

The discovery of moderate non-linear surprises in CMIP6 models

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Abstract

This study presents an automated algorithm for detecting Moderate Non-linear Surprises (MNS) in the outputs of climate models participating in the Coupled Model Intercomparison Project phase 6 (CMIP6), building upon and relaxing existing methodologies for detection of critical transitions in climate models. The approach combines four statistical criteria — standard deviation, maximum 10-year jump, a multimodality test, and deviation over the last 30 years relative to the preindustrial distribution — with a density-based spatial clustering step to objectively identify regions undergoing non-linear transitions, without requiring expert judgment. The algorithm is applied across sea-ice, ocean, land, and atmospheric variables from up to 37 CMIP6 models under four Shared Socioeconomic Pathways (ssp) scenarios. Results highlight multiple MNS in high-latitude ocean and ice regions, and a recurrent signal of hydrological decline over tropical South America, including the Amazon Basin, detected in large fraction of the models with land-surface output. Some models also exhibit significant shifts in the extratropical atmospheric circulation, most notably in the blocking frequency, particularly under the strong ssp585 forcing. These examples demonstrate that the tool offers a systematic, reproducible framework for screening emerging non-linear climate responses in large model ensembles that may not qualify as tipping points, but still challenge the adaptation of human societies and ecosystems.

Author summary

Earth’s climate system is made up of interacting parts — oceans, ice, land, and atmosphere — that do not always respond smoothly to rising global temperatures. Sometimes they shift abruptly instead. Scientists are especially concerned about “tipping points”, i.e. large, often irreversible changes such as the collapse of Arctic sea ice or a slowdown of major ocean currents. However, many important abrupt shifts may be less extreme than classic tipping points and not necessarily permanent — yet they can still disrupt ecosystems and challenge human adaptation. We refer to these events as “moderate non-linear surprises” (MNS). In this study, we built an automated algorithm that scans the output of dozens of state-of-the-art global climate models to systematically detect MNS. Applying it to sea-ice, ocean, land, and atmospheric data under different future warming scenarios, we found recurrent abrupt changes in

high-latitude oceans and ice, a strong and consistent signal of drying over the Amazon rainforest, and shifts in atmospheric "blocking" patterns that influence extreme weather. Our tool offers a reproducible way to flag such emerging abrupt responses across large ensembles of climate models, supporting research and planning for climate impacts that fall short of becoming full tipping points but may nonetheless have significant consequences.

Introduction

Climate is a complex system characterized by a number of components (i.e. atmosphere, ocean, ice, land) interacting at different spatio-temporal scales, in a deeply non-linear way. This is a consequence of its multi-scale non-equilibrium dissipative nature, exchanging energy with its surroundings and achieving, if not externally forced, a statistically steady state. Determining the extent to which a forcing can alter this condition of statistically steady state, and whether a change in the median state can be prompted by an external forcing or by spontaneous non-linear interactions, given the intrinsically chaotic nature of the system [1] is an urgent matter, that is currently being actively tackled by the climate research community.

According to the standard definition provided by the Intergovernmental Panel on Climate Change Assessment Report 6 [2], an abrupt change is a large-scale change in the median state of the system, whose pace is much faster than that of the forcing triggering it. In this respect, tipping points are critical thresholds within the Earth’s climate system, where small perturbations can trigger significant, often irreversible shifts in the climate state. Irreversibility, in this context, is interpreted as a condition in which the recovery time of the median state to the condition prior to the application of the forcing is much larger than the time needed to achieve the abrupt change [3].

There is a pressing need to understand the nature of climate tipping points and to assess whether abrupt changes can be triggered by anthropogenic greenhouse gas emissions, or whether some of these transitions may have already been set in motion by the warming observed to date. Community efforts have been specifically devoted to identifying and documenting tipping points through both models and observations [4, 5], with significant focus on crucial elements such as the Greenland and Antarctic Ice Sheets (GrIS and AIS), Atlantic Meridional Overturning Circulation (AMOC), and North Atlantic Subpolar Gyre (NASPG). These elements are of particular interest due to their potential to trigger cascading effects [6]. Recent research points out that the AMOC, in particular, may be approaching a tipping point [7, 8]. Furthermore, it has often been found that abrupt changes are associated with individual or multiple tipping elements that could undergo critical transitions when certain thresholds are crossed, with one often triggering the transition of another through a cascading mechanism that propagates the anomaly globally [9, 6]. These qualitative shifts in the system’s median state can be driven by various mechanisms, including bifurcation, noise or rate-induced changes [10]. With the aim of addressing the environmental and socio-economic impacts of such abrupt changes, concepts of “early warning signals/indicators” (EWS/I) have been introduced, providing guidance on how to detect the proximity of a system to a tipping point, investigating increased sensitivity to small perturbations as critical thresholds are approached. These signals appear as distinctive statistical patterns in time series data, indicating impending critical transitions [11, 12]. However, applying EWS/I to the inherently irregular and fragmented climate records poses challenges [13].

It is not surprising that climate change and tipping points have led to an intense, at times harsh debate, even in some cases leading to the conclusion that there is no established definition of “tipping point” [14]. In the context of statistical mechanics and dynamical systems, a definition can be rigorously given in terms of the properties of the response operator and its divergence [15, 16]; in a multistable system, a tipping point manifests as an abrupt change from one stable state to another, whose reversal cannot simply be achieved by a forcing of opposite sign. In that case, a hysteresis loop emerges; this has been observed in simple conceptual models of the climate system (such as Budyko–Sellers energy balance models; [17]) and more realistic models (e.g. regarding the AMOC [8]).

Several methodologies have been proposed to address the likelihood and imminent occurrence of an abrupt change, more or less restrictive, relying on a homogeneous set of data or diverse data sources. Among others, we highlight the work by Loriani et al. [18], providing a multi-model multi-source assessment of the confidence associated with tipping points identified in [19]. An algorithm based on a purely multimodel assessment surveying the outputs of the Coupled Model Intercomparison Project, phase 6 (CMIP6) model simulations is provided in [4], later updated and automated in [20]. However, all algorithms so far have been dedicated to more or less strict definitions of critical transitions, either in the sense of self-sustained mean state changes related to feedbacks [18] or to the degree of irreversibility of consolidated changes [4].

In this work, we present a novel algorithm in which we deliberately relax the criteria for the detection of “tipping point”, allowing us to search for what are referred to hereafter as moderate non-linear surprises (MNS). These are non-linear abrupt changes that occur faster than the pace of the applied forcing,

sometimes persisting in a new state, but in other cases recovering to the previous state at a similar pace. According to typical definitions of "tipping point" (e.g. [21]), these latter occurrences do not qualify as "critical transitions", and they do not necessarily involve a mean-state change. Rather, they can be seen as a forced amplified fluctuation of internal variability that substantially exceeds its unforced statistics. Moreover, even in the case of a genuine mean-state change, these would be formally reversible. Overall, we therefore acknowledge that the detection algorithm can identify non-linear growth in perturbations that affect the internal variability of the system [22, 23]. In this context, critical transitions would then constitute a special set of detected events for which irreversibility cannot be excluded. Similarly to proper tipping points, MNSs are policy-relevant, because they challenge the resilience of human systems, society and infrastructure, and their detection is important for impact studies.

The paper is structured as follows. In section 1.1 the list of available datasets that have been retrieved from the CMIP6 repositories is described, whereas the algorithm is briefly described in section 1.2. A map of detected MNSs for some key variables describing some crucial processes within the climate systems are presented in section 2.1, while a focus on the Amazon rainforest is provided in section 2.2. The detection of MNS in indices of general circulation in the extratropical atmosphere is presented in section 2.3. Finally, some discussions and conclusions are given in section 3.

1 Data and methods

1.1 CMIP6 model simulations

The algorithm for MNS was applied to the model outputs from the Coupled Model Intercomparison Project Phase 6 (CMIP6), publicly available on the nodes of the Earth System Grid Federation (ESGF). A set of variables was chosen based on their capability of addressing key potential tipping points and aspects of internal variability, as follows:

- (monthly resolution) sea-ice concentrations (CMOR name "siconc"): for Arctic sea-ice collapse;
- (monthly resolution) ocean salinity and temperature at the surface (CMOR names "sos" and "tos", respectively): for the Atlantic Meridional Overturning Circulation;
- (monthly resolution) precipitation (CMOR name "pr"): for the stability of the Intertropical Convergence Zone (ITCZ) and monsoons;
- (monthly resolution) total runoff and total and surface-layer soil moisture content (CMOR names "mrro", "mrso" and "mrsos", respectively): for the stability of the tropical rainforest, specifically the Amazon, boreal forests and for permafrost thawing;
- (daily resolution) geopotential height at 500 hPa (CMOR name "zg", hereafter z_{500}): for the analysis of extratropical atmospheric dynamics.

In order to maximize the efficiency of data retrieval, the SYNchronize DAta (SYNDA) command line tool was used, scanning for all available datasets upon a query across all ESGF nodes. Out of 51 available models in the ESGF nodes, 37 were found to have monthly mean data for the variables under consideration (see 1.2) stored for both the preindustrial control and at least one of the future projection (ssp126, ssp245, ssp370, ssp585) scenarios. Regarding daily variables needed for the analysis of extratropical atmospheric circulation (see 2.3), 14 out of 51 models could be used. Table 1 lists, for each model, the fields that could be retrieved from the external repository for which at least one MNS was detected.

1.2 Algorithm for detection of Moderate Non-linear Surprises (MNS)

The detection algorithm for MNS is largely based on previous work aimed at providing a catalogue of critical transitions (or strong non-linear surprises, SNS) in CMIP model outputs [4, 20], but incorporates revised criteria and a less stringent set of detection parameters. The two methods were developed in coordination, within the Horizon Europe (HEU)-funded OPTIMESM project, and were meant to minimize reliance on

Table 1. Models and variables for which at least one MNS was detected (see Table 2 and Tables S1–S8 in the Supplementary Material for detailed results). Acronyms: siconc (sea-ice concentration), sos (sea surface salinity), tos (sea surface temperature), tas (near-surface air temperature), pr (precipitation), mrro (total runoff), mrso (total soil moisture), mrsos (surface soil moisture), zg (geopotential height at 500 hPa, daily fields).

