# Ubiquity of human-induced changes in climate variability

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**Abstract.** While climate change mitigation targets necessarily concern maximum mean state changes, understanding impacts
15   and developing adaptation strategies will be largely contingent on how climate variability responds to increasing anthropogenic perturbations. Thus far Earth system modeling efforts have primarily focused on projected mean state changes and the sensitivity of specific modes of climate variability, such as the El Niño-Southern Oscillation. However, our knowledge of forced changes in the overall spectrum of climate variability and higher order statistics is relatively limited. Here we present a new 100-member large ensemble of climate change projections conducted with the Community Earth System Model version
20   2 to examine the sensitivity of internal climate fluctuations to greenhouse warming. Our unprecedented simulations reveal that changes in variability, considered broadly in terms of probability, distribution, amplitude, frequency, phasing, and patterns, are ubiquitous and span a wide range of physical and ecosystem variables across many spatial and temporal scales. Greenhouse warming will in particular alter variance spectra of Earth system variables that are characterized by non-Gaussian probability distributions, such as rainfall, primary production, or fire occurrence. Our modeling results have important implications for
25   climate adaptation efforts, resource management, seasonal predictions, and for assessing potential stressors for terrestrial and marine ecosystems.

## 1 Introduction

Faced with the prospect of substantial future climate change, mitigation and adaptation strategies are increasingly paramount.

30   While mitigation efforts are concerned chiefly with limiting mean state changes, successful adaptation will also require understanding the potentially altered variability of the climate system (Sarachik, 2010). However, the way in which climate variability will change as a result of anthropogenic radiative forcing has not been extensively explored. The spectrum of observed regional-to-global climate fluctuations is characterized by spectral variance peaks superimposed upon a broad noise background (Hasselmann, 1976; Franzke et al., 2020). These peaks are either caused by astronomical forcings or associated

35   with spatio-temporal modes of internal climate variability (Stuecker et al., 2015), such as the El Niño-Southern Oscillation (ENSO). How modes of variability will respond to greenhouse warming has been addressed in a number of modeling studies (Timmermann et al., 1999; Cai et al., 2018), albeit with conflicting results. In contrast, the sensitivity of the spectral background to human-induced climate change is less well-known. Identifying and characterizing human-induced changes in this spectral background, using for example Climate Model Intercomparison Project (CMIP)-type coordinated modeling efforts, has proven

40   difficult due to limited statistics.

The relatively recent advent of Large Ensemble simulations (henceforth termed Large Ensembles) conducted with Earth system models provides a new resource for addressing how climate and ecosystem statistics may evolve in response to anthropogenic forcing across a wide range of timescales (Deser et al., 2020; Schlunegger et al., 2020). Such Large Ensembles

45   with global climate models have existed for more than 15 years (Zelle et al., 2005; Drijfhout et al., 2008; Branstator and Selten, 2009), but earlier studies expressed concern with aspects of process representation and therefore their results with regard to variability changes were inconclusive. Other studies have employed individual model simulations, small (≤10 members) ensembles, or CMIP multi-model ensembles (Rind et al., 1989; Raisanen, 2002; Huntingford et al., 2013; Screen, 2014; Stouffer and Wetherald, 2007; Wetherald, 2009) to address whether surface temperature and precipitation variability may

50   change under global warming. To date Large Ensemble studies of changes in variance have mainly focused on specific quantities, timescales, or regions (Deser et al., 2020; Pendergrass et al., 2017; Maher et al., 2019; Haszpra et al., 2020; Maher et al., 2021). However, to our knowledge, the full power of the Large Ensemble framework has not been applied to gauge broad-scale forced changes in climate statistics, including changes in variance, spectrum, patterns, phase, and variance, for a wide range of quantities, regions, or timescales.

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To study the sensitivity of higher-order climate statistics to anthropogenic climate change, we conducted a new 100-member ensemble of climate change simulations using the Community Earth System Model version 2 (CESM2) (Danabasoglu et al., 2020), which we refer to as CESM2-LE (Methods). The initialization and forcing are described in the Methods section and in **figs. S1-S3** of the Supplementary Materials. An ensemble of this size and duration with a CMIP6-generation Earth system

60   model at 1° spatial resolution is unprecedented. As such, it promises to provide an enhanced framework for documenting and understanding robust forced changes in internal variability, complementing our knowledge of mean-state changes (Simpson et al., 2020; Fasullo, 2020). The simulations were performed for the 1850-2100 period with historical (1850-2014) and SSP3-7.0 (2015-2100) forcings, and the choice of 100 members was motivated by the challenges associated with identifying trends in higher-order statistical moments (Milinski et al., 2020). To this end, substantial resources have been devoted to providing

65   high-frequency output for the atmosphere, land, ocean, and cryosphere. Providing a clearer view of the patterns of altered climate variability should facilitate investigation of the mechanistic drivers of such changes and their implications for impacts of societal and ecosystems relevance. This study presents initial results on forced changes in internal variability across a range of quantities and timescales in CESM2-LE and will serve as the reference publication for CESM2-LE.

