an improvement from the *std* run. The entrainment rate for plume (*entr20-80*) parameterization exhibits the highest skill for the PI period, whereas the convection adjustment time (*tconvadjX2*) parameterization best represents cloud and convective processes for the MH and LGM periods. Considering only the sites common across the time periods (i.e., limited by the number of LGM sites), the *entr20-80* parameterization became one of the poorest performing models for the PI period. However, another entrainment rate scheme, *entr60-40*, emerged as the best performing parameterization for PI. The *tconvadjX2* parameterization remained the best performing scheme for the MH, indicating that the reduced number of data points did not affect the model evaluation for this time period. These results, broadly consistent with best performers derived from satellite comparisons (considering only the proxy sites), suggest that while different cloud and convective scheme settings do not necessarily impose large changes on the model results for the sites considered, the *best* parameterization for each time period varies depending upon the boundary conditions.

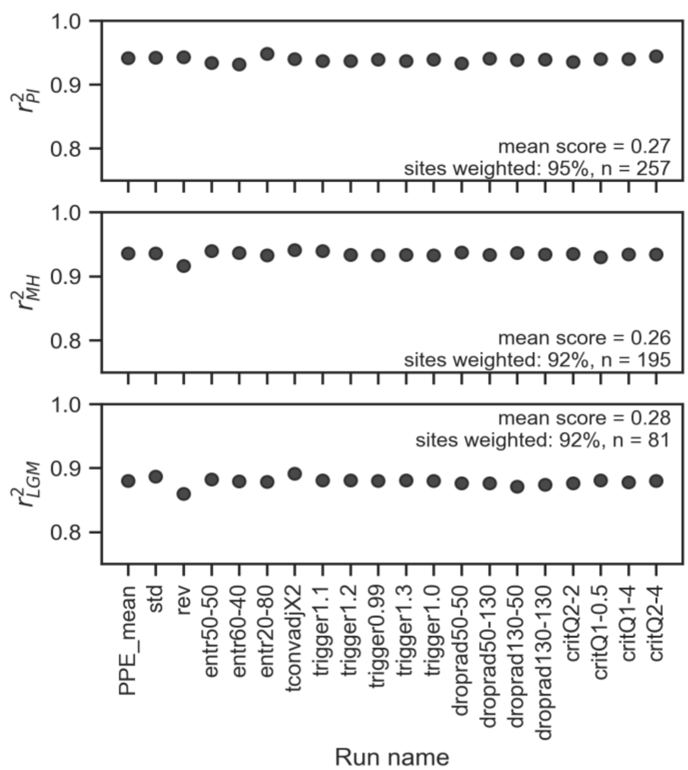

Figure 5. Weighted r^2 values between simulated $\delta^{18}O_p$ and SISAL $\delta^{18}O$. All speleothem $\delta^{18}O$ were converted to their drip water equivalent.

3.4 LGM and MH isotopic changes and model performance

To investigate the impact of parameter changes on the relative shift in $\delta^{18}O_p$, we computed anomalies between the LGM and MH relative to the PI. LGM-PI anomalies consist of 17 records whereas MH-PI anomalies contain 79 records. Similar to the absolute value comparisons, we prescribed weights (extracted from Figure 2) to the simulated $\delta^{18}O_p$ anomalies. The spatial distribution of simulated LGM-PI $\delta^{18}O_p$ in the PPE mean shows an overall depletion over land, with the northern latitudes (i.e., ice sheet over North America and Europe) exhibiting the greatest negative $\delta^{18}O_p$ excursions (Figure 6A). In contrast, the mid-latitudes are only slightly depleted while the Amazon, northern Africa, Himalayas, and oceanic regions show overall positive $\delta^{18}O_p$ anomalies. Comparison with SISAL $\delta^{18}O$ anomalies show moderate and statistically significant ($p < 0.011$) proxy-model relationship (Figure 6B, Figure 7) with at least 70% of the records sharing similar signs. The strong positive and negative anomalies observed in Paraiso cave, Brazil, and Sofular cave, Turkey, respectively, are not captured by the models, where simulated $\delta^{18}O_p$ changes instead show values closer to zero. The spread among the weighted r^2 values remains small ($\sigma < 0.08$, Figure 7). The *tconvadjX2* parameterization outperformed the *std* run, exhibiting the lowest proxy-model mismatch compared to other parameterization results (Figure 7). Notably, this simulation also performed best in the absolute value comparisons for the LGM period.