Model	Reference	siconc	sos	tos	tas	pr	mrro	mrso	mrsos	zg
ACCESS-CM2	[24]	✓	✓	✓	✓	✓	✓	✓		✓
ACCESS-ESM1-5	[25]		✓	✓	✓	✓	✓	✓		
AWI-ESM-1-REcoM	[26]						✓	✓	✓	
BCC-CSM2-MR	[27]	✓	✓	✓	✓	✓		✓		
CAMS-CSM1-0	[28]	✓	✓	✓	✓					
CanESM5	[29]	✓	✓	✓	✓	✓				✓
CanESM5-1	[30]	✓	✓	✓	✓	✓	✓	✓		
CESM2-WACCM	[31, 32]	✓	✓	✓	✓	✓	✓	✓		✓
CIESM	[33]						✓	✓		
CMCC-CM2-SR5	[34]						✓		✓	
CMCC-ESM2	[35]						✓		✓	
EC-Earth3	[36]						✓	✓	✓	
EC-Earth3-AerChem	[37]						✓		✓	
EC-Earth3-Veg	[36]						✓	✓	✓	
EC-Earth3-Veg-LR	[36]						✓	✓	✓	
FIO-ESM-2-0	[38]	✓	✓	✓	✓					
GFDL-CM4	[39]									✓
IITM-ESM	[40]	✓	✓	✓	✓	✓				
INM-CM4-8	[41]	✓	✓	✓	✓		✓	✓		
INM-CM5-0	[42]	✓		✓	✓		✓			✓
IPSL-CM5A2-INCA	[43, 44]						✓	✓	✓	
IPSL-CM6A-LR	[45]						✓	✓	✓	✓
KACE-1-0-G	[46]		✓	✓	✓	✓	✓			
KIOST-ESM	[47]					✓				
MIROC6	[48]	✓	✓	✓	✓	✓	✓			✓
MPI-ESM1-2-HAM	[49, 50]	✓	✓	✓	✓					
MPI-ESM1-2-LR	[51]						✓	✓	✓	✓
MRI-ESM2-0	[52]	✓	✓	✓	✓	✓	✓	✓		✓
NESM3	[53]	✓	✓	✓	✓					
NorESM2-LM	[54]							✓	✓	✓
NorESM2-MM	[54]						✓	✓	✓	✓
TaiESM1	[55]	✓			✓	✓	✓	✓		

expert judgment in the detection of critical transitions responding to an external forcing across model simulations and system's components.

The algorithm takes as input the CMOR variable names of the observables to be scanned through, the models, scenarios and path where the data are stored. Then, the core of the algorithm consists of four main steps:

1. Remapping the initial dataset to a $1^\circ \times 1^\circ$ rectilinear spatial grid common to every model;
2. Performing a 10-yr moving average;
3. Detecting MNSs at every gridpoint, analysing the time series throughout the forced period;
4. Clustering neighboring gridpoints and applying a threshold on the area of each cluster to sub-select sufficiently large clusters.

The core of the automated procedure is in the objective selection of the clustered regions encompassing gridpoints that satisfy the criterion for MNS detection. For this, we adopted a density-based clustering methodology [56, 57], a simple and well documented technique that separates high-density from low-density regions, which depends on two parameters: the radius ϵ , i.e. the maximum distance within which two points are considered neighbours (and hence part of the same cluster), and the minimum number of points required to form a cluster. The ϵ parameter is set to 750 km, the threshold on the size of the cluster to 150 gridpoints, which corresponds to about 1.8×10^6 km² at the Equator.

1.2.1 Criteria for non-linear changes selection

The gridpoint selection in point 3 is a combination of statistical tests that compare the time series from the forced simulations against the corresponding timeseries from the preindustrial control simulation. If at least 3 out of the 4 criteria listed below are met, the gridpoint is selected:

- Standard deviation: the standard deviation for the detrended time series is computed. If it exceeds a given percentile of the spatial distribution of standard deviation in the preindustrial run, the criterion is met;
- Maximum 10-year jump: the maximum jump across 10 years is computed by applying a sliding window on the forced time series. If the maximum jump exceeds a given percentile of the maximum 10-year jump for the preindustrial scenario, the criterion is met;
- Test for multimodality: the dip test of Hartigan and Hartigan [58] is applied, in order to test the null hypothesis that the time series reflects a unimodal distribution and therefore does not exhibit a multistable state;
- Last 30 years change: each year in the last 30 years of the forced runs is compared with the preindustrial distribution. If it lies beyond two given percentiles of the preindustrial distribution, the criterion is met.

The standard-deviation and maximum 10-year jump criteria are adopted directly from [4]. For the assessment of multimodality, however, we follow [20] in applying the Hartigan and Hartigan dip test, rather than the criterion used in [4].

The choice of parameters for the detection exercise is summarized as follows:

- Threshold for standard deviation exceeding preindustrial standard deviation: 95%
- Threshold for maximum 10-year jumps exceeding preindustrial distribution: 95%
- Maximum p-value for Dip test of unimodality: 5%
- Thresholds for yearly values exceeding the preindustrial distribution over the last 30 years of simulations: 5% and 95%

2 Results

2.1 Non-linear surprises in key variables across ssp projections

The result of the detection on the monthly mean fields across available CMIP6 models and ssp scenarios is summarized in Figure 1. Details of the catalogue are provided in Tables S1–S8 in the Supplementary Material. It should be noticed that, given that the detection is model-specific, the boundaries of the identified clusters may differ slightly for different models, scenarios or variables. Therefore, macro-regions encompassing clusters are given a descriptive name in the table. The boundaries of these macro-regions are denoted in red in Figure 1; clusters detected by individual models are labeled according to the larger domain in which they fall.

We notice that high latitudes feature many occurrences of MNSs. Areas of the Southern Ocean surrounding East Antarctica, the Arctic Ocean north of Siberia and the North Atlantic into the Arctic Ocean north of Scandinavia, are prone to non-linear changes in surface salinity and/or temperature some time during the forced run, with this occurrence spanning one third to half of the models that have been analysed.

Non-linear changes also affect precipitation over oceanic tropical regions, such as the Indo-Pacific warm pool or the Equatorial Pacific. We argue that this is related to a meridional shift in the regional component of the ITCZ, but more work is needed in order to substantiate this hypothesis. Finally, the detection algorithm emphasizes non-linear salinity changes in several areas of the Arctic ocean. We argue that this could be explained as a consequence of changes in river runoff from neighboring land areas. A preliminary inspection indeed suggests a link between the non-linear changes in runoff and soil moisture over Siberia (BF (Siberia) in Fig 1) and those in surface salinity north of Siberia, via river discharge into the Kara and Laptev Seas. Non-linear changes in land-surface hydrology elsewhere are examined in more detail in Section 2.2.

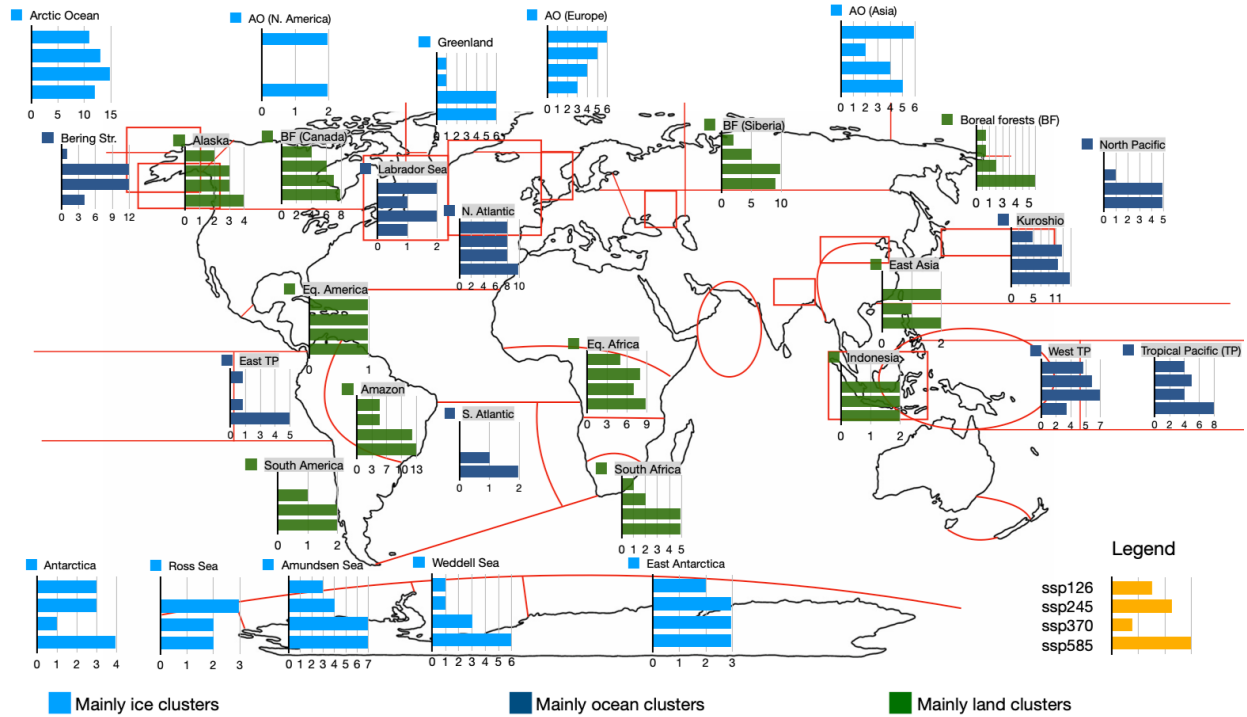


Fig 1. Global map showing locations of clusters exhibiting MNSs as a function of different ssp scenarios. For each region, a histogram denotes the number of models exhibiting MNS for at least one of the considered variables in each of the four scenarios. Histograms are shown only for regions in which more than one model exhibits MNS across at least two scenarios. Red lines are the boundaries of the regions listed in Tables S1–S8 (Supplementary Material). Histograms are denoted by different colors depending on the prevailing domain; light blue denotes clusters mainly including ice sheet or sea ice grid points, dark blue mainly ocean grid points, dark green mainly land grid points.

2.2 Abrupt hydrological shifts over tropical South America

The Amazon rainforest plays a crucial role in the global hydrological cycle, acting as a major reservoir of moisture and a key driver of regional and global climate dynamics. Across the CMIP6 ensemble, our diagnostic algorithm identifies tropical and subtropical South America, together with Equatorial Africa, as the two most recurrent land hotspots of moderate non-linear hydrological change: 18 models exhibit MNS in at least one of surface soil moisture (*mrsos*), total soil moisture (*mrso*) and total runoff (*mrro*) over the region, 15 of them over clusters centered on the Amazon Basin, in scenarios ranging from ssp126 to ssp585. This is more than the number of models detecting a MNS in any variable over the Arctic Ocean (17) or the Southern Ocean (14), and comparable to Equatorial Africa (19 models). The signal is also multi-variable: 11 of the 18 models flag a non-linear change in at least two hydrological variables within the same scenario, and one of them (IPSL-CM6A-LR) in all three, under ssp245, ssp370 and ssp585. We focus on this region because the Amazon rainforest is one of the core tipping elements of the Earth system [19, 59].

These signals emerge in models with substantially different land-surface schemes: among others, ACCESS-CM2 is based on CABLE [24], CESM2-WACCM and NorESM2-MM on CLM5 [31, 54], CMCC-CM2-SR5 and CMCC-ESM2 on CLM4.5 [34, 35], MPI-ESM1-2-LR with JSBACH [51], IPSL-CM6A-LR on ORCHIDEE [45], and the EC-Earth3 family on HTESSEL, coupled to the LPJ-GUESS dynamic vegetation model in EC-Earth3-Veg and EC-Earth3-Veg-LR [36]. The detected transitions are therefore not tied to one particular land-surface formulation. It is worth noting that this structural diversity supports the statistical result only, and not a common mechanism: only a minority of these models, including EC-Earth3-Veg and EC-Earth3-Veg-LR, carry interactive vegetation dynamics, whereas others, such as ACCESS-CM2 (CABLE), CESM2-WACCM (CLM5) and IPSL-CM6A-LR (ORCHIDEE) run with prescribed vegetation distributions and cannot, by construction, reproduce a vegetation dieback. What they can represent, and what the algorithm detects, is a threshold-like reorganisation of land-surface water availability. The EC-Earth3 family offers a useful comparison in this respect: the standard EC-Earth3 configuration, which runs with prescribed vegetation, flags MNS in Amazonian soil moisture and runoff, same as EC-Earth3-Veg and EC-Earth3-Veg-LR, which instead include LPJ-GUESS dynamic vegetation. Since these configurations share the same component models, this suggests that interactive vegetation is not necessary for the detected transitions to occur; whether it modulates their amplitude or spatial extent would require a dedicated comparison.