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## 2 Methods

### 2.1 Model Configuration

The simulations consist of a 100-member Large Ensemble suite conducted with CESM2 with the Community Atmosphere Model version 6 (CAM6) (Danabasoglu et al., 2020), namely the CESM2-LE. The simulations which cover the period from 1850-2100 follow the historical and SSP3-7.0 forcing protocols provided by the CMIP6 (Eyring et al., 2016), although with some differences noted below for the representation of biomass burning in 50 of the 100 ensemble members. CESM2 has been demonstrated to fare well when evaluated against skill metrics with other models (Fasullo, 2020). The choice of the SSP3-7.0 scenario forcing follows CMIP6 recommendations (O'Neill et al., 2016) that emphasize the value of this « relatively high forcing level » precisely for the purpose of quantifying forced changes in natural variability. This choice should also provide a useful contribution towards an eventual CMIP6 Large Ensemble intercomparison

The CESM2 components use nominal 1° horizontal resolution. Specifically, CAM6 has a resolution of 1.25° in longitude and 0.9° in latitude, and 32 vertical levels with a top at 2.26 hPa, or approximately 40km. The ocean and sea-ice models are the Parallel Ocean Program version 2 (POP2) (Danabasoglu et al., 2020; Smith et al., 2010) and the CICE Version 5.1.2 (CICE5) (Bailey et al., 2020). CESM2 offers a number of improvements pertinent to our scientific interests relative to early versions of CESM1 that motivated our choice of this model. A few of the important advances with the present model configuration relative to what was available for the CESM1 Large Ensemble (Kay et al., 2015) are advances in the surface boundary layer representation for the ocean (Li et al., 2016), as well as for cloud microphysics (Gettelman et al., 2015). The ocean biogeochemistry model used with the POP2 model is the Marine Biogeochemistry Library (MARBL), which represents an updated version of what was previously known as the Biogeochemistry Elemental Cycle (Moore et al., 2001; Moore et al., 2004; Moore et al., 2013).

An important advance of great value to Large Ensemble investigations is achieved through new developments incorporated into the Community Land Model Version 5 (CLM5) (Danabasoglu et al., 2020; Lawrence et al., 2019; Lombardozzi et al., 2020). This model has been demonstrated to address a number of well-known limitations, including enhanced simulated cumulative $CO_2$ uptake over the historical period relative to previous versions of CLM (Bonan et al., 2019). There have also been important improvements in the implementation of the prognostic fire model and the explicit representation of agricultural management (Lombardozzi et al., 2020; Li et al., 2013; Li and Lawrence, 2017). The improvements have been extensively documented through evaluation of model simulations against the International Land Model Benchmarking (ILAMBv2.1) package (Collier et al., 2018; Danabasoglu et al., 2020; Lawrence et al., 2019). In addition to the significant improvement to net ecosystem production (NEP) highlighted in our analysis of phenology changes, improvements are found across a broad range of simulated variables in CLM5, relative to earlier versions of CLM.

### 2.2 Large Ensemble Initialization

For the CESM2-LE initialization procedure, the experimental configuration was designed to respond to broad community demand for a mix of macro- and micro-perturbations (where for micro-perturbations members differ only in a small random perturbation applied at initialization). To satisfy this demand and allow for exploration of the impact of initialization type, it was decided to initialize members from various years between 1001 and 1301 of a pre-industrial simulation conducted with CESM2 (Danabasoglu et al., 2020), as this corresponds to a time when model drift is relatively small, with the initialization procedure highlighted in **fig. S1**.

    i.    Micro-initializations start from four different years: 1231, 1251, 1281, and 1301. Twenty members were runs for each start year, with ensemble spread introduced by a random perturbation to the temperature field

110    at initialization (commonly referred to as « pertlim »), as was used for all members of the CESM1 large
       ensemble (Kay et al., 2015).

ii.    Macro-initialization (one run for each initialization date) using initialization years 1001, 1011, 1021, 1031,
       1041, 1051, 1061, 1071, 1081, 1091, 1101, 1111, 1121, 1131, 1141, 1151, 1161, 1171, 1181, 1191, i.e. using
       20 independent restart files at 10-year intervals over 1001-1191. Note that for this case no explicit
115    perturbation was required from the pre-industrial control simulation. Taken together, if one includes one
       member from each of the micro-perturbation runs, then a total of 24 macro-perturbation runs are available.