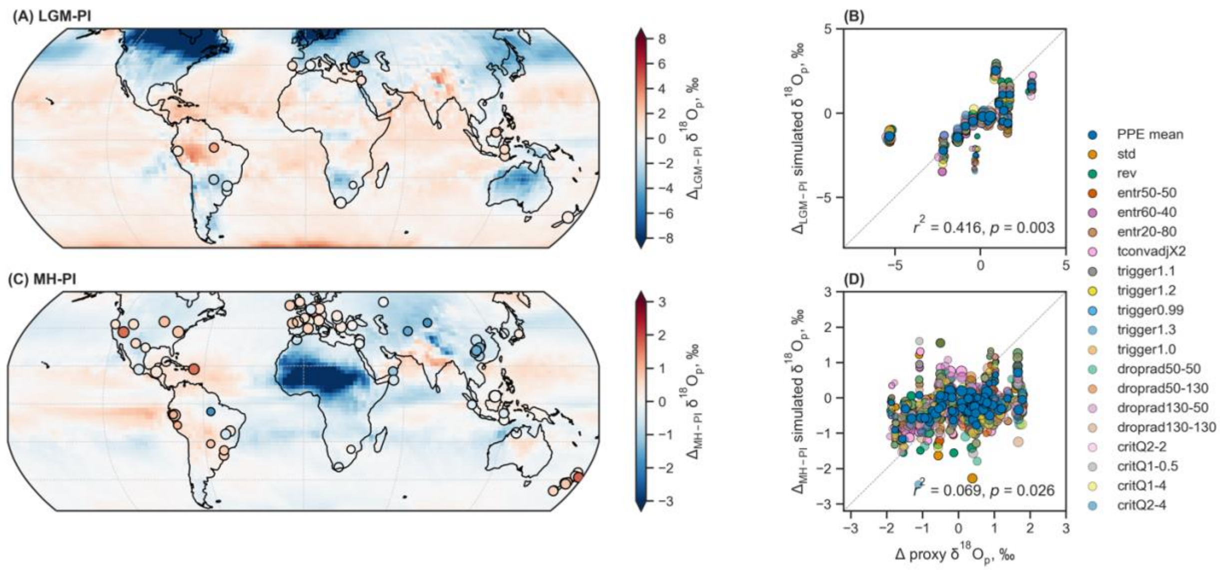

Figure 6. Comparison of simulated $\delta^{18}O_p$ anomalies (background) with speleothem $\delta^{18}O$ (filled circles) for each time slices: (a) LGM-PI (n = 17), (c) MH-PI (n = 79). Background and extracted data points are from the PPE mean. Scatterplots between simulated and proxy $\delta^{18}O_p$ for the respective time periods (b, d). PPE members are differentiated by color. Gray dashed lines represent the 1:1 line. Weighted r^2 for the PPE mean is reported in the lower right corner of each scatterplot. The size of the circles in all plots are scaled to the sensitivity scores derived in Figure 2. Results for each ensemble member are in Figure S10-a to S10-s in the supporting information.

Compared to LGM variations, MH changes relative to PI are more modest. Interior South America, India and Australia show positive $\delta^{18}O_p$ anomalies in the PPE mean (Figure 6C). In contrast, North America, Eurasia, Himalayas, and East Asia show negative $\delta^{18}O_p$ anomalies, with the western and central African region showing the greatest negative $\delta^{18}O_p$ excursions. Proxy-model agreement across runs lack skill in replicating MH-PI isotopic changes observed in the SISAL records (Figure 6D, 7), with only 40% of the records showing similar signs in the PPE mean. Isotopic changes over East Asia and the Maritime Continent are quite robust with respect to the proxies. The largest deviations are found in North and Central America (South America) where positive (negative) anomalies are not reflected in the simulated $\delta^{18}O_p$ changes. Overall, the magnitude of change is consistently smaller in the simulations (Figure 6D). Of the 19 simulations, only 9 PPE members show statistically significant (p < 0.04) relationship, outperforming the *std* $\delta^{18}O_p$ run (Figure 7). The best performing parameterization is *droprad130-50* (weighted r^2 = 0.11, Figure 7), where 59% of the data points now share similar signs. Notable regions of observed improvement are in Europe and Central Asia (Figure S10 in the supporting information). Reducing the number of datapoints to match the sites from the LGM-PI changes shows a different result such that the *critQ2-4* parameterization now shows the highest skill (weighted r^2 = 0.45).