Two examples illustrate the range of behaviors detected. In EC-Earth3-Veg, a MNS in *mrsos* is detected in all four scenarios, and the detected cluster covers most of tropical and subtropical South America, extending well beyond the Amazon Basin (Fig 2). The cluster footprint is largely consistent across the four scenarios (Fig 2e). Averaged over it, *mrsos* declines throughout the record, from about 35 mm in the mid-19th century to between about 31 (ssp126) and 29 mm (ssp585) by 2100, with a steeper drop in the second half of the 21st century under the higher-forcing pathways (Fig 3). Under the higher-forcing pathways the decline steepens in the second half of the century. Part of this acceleration reflects the faster increase in forcing, so it does not by itself distinguish the detected signal from a forced trend. What sets the signal apart is the combination of criteria met by the algorithm, which holds in all four scenarios, including ssp126 where no acceleration is apparent. In IPSL-CM6A-LR, the algorithm flags all three hydrological variables under available ssp245, ssp370 and ssp585 scenarios. In the extension of ssp585 to 2300 (Fig 4) all three variables decline together until about 2150 and then stabilize at lower values, with no recovery by 2300: soil moisture drops by about 20%, runoff by about 75%. It is this disproportionate runoff response, rather than the soil-moisture decline itself, that is most relevant from an impacts perspective. For this model no coincident MNS in precipitation is reported over the same cluster, suggesting that the land-surface transitions detected here need not be driven by a non-linear change in the atmospheric supply of water.

A growing body of literature suggests that the Amazon system may be prone to non-linear responses to warming and drying, potentially crossing thresholds that trigger large-scale vegetation decline and long-lasting reductions in soil water availability, processes broadly referred to as "Amazon dieback" [60, 59, 61]. It is also well established that most CMIP5 and CMIP6 models do not reproduce a full dieback, and that where dieback-like behavior appears it tends to be localized [62, 63]. The transitions detected here should be read in this light: while full dieback remains the exception within a largely conservative ensemble, threshold-like hydrological shifts over the region are common, and their interest lies precisely in that contrast.

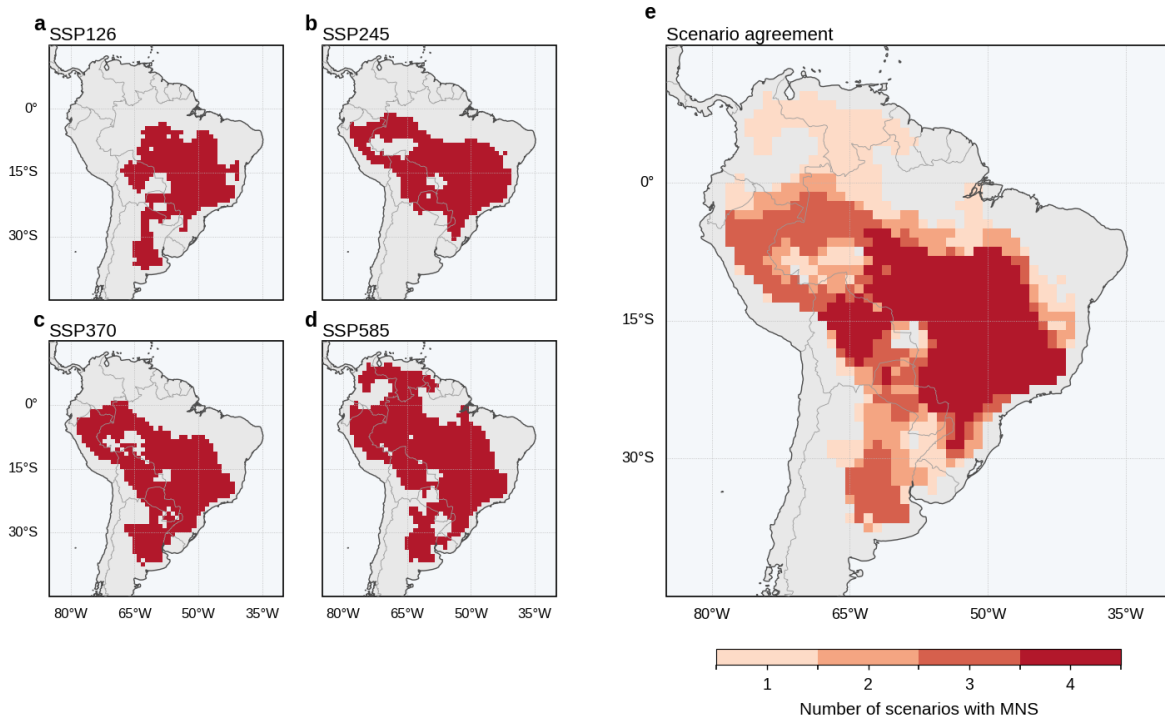


Fig 2. Clusters where an MNS in surface soil moisture (*mrsos*) is detected for the EC-Earth3-Veg model under (a) ssp126, (b) ssp245, (c) ssp370 and (d) ssp585, and (e) number of scenarios in which each gridpoint belongs to the detected cluster.

The multi-model and multi-variable consistency of the detected shifts, spanning surface soil moisture (*mrsos*), total soil moisture (*mrso*) and total runoff (*mrro*), is consistent with the hydrological component of the dieback mechanism, but the algorithm is agnostic to mechanism by design, and most of the models in which these transitions appear are unable to represent the vegetation feedbacks that the mechanism invokes. Establishing whether these signals are early hydrological signatures of an emerging vegetation-mediated transition or merely a land-surface response unrelated to such a transition requires examination of vegetation and carbon-cycle variables available only in a subset of models. We leave this question for future work.

2.3 Diagnostics of atmospheric circulation and detected MNS

For illustrative purposes, some fundamental features of atmospheric circulation are addressed here using daily fields of geopotential height. We focus on features of extratropical low-frequency variability, by looking at the blocking frequency, and at the North Atlantic Oscillation (NAO) and Pacific-North American (PNA) indices for the dominant circulation patterns in the North Atlantic and North Pacific, respectively.

For the computation of blocking diagnostics, the Tibaldi-Molteni index [64] was adopted, in the version updated for use in the MiLES diagnostics package [65, 66]. As a first step, model outputs are preprocessed in order to select the December–March (DJFM) season and the entire Northern Hemisphere. A rounding algorithm is then implemented to ensure selection of the 500 hPa pressure level or its nearest vertical neighbor. The meridional gradient reversals of the z_{500} are computed at every gridpoint as:

$$GHGS(\lambda_0, \phi_0) = \frac{z_{500}(\lambda_0, \phi_0) - z_{500}(\lambda_0, \phi_S)}{\phi_0 - \phi_S} \quad (1)$$

$$GHGN(\lambda_0, \phi_0) = \frac{z_{500}(\lambda_0, \phi_N) - z_{500}(\lambda_0, \phi_0)}{\phi_N - \phi_0}, \quad (2)$$

where ϕ_0 ranges between 30°N and 75°N, whereas $\phi_S = \phi_0 - 15$ and $\phi_N = \phi_0 + 15$. At every longitude λ_0 a blocking event is counted if at any latitude ϕ_0 between 30N and 75N there is at least a latitude point for

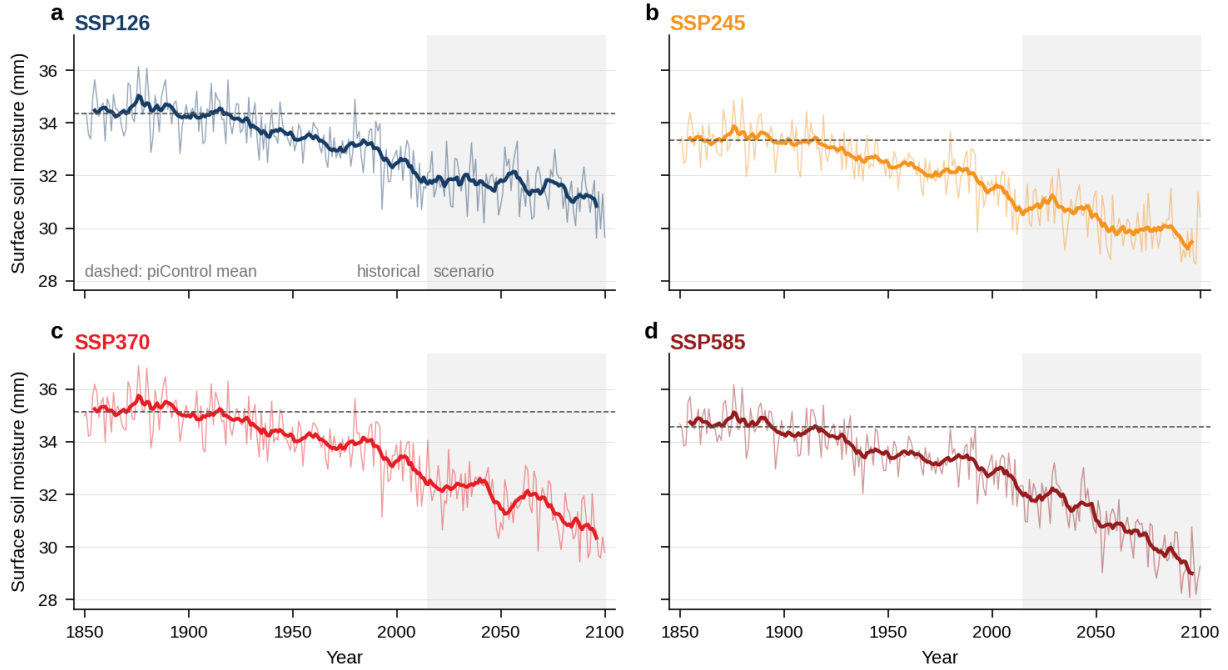


Fig 3. Temporal evolution of *mrsos* (mm) for EC-Earth3-Veg under (a) ssp126, (b) ssp245, (c) ssp370 and (d) ssp585. Each series is averaged over the cluster detected for that scenario (Fig 2) and concatenates the historical simulation (1850–2014) with the corresponding scenario (2015–2100, grey shading); for this reason, the historical segments differ slightly across panels. Thin lines show annual means, thick lines the 10-year running mean used by the detection algorithm. Dashed lines indicate the piControl mean over the same cluster.

which the following conditions are satisfied:

$$GHGS(\lambda_0, \phi_0) > 0; \quad GHGN(\lambda_0, \phi_0) < -10m(^{\circ}lat)^{-1} \quad (3)$$

The frequency of blocking as a function of longitude is then the ratio between the number of blocking events and total number of days in the season. For each model, a longitudinal section is produced, as in the example of Figure 5. We notice that for the IPSL-CM6A-LR model the time-averaged longitudinal section across the four scenarios exhibits substantial differences compared to the preindustrial control run. In addition to that, the most extreme scenario, i.e. ssp585, has substantially lower blocking frequencies along most of the longitudes. This is consistent with the emergence of a MNS (cfr. Fig 6).