Importantly, as can be seen in **fig. S1b**, for the initialization points of years 1231, 1251, 1281, and 1301 were specifically
chosen for the micro-initializations to correspond to years of maximum, decreasing, minimum, and increasing Atlantic
Meridional Overturning Circulation (AMOC) transport, respectively, relative to the preindustrial control simulation. For the
120    analysis considered in this study, where the emphasis is on the two periods 1960-1989 and 2070-2099, we have assumed that
the memory of the climate system of differences in the initial conditions from the control run (black lines in **fig. S1**) is no
longer contributing to differences between ensemble members by 1950. Further quantitative exploration of the specific
duration over which initial condition memory is retained is the subject of a separate ongoing study.

125    The macro-perturbation runs initialized in 1011, 1031, 1051, 1071, 1091, 1111, 1131, 1151, 1171, and 1191 have greatly
enhanced output at high-frequency to meet the needs of broader community interests for large ensemble output. This includes
6-hourly snapshots of three-dimensional temperature, winds, and specific humidity for the Coordinated Regional Climate
Downscaling Experiment (https://cordex.org) simulations.

### 2.3 Large Ensemble Forcing

130    A choice was made to use two different sets of forcing fields to represent the effects of variability in biomass burning emissions
for the CESM2-LE (see **figs. S2-S3**). The biomass burning aerosol fluxes are imposed at the surface. As such, they are not
prognostic, meaning that they are not generated by the model's internal prognostic fire model. The first 50 members of our
Large Ensemble follow CMIP6 protocols (Van Marle et al., 2017), with biomass burning following the description in the
CESM2 overview paper (Danabasoglu et al., 2020). For the second set of 50 members, which we refer to as SMBB (for
135    smoothed biomass burning fluxes), the CMIP6 biomass burning emissions of all relevant species for CAM6 were smoothed
in time through an 11-year running mean filter. The averaging impacted variability in biomass burning fluxes over 1990-2020.
The temporal smoothing of the forcing is applied to the biomass burning emissions at each grid point subsequent to being
regridded to the CESM2 grid. The high 1990-2020 CMIP6 biomass burning variability (ensemble members 1-50, namely
CMIP6) relative to the smoothed forcing (ensemble members 51-100, namely SMBB) has a discernable impact on large-scale
140    climate, as documented by the accelerated loss of September Arctic sea ice and Northern Hemispheric and tropical Pacific
warming (**fig. S3a,c**).

### 3 Results

### 3.1 Mean State Changes

During the historical period the evolution of key simulated annual-mean climate indicators in CESM2-LE (**Fig. 1**; **fig S4**)
145    agrees well with observations. The range across the ensemble members, which results from internal variability and its forced
changes, spans the observed climate state much of the time, with a notable exception being Southern Ocean sea-ice (**Fig. 1e**).
The results here and the general model behavior are qualitatively consistent with those of similarly-forced CMIP6-generaion
models (Fasullo, 2020; Kwiatkowski et al., 2020; Arora et al., 2020), although projected temperature changes (**Fig. 1c**) are in
the upper range of the CMIP6 models owing to the relatively high sensitivity of CESM2 (Gettelman et al., 2019). The

150   progressive weaking of the AMOC in CESM2 over the 21st century (**Fig. 1f**) is largely consistent with other CMIP6 models (Weijer et al., 2020). We also find a substantial increase in land primary productivity (**Fig. 1g**), which contributes to the uptake of carbon in the terrestrial biosphere. Marine net primary productivity (NPP) (**Fig. 1h**) remains relatively constant throughout the simulation, and the overall uptake of carbon by the ocean reflects the re-emergence of anthropogenic carbon into the mixed layer (Toyama et al., 2017; Rodgers et al., 2020) and changes in the $CO_2$ buffering capacity of seawater (Revelle and Suess,

155   1957).   For the analysis that is presented in **Fig. 1** for sea-ice, daily-mean output fields are used for both the model and the data product.  In representing sea-ice extent a threshold of 15% was used, whereby each grid cell is identified as being ice covered. For the net land fluxes of $CO_2$, we use the variable net biome production which includes the effects of not only photosynthesis and respiration, but also fire and land-use change.