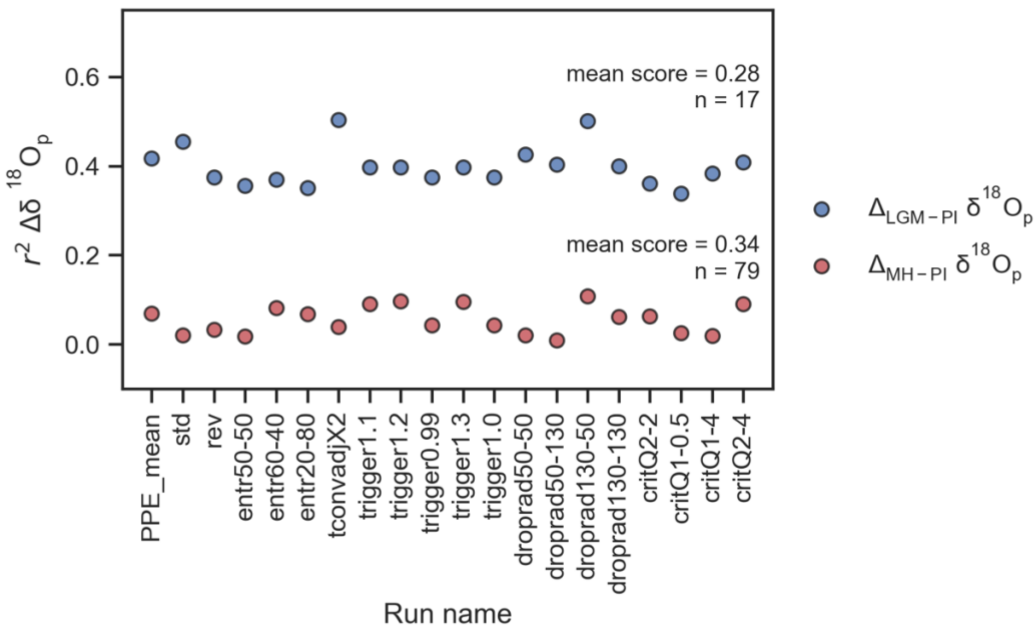

Figure 7. Weighted r^2 values between simulated $\delta^{18}O_p$ and SISAL $\delta^{18}O$ anomalies.

4 Discussion and Conclusions

In this study, we have identified parts of the world that are most sensitive to convective and cloud parameterizations, which may provide the best opportunity for constraining key metrics in climate models. Parameter-sensitive sites are different between the balanced and unbalanced versions of the models with the latter showing more regions of lower sensitivity scores. This is likely related to the greater variability among PPE members induced by random changes in certain variable fields by the parameter perturbations, affecting more indiscriminate regions in the world. This outcome from the unbalanced version is less useful in constraining biases related to cloud and convective parameterizations.

Our satellite-model analyses, stratified by global and proxy-specific skill scores, reveal that the distribution of proxy sites here lie outside of the spatial domains most impacted by cloud and convective parameterization choices. This suggests a need for additional optimally suited sites distributed across more complex convection-cloud schemes to constrain global simulations. Additionally, conducting these experiments using different coupled atmosphere-ocean-vegetation models could provide an excellent framework for targeted paleoclimate fieldwork to develop archives from these convective- and parameter-sensitive areas across the world.

Though the proxy sites sample less complex atmospheric scenes, the first order spatial pattern of $\delta^{18}O_p$ is in excellent agreement between proxy data and all PPE members across all time periods. Also supported by the satellite analyses, two parameterizations with highest model skill emerged: a 20:80 split of entrainment rate for plume (*entr20-80*) for the PI period and doubled convection adjustment time (*tconvadjX2*) for the MH and LGM periods. The simulations are able to capture broad scale LGM-PI $\delta^{18}O_p$ patterns where *tconvadjX2* parameterization performed best among parameterizations. On the other hand, model skill is significantly reduced in the MH-PI runs where the magnitude of change is consistently smaller in all simulations compared to the proxies.

It is highly likely that the coupled simulations of these same experiments will exhibit a greater range of variability across simulations. The fixed SSTs in our runs allowed us the ability to explore this approach with computationally inexpensive simulations; however, it also throttles coupled feedbacks muting LGM and MH variability across ensemble members and precluded us from calculating ECS for every perturbed parameter. Further, these fixed surface ocean conditions limit the paleoclimate constraints to land-based proxy archives. Other potential sources of model discrepancies are related to ice sheet topography changes and dust concentrations (LGM), along with the lack of vegetation and dust concentration feedbacks (LGM and MH) (Crucifix and Hewitt, 2005; Harrison *et al.*, 2014; Masson-Delmotte *et al.*, 2006; Ullman *et al.*, 2014), which may be best evaluated using fully coupled atmosphere-ocean models.