Consistently with the model intercomparison described in [65], we finally average the blocking frequency inside two areas of relevant blocking activity, i.e. the Euro-Atlantic (27°W-48°E, hereafter "EAB") and the Northern Pacific (116°E-180°E, hereafter "NPB"), then retrieve the blocking frequency timeseries and apply the MNS algorithm to discern whether the blocking frequency in the two regions may undergo a MNS across the investigated scenarios. Time series of blocking index inside the EAB and NPB exhibiting detected MNS are shown for IPSL-CM6A-LR in Figure 6, as an illustrative example of what occurs with other models featuring MNS in blocking indices (not shown). Both domains indicate a progressive reduction, consistently with a possible increase in the intensity of the zonal flow, particularly evident across the Atlantic, as discussed further below.

Concerning NAO and PNA indices, we retrieve daily fields of z_{500} in the 30°N-85°N latitudinal channel and subset two domains: the 80°W-40°E and the 180°W-40°W longitudinal sectors. We remove the mean and seasonal cycle, then compute the principal components (PC) for the first Empirical Orthogonal Function (EOF) in both domains, applying latitudinal weights as the cosines of latitude. The PCs are then standardized; the resulting indices for the 80°W-40°E and for the 180°W-40°W longitudinal sectors are taken

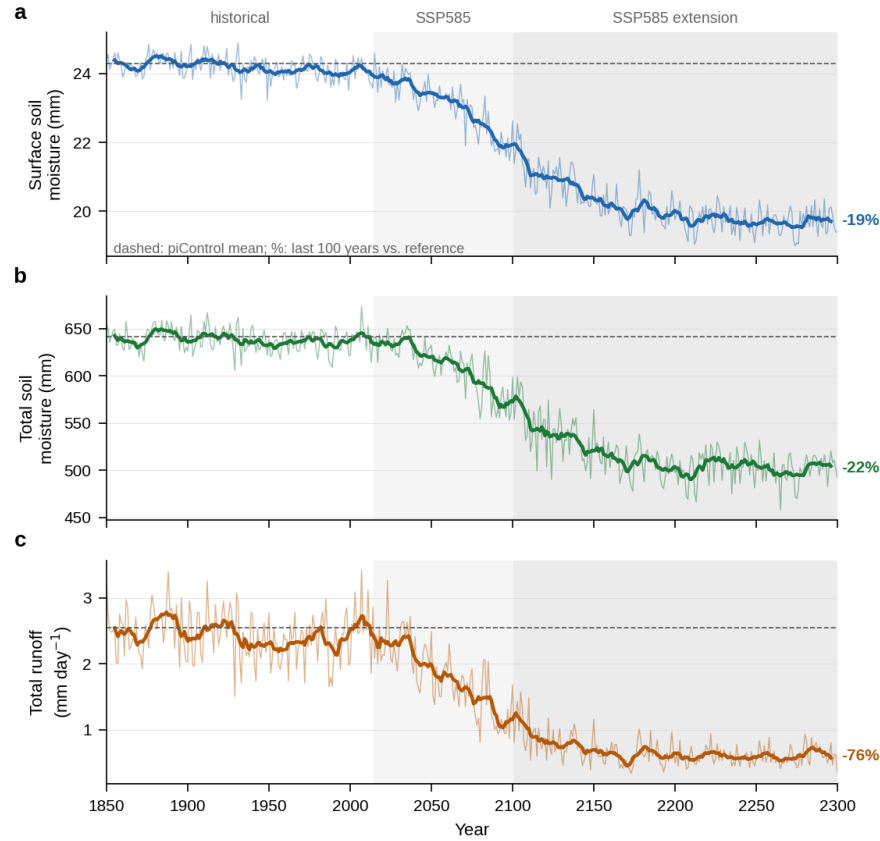


Fig 4. Abrupt transitions over the Amazon region for IPSL-CM6A-LR under ssp585 and its extension to 2300: (a) surface soil moisture (*mrsos*), (b) total soil moisture (*mrso*) and (c) total runoff (*mrro*). Each variable is averaged over the cluster detected for that variable. Thin lines show annual means, thick lines the 10-year running mean; shading marks the ssp585 period (2015–2100) and its extension (2101–2300). Dashed lines indicate the piControl mean over the same cluster, and percentages give the change of the last 100 years of the integration (2201–2300) relative to it.

as measures of the NAO and PNA, respectively [67, 68].

Table 2 summarizes results for 14 models providing daily fields of z_{500} for at least one of the four ssp scenarios (see Table 1 for reference on the available datasets). 26 instances were found, 23 for the blocking index, 3 for NAO, 8 of them under ssp585, the most extreme scenario. Instances were comparatively more frequent (13 instances vs. 10 instances) for the North Pacific domain than for the Euro-Atlantic domain. Regarding NAO and PNA, we also show detected instances when the last-30-years criterion plus any other criterion are not met. This is justified by the fact that under strong forcing some models may feature an inconsistent dominant EOF pattern, making a comparison with the preindustrial indices unreliable. Under this criterion, models featuring MNS in ssp585 are IPSL-CM6A-LR, CanESM5, CESM2-WACCM. In contrast, a change in the pattern of variability of the NAO/PNA indices may consolidate even if the standardized index may not fall outside of the 5th–95th percentile range of the preindustrial distribution. When this eventuality is taken into account, several other instances of MNSs emerge (accounted for in italics), more commonly for PNA than for NAO. It is worth noting that in this case, only ACCESS-CM2, for what concerns NAO, and NorESM2-LM, for what concerns PNA, feature a MNS in the most extreme scenario.

An example of what the algorithm gives as output is shown in Figure 7 for NAO in MIROC6. The left column shows the first EOF as computed from the preindustrial run and from the four ssp scenarios, whereas the right column shows the evolution of the standardized first PC. The positive NAO (NAO+) pattern is clearly preserved across all scenarios, with the European lobe progressively weakening towards more extreme

scenarios. However, time series suggest that, while the interannual variability is to some extent preserved across scenarios, the index for ssp585 shifts towards persistently negative values, making it a possible candidate for MNS. While there is no robust argument in favor of models featuring a transition to a permanent NAO- state in future scenarios (cf. [69]), this behavior is not unreasonable, taking into consideration that the AMOC asymmetrically projects onto the NAO- state rather than NAO+ in many CMIP6 models, as outlined in [70]. It is beyond the scope of this paper to discuss these aspects; we rather highlight that our detection algorithm could help detect cascading transitions, such as those that would link possible AMOC collapse to large-scale atmospheric dynamics.

Table 2. Summary of MNSs detected in indices of extratropical atmospheric circulation across models providing daily fields of z_{500} . EAB: Euro-Atlantic blocking. NPB: North Pacific blocking. In italics, instances of MNS when the standardized NAO-PNA indices consolidate within the range of 5-95 percentiles of the preindustrial distribution.

Model	EAB	NPB	NAO	PNA
ACCESS-CM2		ssp245, ssp370, ssp585	<i>ssp585</i>	
CanESM5			ssp585	
CESM2-WACCM		ssp585	ssp585	
EC-Earth3				
GFDL-CM4	ssp585, ssp245	ssp585, ssp245	<i>ssp245</i>	<i>ssp245</i>
INM-CM4-8				
INM-CM5-0	ssp126, ssp370			
IPSL-CM6A-LR	ssp585	ssp585	<i>ssp126</i> ssp585	<i>ssp126</i>
MIROC6				
MPI-ESM-1-2-HAM				
MPI-ESM1-2-LR	ssp370	ssp370		
MRI-ESM2-0	ssp126, ssp585	ssp245, ssp370, ssp585		<i>ssp126, ssp370</i>
NorESM2-LM	ssp126	ssp126		<i>ssp585</i>
NorESM2-MM	ssp370	ssp370		<i>ssp245, ssp370</i>

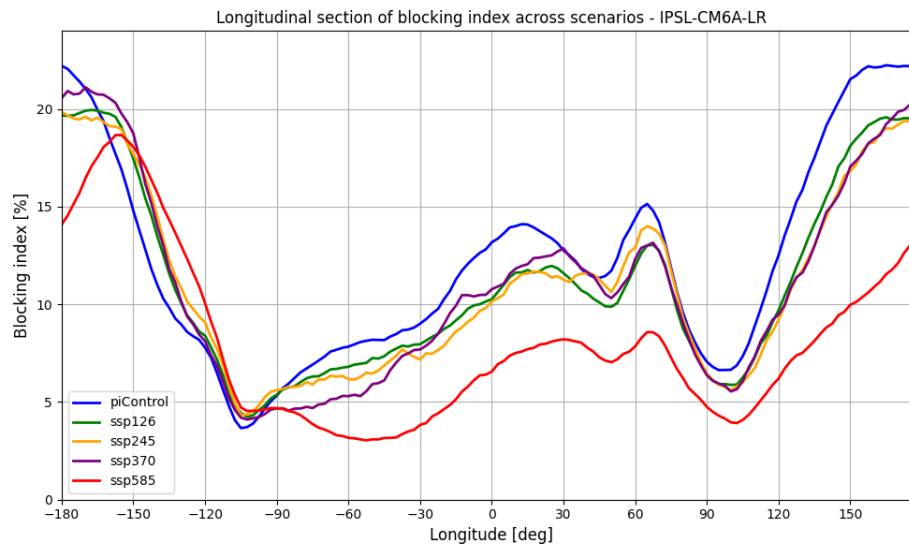


Fig 5. Blocking frequency (in percentage) as a function of longitude (in degrees) for IPSL-CM6A-LR model for the four considered ssp scenarios, compared to the piControl reference.