160   The pattern of mean state surface temperature change, shown as the difference between the periods 2070-2099 and 1960-1989 (**Fig. 2**, central; 2m reference temperature shown in **fig. S4**), exhibits preferential warming of the eastern relative to the western equatorial Pacific, Arctic amplification, and a pronounced warming hole over the subpolar North Atlantic. These features are associated with the known mechanisms of the enhanced equatorial warming pattern (Xie et al., 2010), and more positive polar feedbacks (Goosse et al., 2018) including the Arctic heat capacitor (Chung et al., 2021), and the slowdown of the AMOC

165   (Rahmstorf et al., 2015; Menary and Wood, 2018), respectively. For precipitation (**Fig. 2**, central; **fig. S4e**), changes include marked precipitation increases along the equatorial Pacific, within the Arctic Ocean, and decreases over the subtropical regions (Stocker et al., 2013).


### 3.2 Forced Changes in Amplitude, Frequency, and Phase

**Figure 2** illustrates the ensemble-aggregated Fourier amplitude spectra and probability density functions (PDFs) for five key

170   climate and ecosystem quantities (complementary quantities are shown in **fig. S5**). For the spectral analysis in **Fig. 2**, each Fast Fourier Transform (FFT) spectrum is calculated for the timeseries of raw data over a given variable for the full 35-year interval. This includes all timescales shorter than 35 years and longer than 2 days (months) for daily (monthly) time-resolution data. The spectrum is calculated first at each horizontal grid point and for each ensemble member, and then averaged over the designated region and over the 100 ensemble members. The spectral calculations are performed to represent amplitudes of

175   signals. The AMOC is defined as a maximum transport at 40°N. For the spectrum of internal variability of the AMOC, the ensemble-mean is subtracted from the raw data to remove a forced response. The surface chlorophyll concentration fields analyzed here represent total chlorophyll concentrations taken as a sum of diatom, diazatroph, and small phytoplankton chlorophyll.


180   For a wide range of Earth system variables, we find substantial changes of the projected 21st century probability distributions, impacting mean state, variance, and higher order statistical moments (**Fig. 2**). Human-induced alterations of climate probability distributions automatically translate into changes of the average return time of climate events. Averaging the spectra over 100 ensemble members and individual grid boxes within each region creates enough data to reveal spectral characteristics that might otherwise be obscured. The dominant feature for most quantities examined is the spectral peak at the annual frequency,

185   along with higher-order harmonics that result from deviations of the seasonal cycle from a pure sinusoid. Future changes of the annual cycle overtone spectrum can be caused by forced non-sinusoidal distortions of the annual cycle, generated e.g. by shifts in phenology, as discussed below. For nearly all variables under consideration, the seasonal cycle amplitude responds to the external forcing. Near-annual combination modes (C-modes) of ENSO and the seasonal cycle (Stuecker et al., 2015) and its overtones can be clearly identified in some spectra, particularly for precipitation over the equatorial Pacific. In addition to

190   representing the C-modes as deterministic components of the system, CESM2-LE also exhibits shifts in the frequency of the C-modes due to future reductions in ENSO's dominant frequency (**Fig. 3a**). The C-mode peaks also strengthen in the future,

reflecting that the amplitude of precipitation and the corresponding C-mode-generating non-linearity increase at both ENSO and annual frequencies.

195 For most of the variables shown in **Fig. 2** (and **fig. S5**) there are changes in the amplitude of the spectrum across the entire range of frequencies from decadal to interannual to intra-seasonal to synoptic, revealing the ubiquity of variance changes. Importantly, frequency-independent shifts in variance can be seen in the three variables shown here, which exhibit a strong non-Gaussian skewed PDF, namely the spectra of California wildfire occurrence, surface chlorophyll concentrations over the subpolar North Atlantic (40°N-60°N, 60°W-15°W), and precipitation over the Niño3.4 region (5°S-5°N, 170°W-120°W). For

200 these positive definite variables, which are all characterized by a highly-skewed probability distribution, forced changes in the mean state are accompanied by a stretching (squeezing) of the associated PDFs, thereby causing enhancement (or reduction) of variance and extremes. For stochastic processes, the associated variance changes manifest as timescale-independent variance changes, thereby accounting for the shown spectral background shifts. For California fire counts and Niño3.4 precipitation, mean state increases are therefore also accompanied by increases in variance occurring over a wide range of

205 timescales. For North Atlantic chlorophyll, the mean state decrease is associated with a timescale-independent decrease in variance, with expected impacts for higher trophic levels in the ocean, leading to potential disruptions to ecosystems.