Speleothem proxy climate records have their own set of uncertainties. Speleothem $\delta^{18}O$ primarily reflects local and regional climate signals controlling $\delta^{18}O_p$. However, this signal may be altered as it enters the soil zone and epikarst, a zone that stores infiltrated rainwater, through mixing with existing waters, seasonality of recharge rates, and fractionation by evaporation before reaching the cave system (Baker *et al.*, 2019; Hartmann and Baker, 2017). Within the cave itself, the calcite $\delta^{18}O$ signal can be further altered by non-equilibrium fractionation processes and temperature-dependent fractionation during speleothem deposition (Baker *et al.*, 2019; Hartmann and Baker, 2017; Lachniet, 2009). Using $\delta^{18}O_s$ instead of $\delta^{18}O_p$ in the comparisons did not show an improvement either (Figure S8, S9 in the supporting information). These cave specific factors are not reproduced in the models, exacerbating discrepancies between proxies and simulations. Converting speleothem $\delta^{18}O$ to its drip water equivalent similarly introduces uncertainties as past cave temperatures are unknown (Comas-Bru *et al.*, 2019). A natural next step to better comparing the models to proxies is to convert the model output into proxy space via proxy system models, an area of ongoing research (Dee *et al.*, 2017; Evans *et al.*, 2013).

While model biases and proxy uncertainties remain, our initial results add to the growing body of work that demonstrates the utility of paleoclimate data in better constraining model skill, particularly at the model development stage (Tierney *et al.*, 2020a, 2020b; Zhu *et al.*, 2019). Our approach and results may be extended to other GCMs and could be especially useful for other models using similar parameters in their cloud and convective parameterization setups. Because cloud feedbacks within the climate system are non-stationary under varying boundary conditions (Zhu *et al.*, 2019), hence leading to differences in which parameterization experiment performs best for each time period, fine-tuning future simulations requires determining all plausible parameter combinations and testing the limits of parameter values used in this study. Future work applying this framework to coupled ocean-atmosphere simulations and incorporating vegetation and dust change is needed to fully investigate the impact of parameter choices on paleoclimate simulations. Incorporation of other land-based water isotope proxies such as those from ice cores, and inclusion of SST proxies which reflects expected changes in radiative balance, will allow for further model evaluation. Techniques like paleoclimate data assimilation could also be leveraged to identify optimal parameter choices that best matches the paleorecord, and subsequently better constrain ECS.

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Open Research

Our perturbed parameter configurations were evaluated using multiple present-day satellite climatologies provided by the Obs4MIPS project (https://esgf-node.llnl.gov/projects/obs4mips/) hosted on the Earth System Grid Federation (https://esgf.llnl.gov/). Top of the atmosphere absorbed shortwave (SWabsTOA) and outgoing longwave radiation (OLR), along with cloud radiative forcing estimates (SW_CRE, and LW_CRE) are provided by the CERES EBAF Edition 4.1 product (Kato *et al.*, 2018; Loeb *et al.*, 2018, 2020). Temperature and water vapor profiles are provided by AIRS Version 6 retrievals (Tian *et al.*, 2019; Tian and Hearty, 2020) for altitudes at and below 600 hPa, and by MLS Version 4 satellite retrievals (Waters *et al.*, 2006) at and above 200 hPa. Column integrated total (cloud plus precipitating) liquid water estimates (TLWP) are provided by the MAC-LWP (Elsaesser *et al.*, 2017) and TRMM 3A12 (Kummerow *et al.*, 2001) products, while the column integrated ice counterparts (TIWP) are provided by the CloudSat 2C-Ice (Deng *et al.*, 2015) R05 and MODIS C6 (Marchant *et al.*, 2016; Platnick *et al.*, 2015; Yi *et al.*, 2017) products. Total precipitation (prec) is provided by GPCP Version 2.3 (Adler *et al.*, 2003) and TRMM TMPA (Adler *et al.*, 2009; Huffman *et al.*, 2007) Version 7 products. Convective precipitation (prec_mc) is provided by the GPM Dual-frequency Precipitation (DPR) Radar product (Iguchi *et al.*, 2012). Global total cloud cover (tcc_isccp) is provided by the ISCCP (Rossow and Schiffer, 1999) D1 total cloud fraction product, while surface wind estimates are provided by the QuikSCAT satellite and Remote Sensing Systems surface wind products (Wentz and Schabel, 2000; Wentz *et al.*, 2007). The water isotope proxies were derived from the Speleothem Isotope

Synthesis and Analysis (SISAL) version 2 database (Comas-Bru *et al.*, 2020) and can be accessed through https://researchdata.reading.ac.uk/256/.

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