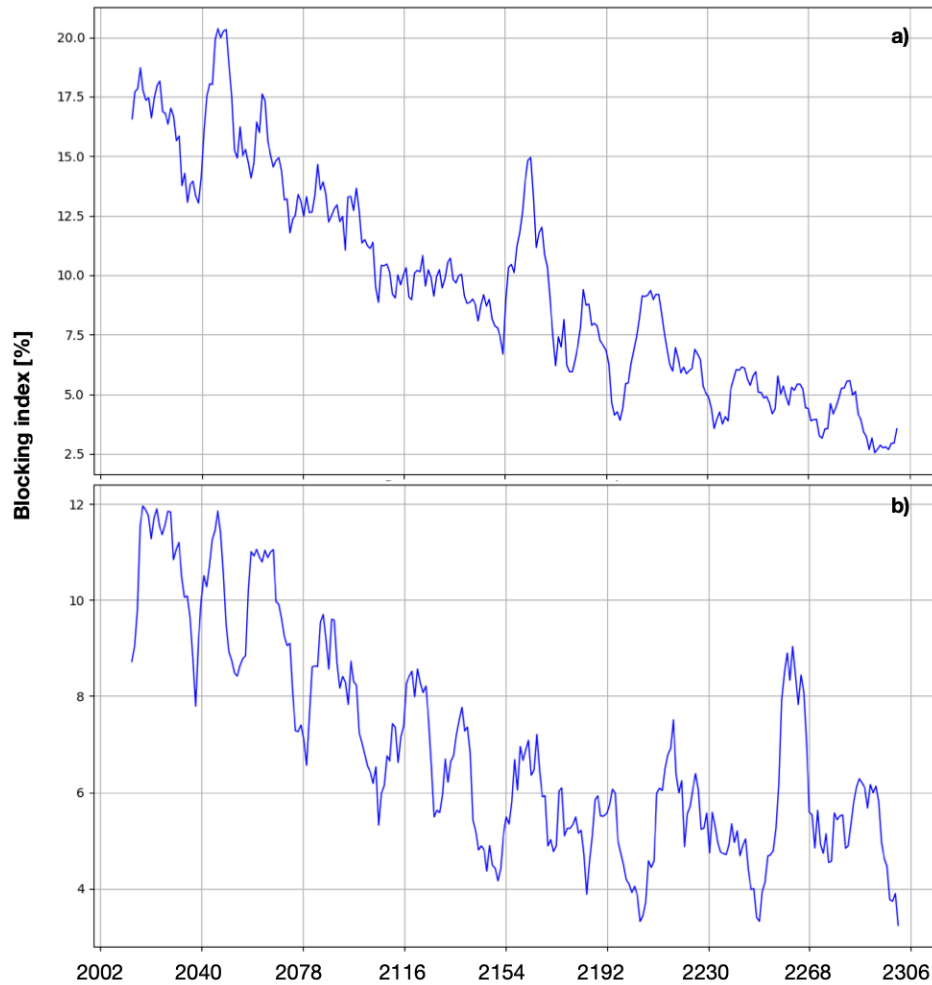


Fig 6. Time series of blocking index (in percentage) for EAB (a) and NPB (b) in IPSL-CM6A-LR model under ssp585 and its extension to 2300.

3 Discussion and Conclusions

We presented here a novel approach to detect non-linear transitions in CMIP model outputs, which encompasses both strong non-linear surprises (sometimes referred to as critical transitions or tipping points) and moderate non-linear surprises (here referred to as MNS). The algorithm is designed to objectively and systematically detect MNSs in large ensembles, as in the case of the CMIP6 data. A necessary drawback of this approach is that the algorithm neither provides information on the timing of the MNS nor makes any a priori assumption about the region encompassed by the cluster. The latter limitation is however overcome by the fact that a threshold is imposed on the size of the cluster, so that only large clusters, possibly representative of similar large scale domains, are taken into account.

The effectiveness of this algorithm has been demonstrated through different examples, the first one regarding a hydrological transition over the Amazon towards a drier soil-moisture state. Generally, we found that this is model dependent, but with large similarities across analysed models. In particular, we showed that one model, in particular, EC-Earth3-Veg, features a MNS in surface soil moisture across most of South America for all four ssp scenarios; this signals an overall stark decrease in this quantity during the 21st Century. For IPSL-CM6A-LR, for which all three hydrological variables and the extension to 2300 could be analysed, the results confirm that the algorithm is capable of detecting a substantial and persistent hydrological transition over the Amazon, with soil moisture decrease and reduced runoff that persist with no

NAO, MIROC6

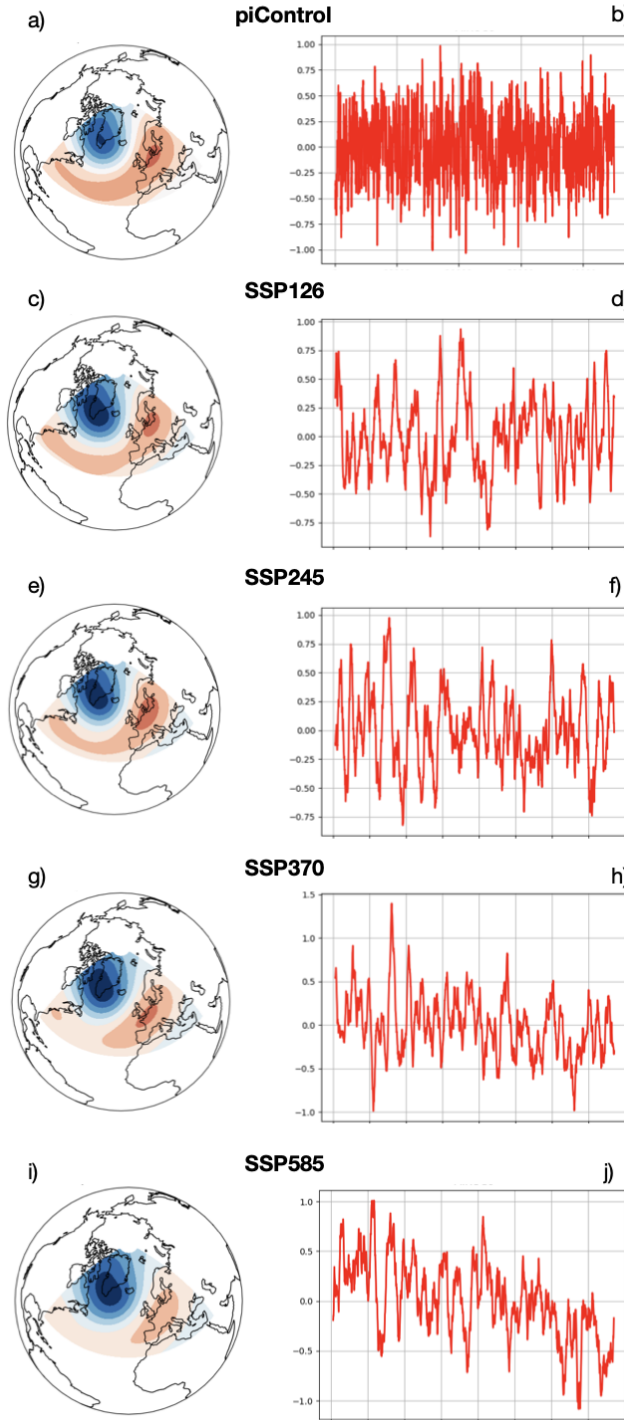


Fig 7. (a,c,e,g,i) Maps of the first EOFs of z_{500} in the Euro-Atlantic sector, as described in the text; (b,d,f,h,j) time series of the first PC for piControl, ssp126, ssp245, ssp370, ssp585 scenarios in MIROC6 model.

sign of recovery until the end of the integration period. This outcome is well in line with emerging literature on the Amazon rainforest as a potential tipping element.

The second example (Section 2.3) introduces a relatively novel approach, involving the analysis of atmospheric fields available at high temporal resolution (i.e. daily), in order to detect possible shifts in indices representative of the dominant weather patterns. We provided as examples the blocking index over the Pacific and Atlantic domains, as well as the NAO and PNA indices. MNSs in time series of blocking index were found to be relatively common, especially for high forcing scenarios, and were mainly characterized by a reduction in the blocking frequency (here shown for IPSL-CM6A-LR, but also common to other models), suggestive of an increased zonality dominating the most extreme scenarios. This feature would be consistent with a weakening of the AMOC and a consolidation of the North Atlantic cold blob, regionally increasing the meridional temperature gradient, deserving further investigations in particular under idealized AMOC collapse scenarios (e.g. TIPMIP-OCEAN, [71]). For NAO and PNA, in all instances only 2 out of 4 criteria were met, mainly because the shift would not consolidate at the end of the run or because the consolidated change would not exceed the threshold of 5-95 percentile of the preindustrial distribution. This indicates that instances for which the dominant weather pattern would not persist steadily under different forcings are uncommon (as it was shown for the MIROC6 model case), implying that NAO and PNA tends to remain stable across the scenarios.

In summary, the MNS detection algorithm, presented here through a number of examples covering diverse aspects of the long-term response of the climate system to an external forcing, shows that an objective, systematic, pattern-based methodology provides useful preliminary information about non-linear changes in response to the forcing. This information can be used to enhance understanding of non-linear phenomena, including but not restricted to critical transitions, with no prior assumption about the underlying processes, nor about the elements of the system that are prone to be affected by such changes.

4 Supplementary Material

S1 Table. MNS catalogue: summary of detected MNS instances across available monthly mean fields, as in Figure 1 of the main document. Labeled regions coincide with those denote by red solid lines in Figure 1 of the main document. An ID is given to each occurrence. Each row groups the models that exhibit a MNS in the same macro-region, for the same set of scenarios and in the same set of variables; the variables listed in a row therefore apply to every model in that row.

S2 Table: same as S1 Table: part 2.

S3 Table: same as S1 Table: part 3.

S4 Table: same as S1 Table: part 4.

S5 Table: same as S1 Table: part 5.

S6 Table: same as S1 Table: part 6.

S7 Table: same as S1 Table: part 7.

S8 Table: same as S1 Table: part 8.

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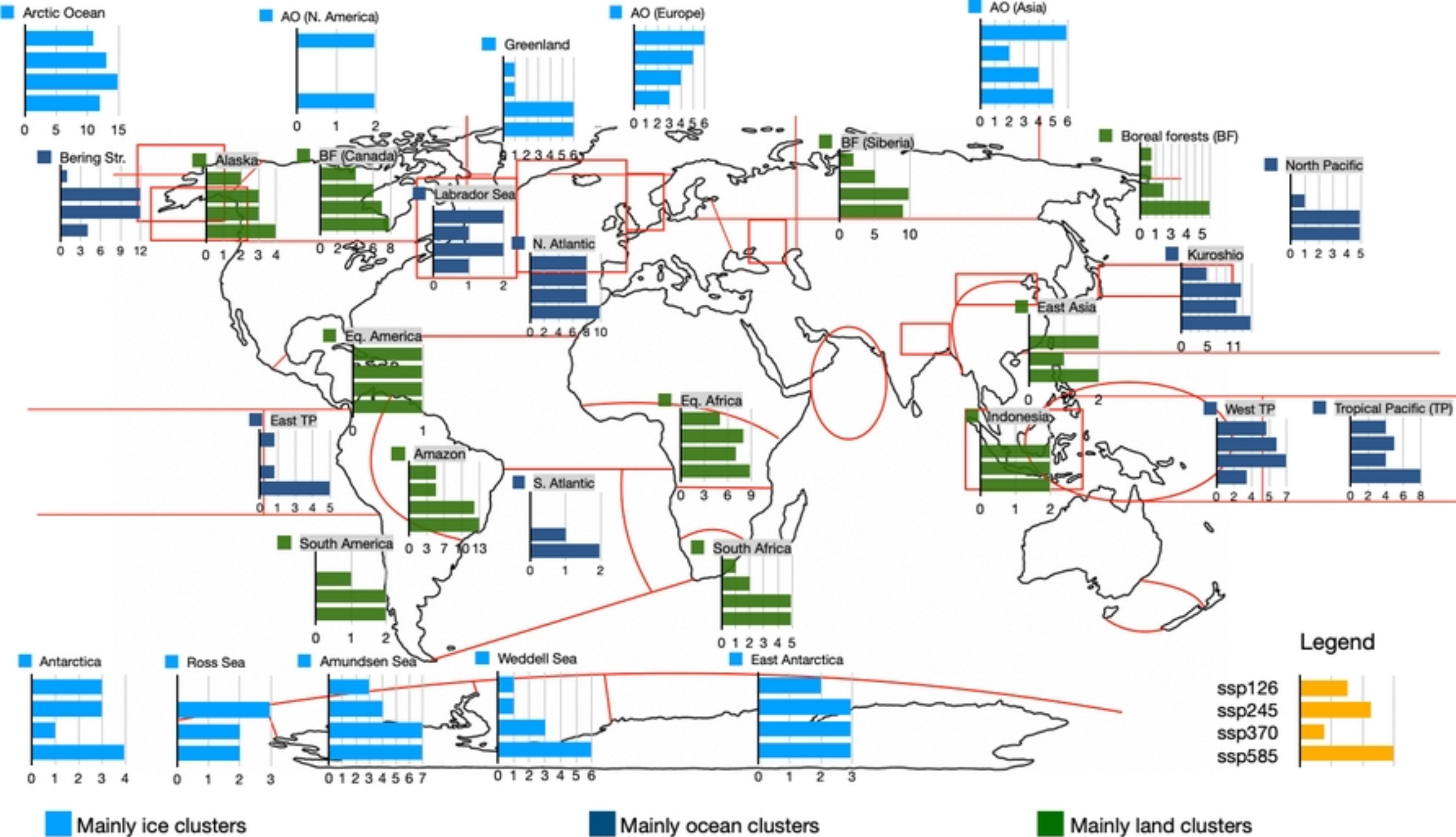