For variables that are not positive-definite and less skewed, a diversity of responses is found. Forced changes in sea surface temperature (SST) variability in the Niño3.4 region are confined to interannual timescales in associated with a decrease in

210 ENSO amplitude and a slight shift toward higher frequencies. On the other hand, for NEP over the Amazon, reflecting natural $CO_2$ exchange between the land and the atmosphere, there is an increase in variance over all timescales, accompanied by a shift in the broad interannual peak towards higher frequencies.

We next turn our attention to an expanded view of the temporal evolution of both frequency and amplitude modulations of

215 SST and precipitation over the Niño3.4 region over the period 1960-2100. For the wavelet analysis in **Fig. 3**, we apply a Morlet wavelet normalized by $\overline{\sigma}^{-2}$, where $\overline{\sigma}$ is the ensemble mean standard deviation of the respective timeseries. For analyses of patterns of changes in variance, an adjusted Welch's $t$-test (Torrence and Compo, 1998) was applied. The general approach is to first calculate the equivalent sample size $\hat{n}$, to account for potential serial correlations of the time series. This is then used to calculate the degrees of freedom of the Welch's $t$-test, which is an adjusted version of the Student's $t$-test that allows for the

220 two samples to have unequal variance (i.e., heteroskedasticity). First, the decorrelation timescale $T_e$ was calculated at each grid point, and for each period, based on the e-folding timescale of the autocorrelation function $r(\tau)$, defined as the smallest lag $\tau$ for which $r(\tau) < e^{-1}$. Then the equivalent sample size $\hat{n}$ was defined as $\hat{n} = \frac{N}{T_e}$, where $N = 30$ is the total sample size in our case. The equivalent sample size was then used to calculate the degrees of freedom of the standard Welch's $t$-test. Note that this test may still be liberal if the equivalent sample sizes are small, i.e. in areas of high serial correlation.

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Ensemble wavelet analysis of SST (**Fig. 3a**) and precipitation (**Fig. 3b**) within the Niño3.4 region has been conducted after first removing the ensemble-mean trend over the full period from each ensemble member while retaining the seasonal cycle. The wavelet analysis is conducted for each ensemble member and then averaged. We consider the normalized variance to highlight the amplification above the white noise level, and in contrast to **Fig. 2** represent variance with a linear scale to

230 emphasize temporal modulation of the amplitude of the maxima. For SST a clear separation is seen between the maxima for interannual variability and the annual cycle (**Fig. 3a**). At interannual timescales, there are two notable features. The first is a shift in the ENSO peak period from 3.5 years to 2.5 years between the end of the 20th century and the end of the 21st century. The second feature with interannual variability is that variance does not change monotonically, but rather exhibits a maximum midway through the 21st century, similar to what has recently been reported elsewhere (Kim et al., 2014). This stands in

235   contrast to precipitation over the same region (**Fig. 3b**), for which there is a monotonic increase in variance, following a similar shift in the period of the peak that was found for SST. For precipitation, the amplitude of the seasonal cycle increases over 1960-2100, consistent with the notion of variability enhancement over the tropics due to thermodynamic and dynamic processes (Yun et al., 2021).

240   The forced changes over 1960-2100 in the structure of the seasonal cycle for the ensemble mean of SST (**Fig. 3c**), the ensemble-mean of precipitation (**Fig. 3d**), the standard deviation (SD) of SST (**Fig. 3e**), and the SD of precipitation (**Fig. 3f**) are also considered for the Niño3.4 region using daily-mean model output. The maximum (red dots) of ensemble-mean SST occurs in May and the minimum (blue dots) in October in the late 20th century (**Fig. 3c**), with both showing monotonic increases over 1960-2100. The maximum trends to two weeks later and the minimum trends to two weeks earlier by the end of the 21st

245   century, with this modest perturbation to the phase of the seasonal cycle being accompanied by a modulation of seasonal amplitude. The ensemble-mean seasonal amplitude in precipitation (**Fig. 3d**) occurs approximately one month before the ensemble-mean maximum in SST (**Fig. 3c**), and a second maximum in precipitation in late January becomes evident during the second half of the 21st century. On the other hand, the ensemble-mean minimum in precipitation occurs approximately two weeks after the local minimum in temperature. The increase in the amplitude of the seasonal cycle is thereby accompanied by

250   changes in the phasing of the seasonal cycle for both SST and precipitation.