Figure 1

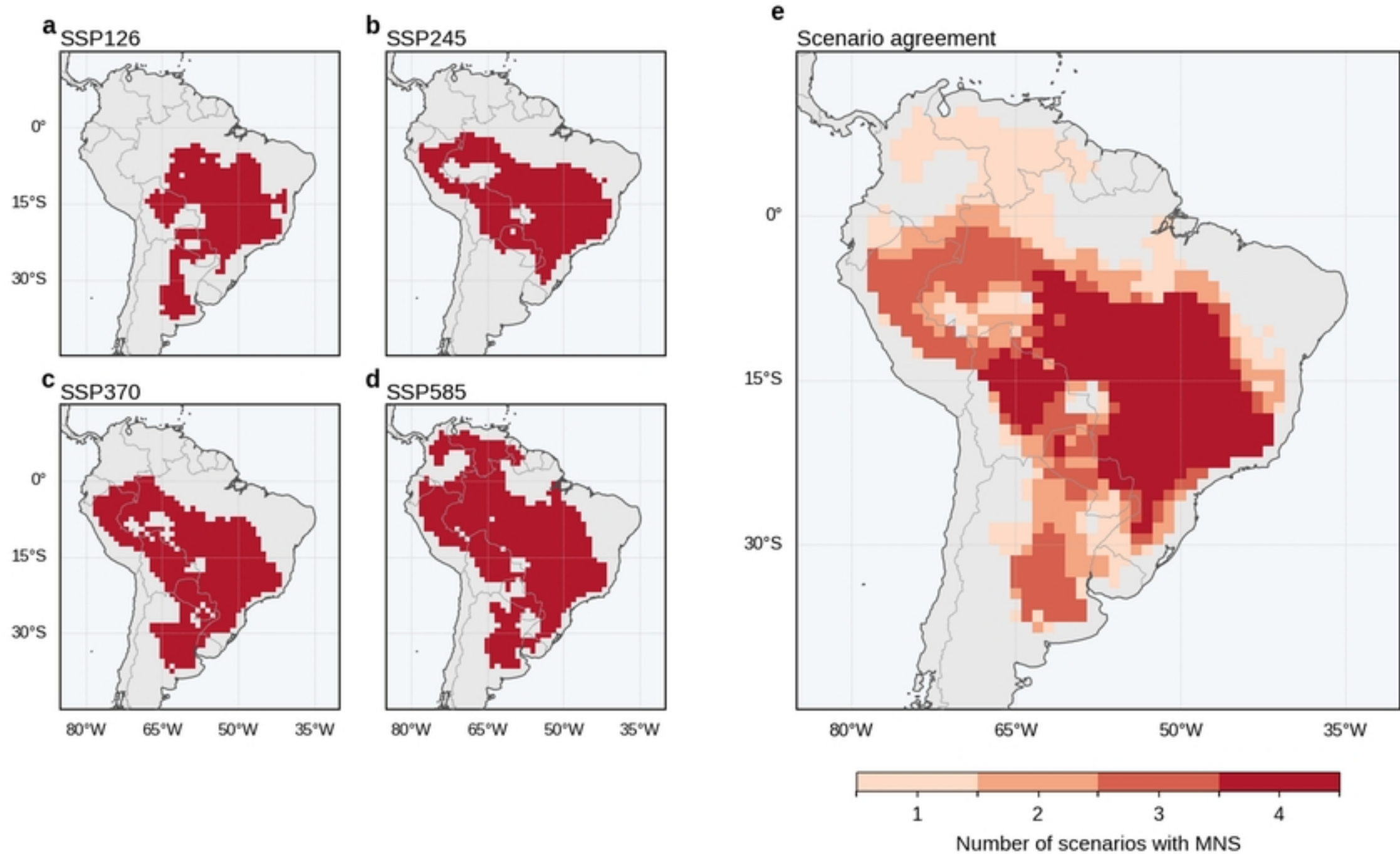


Figure 2

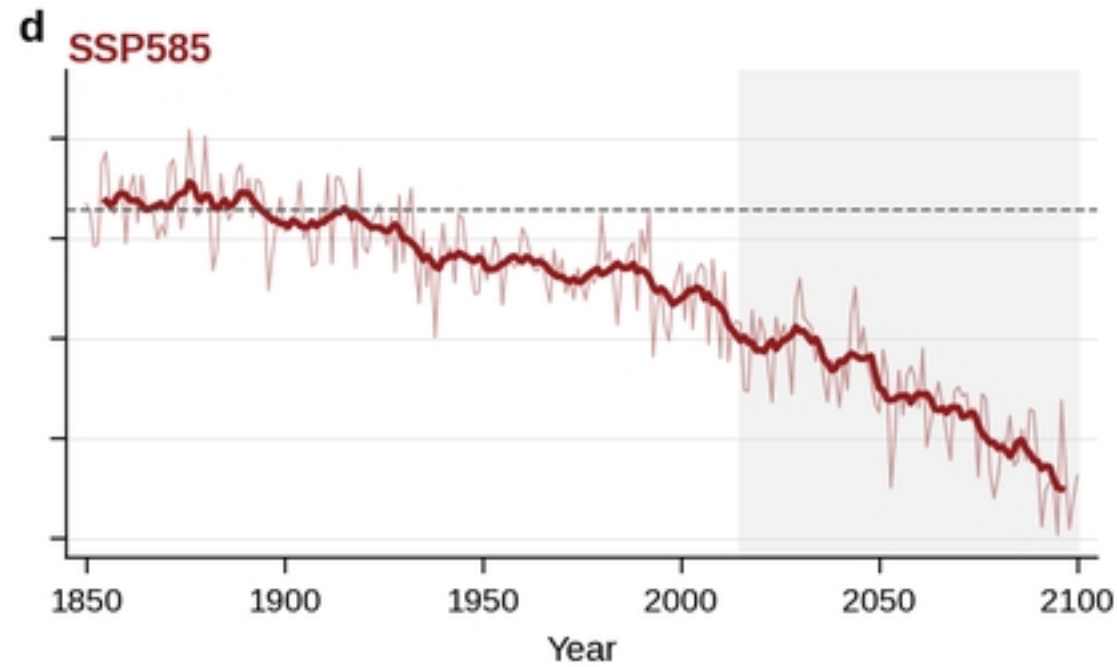
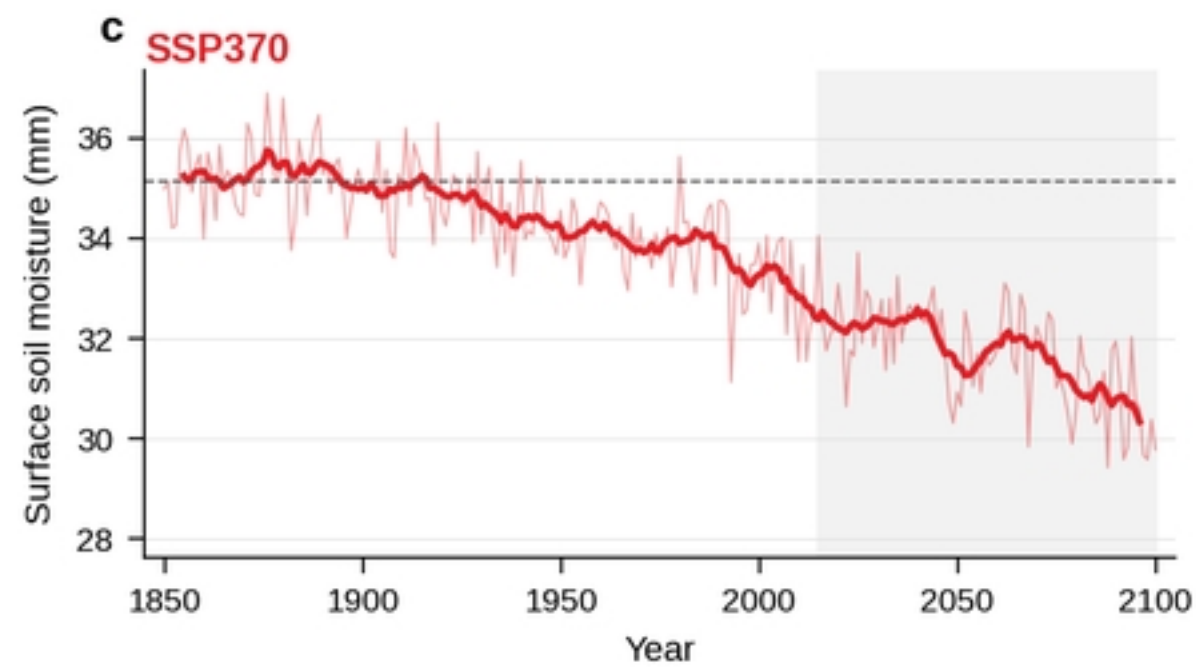
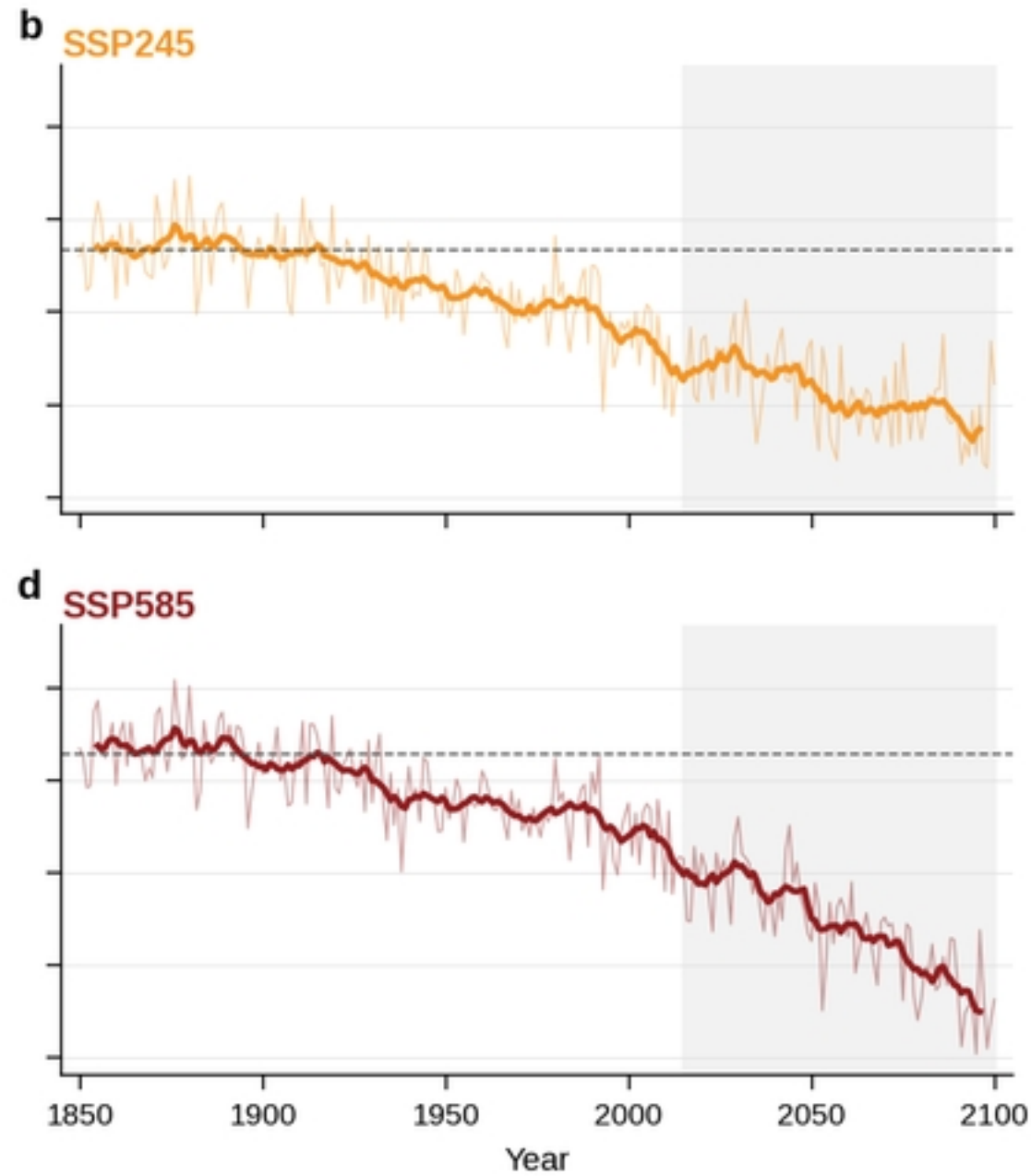
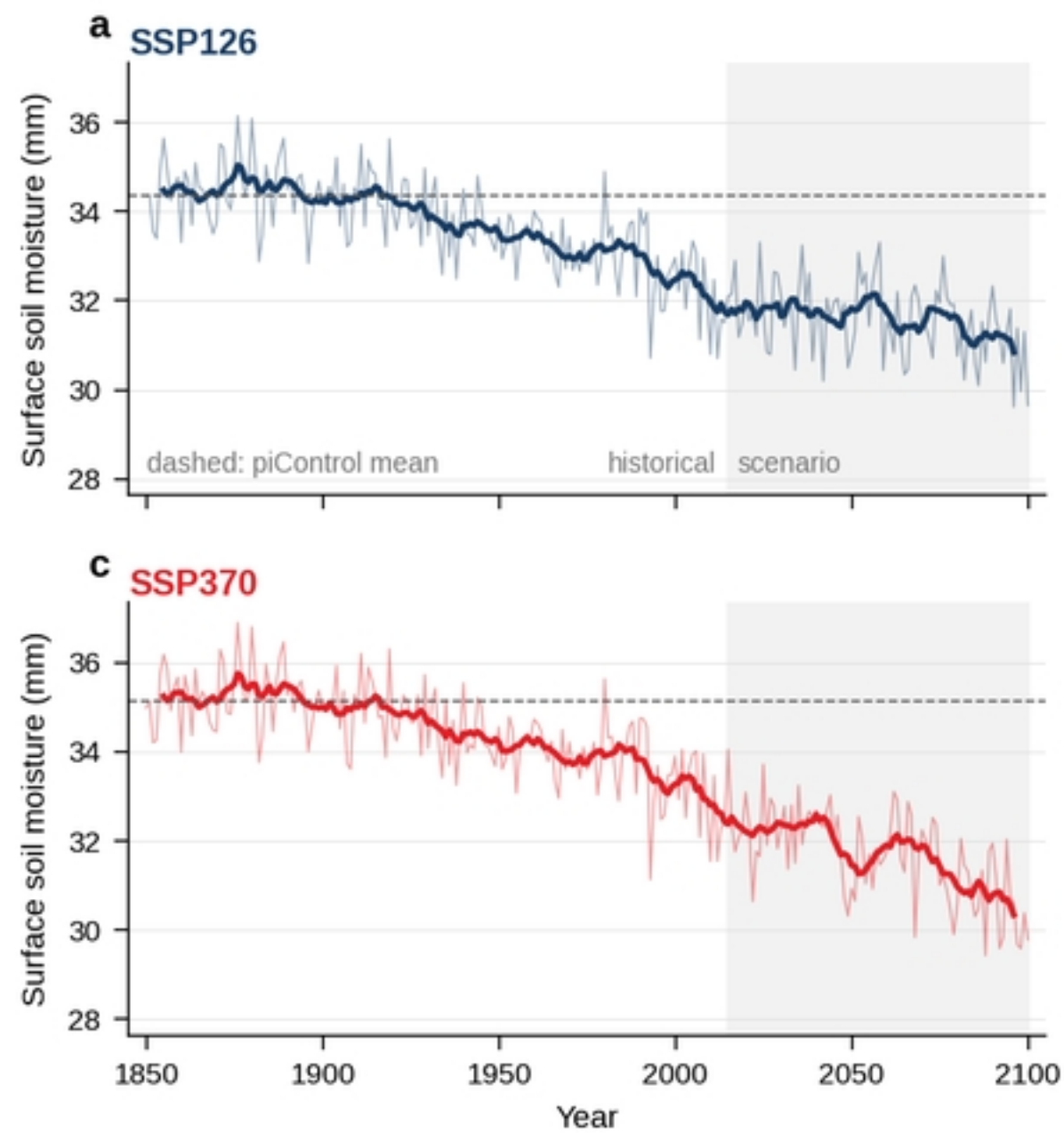


Figure 3

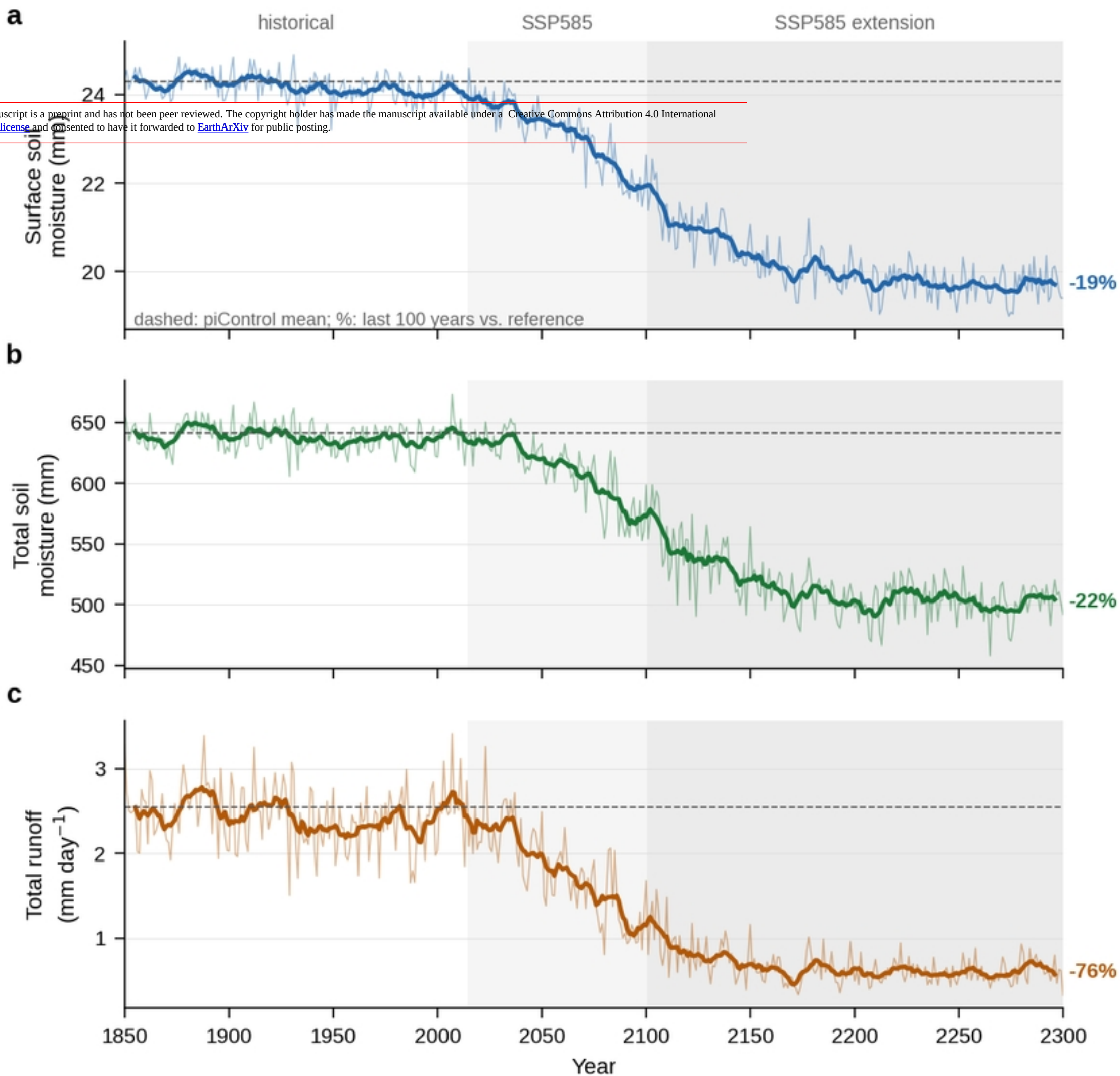


Figure 4

Longitudinal section of blocking index across scenarios - IPSL-CM6A-LR

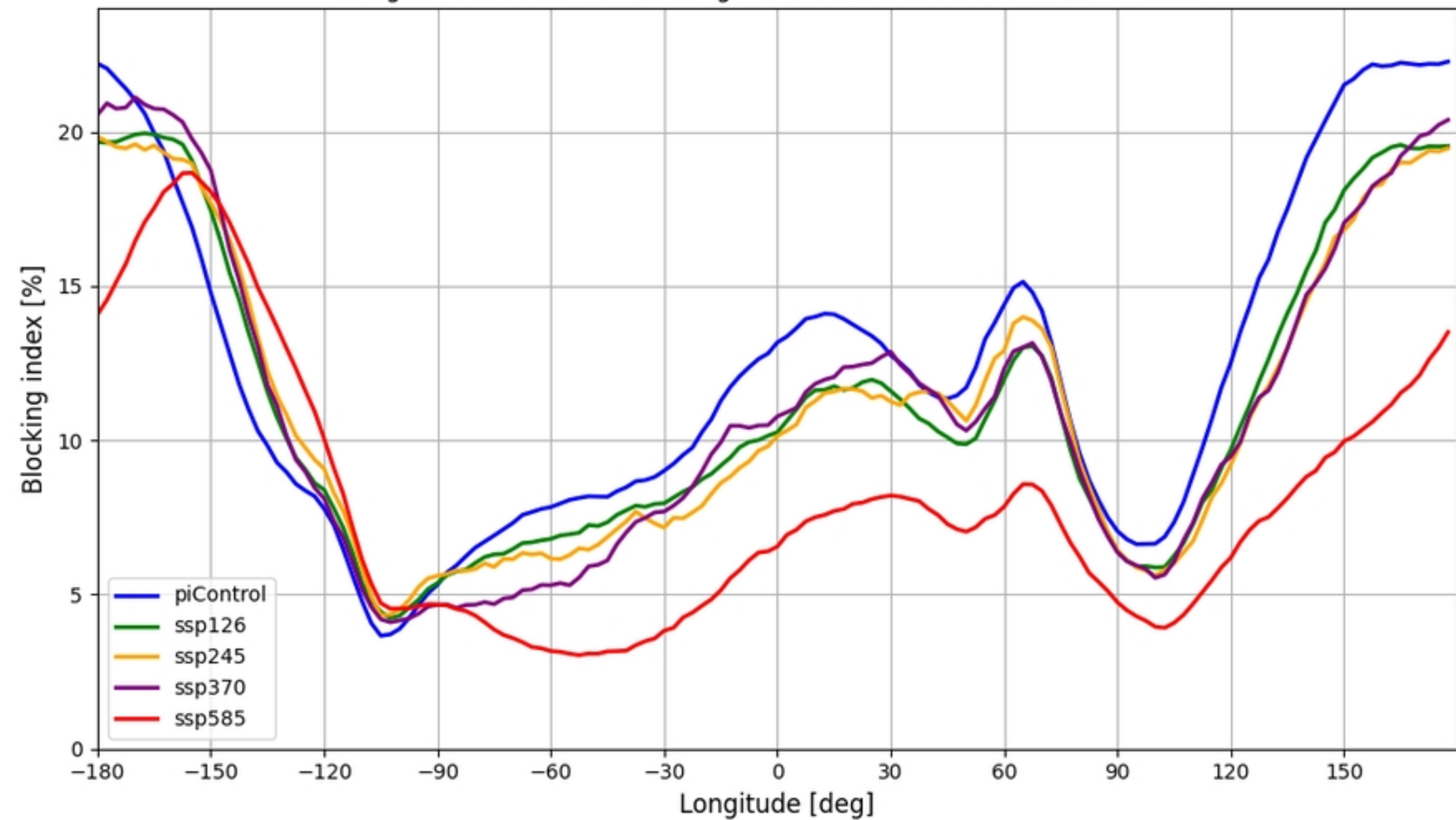


Figure 5

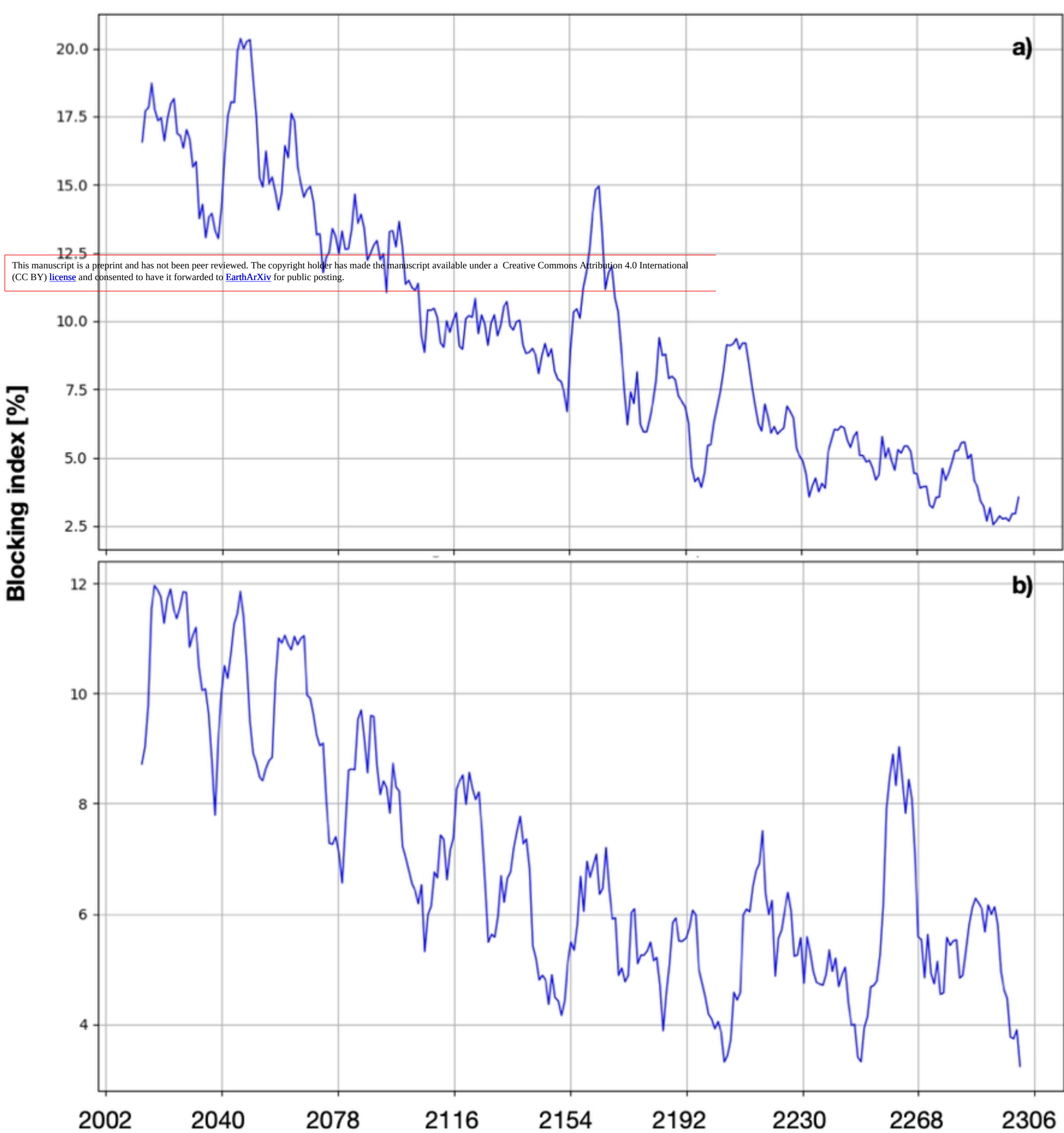


Figure 6

NAO, MIROC6

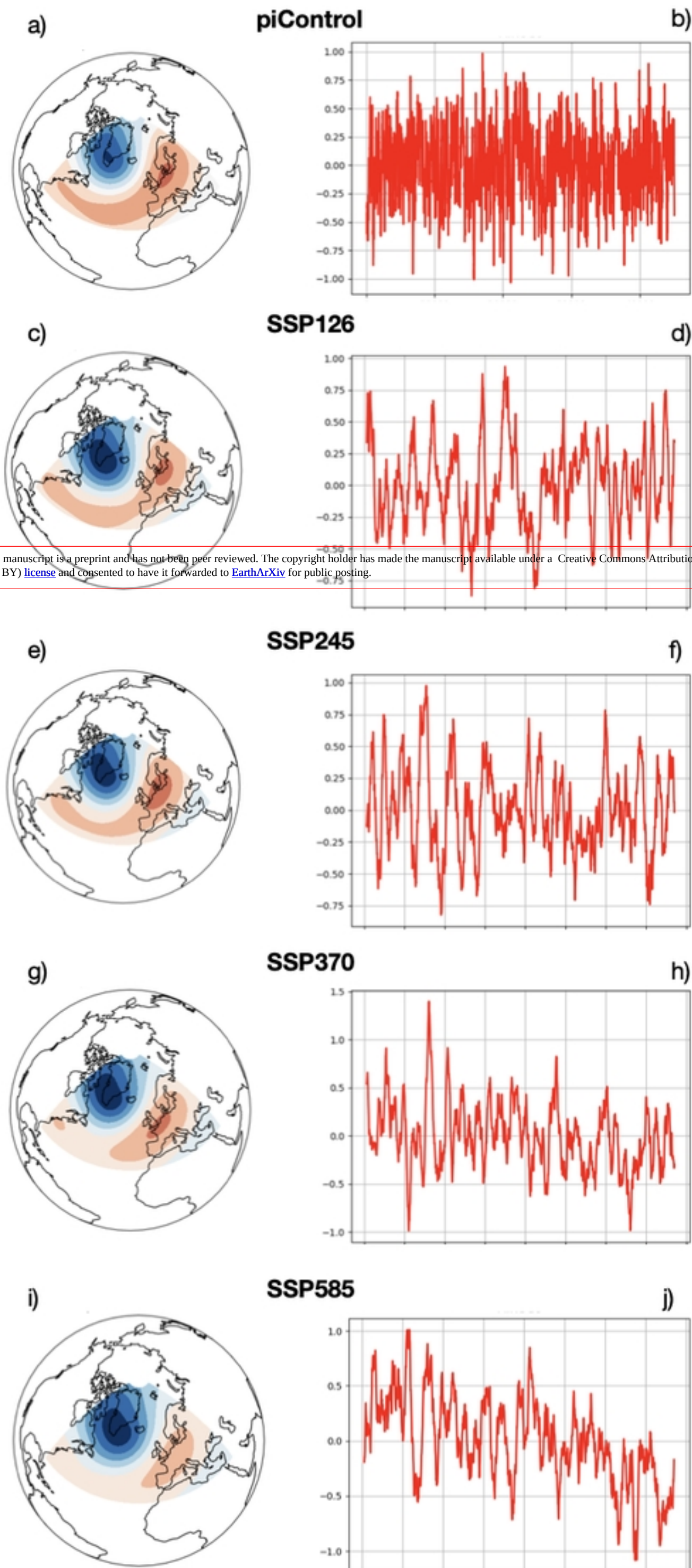


Figure 7