The seasonally-stratified maximum cross-ensemble SD in SST (**Fig. 3e**), associated with peak ENSO variability, exhibits a trend towards an earlier occurrence by approximately one month over 1960-2070. This is accompanied by a modest decrease in amplitude (line plot). The SD minimum for SST occurs in July for the 20th century, with a secondary minimum in the SD

255   developing over the first half of the 21st century in May. Subsequently the SD minimum in May becomes more pronounced and becomes the dominant minimum n the SD of SST by the end of the 21st century. For the SD of precipitation (**Fig. 3f**), there is a monotonic strengthening of the seasonal maximum in late January, corresponding roughly to the time of peak ENSO variability, and a weakening of the seasonal minimum in October, over the interval 1960-2100. Whereas the seasonal minimum in the SD of precipitation (**Fig. 3f**) occurs nearly in phase with the seasonal minimum of ensemble-mean SST (**Fig. 3c**), the

260   seasonal maximum for the SD of precipitation does not coincide with the seasonal maximum of ensemble-mean SST. Rather, it coincides with the secondary seasonal maximum in ensemble-mean precipitation in late January (**Fig. 3d**).

### 3.3 Changes in Variance and Co-variance Patterns

Along with modulations in the frequency domain, the spatial patterns of variance are altered in response to changing climate conditions. The analysis of patterns of variance and co-variance in **Fig. 4** uses cross-ensemble calculations of annual-mean

265   standard deviations, with the cross-ensemble calculations applied for identical time records for each ensemble member. For the case of precipitation, averaged over December, January, February (DJF) (**Fig. 4a**), and surface temperature for DJF (**Fig. 4b**), the standard deviations calculated separately over all years spanning 1960-1989 and 2070-2099 were first calculated, and then averaged over the two respective periods. The intention with the calculation of both standard deviations and correlations is to harness the full power of the Large Ensemble, and is analogous to the empirical orthogonal function (EOF) EOF-E

270   snapshot method previously applied with empirical orthogonal functions (EOFs) (Maher et al., 2018).

We begin by considering interannual variance changes in boreal winter (December-January-February, DJF) by evaluating relative changes in the cross-ensemble SD of surface temperature and precipitation for the same periods as with the spectra in **Fig. 2** (1960-1989 and 2070-2099). The background cross-ensemble SD averaged over 1960-1989 is shown in shading (**Fig.**

275   **4a,b**). Surface temperature (**Fig. 4a**) reveals modest decreases in variability across the equatorial Pacific and Indian Oceans, consistent with **Fig. 2**. Variability decreases over much of the higher latitudes of the Northern Hemisphere, with exceptions

over the Arctic and the North Atlantic, and with exceptions in the Southern Hemisphere found over Southern Africa and parts of Antarctica (**Fig. 4a**). For precipitation (**Fig. 4b**) a relative increase in SD is seen over most regions with particularly pronounced enhancements occurring in the eastern equatorial Pacific, the Indo-Pacific warm pool including the South Pacific

280 Convergence Zone, the western Arabian Sea, the poles, and most land areas. The equatorial Pacific changes represent an eastward broadening in the centers of convection in response to the enhanced equatorial Pacific warming and the reduction of the overall zonal SST gradient (**Fig. 2**, **center**). In contrast, there is a decrease in the northern equatorial Atlantic Ocean as well as in some trade wind regions of the eastern Pacific.

285 Another important question to address is whether greenhouse warming can also impact the co-variability of different climate components and the global teleconnections of major modes of climate variability. This is illustrated here by examining the projected changes in the local correlation coefficients between the Niño3.4 SST index and surface temperature from 1960-1989 and 2070-2099 (**Fig. 4c**), with the background correlation coefficients shown in shading and their respective future changes shown in circles. Our analysis reveals a systematic strengthening of ENSO's remote temperature correlation over the

290 Amazon basin and in the equatorial Atlantic, the Philippines and Japan in the western Pacific, throughout Africa, in Northern India and across eastern Canada and the Southern U.S. Co-variance decreases over western Canada and Alaska, and zonally across the equatorial Indian Ocean.

The future changes in the correlation between the Niño3.4 index and precipitation (**Fig. 4d**) indicate a pattern of enhanced co-

295 variance over the western Pacific region surrounding the Philippines, much of Africa and South America, and western China, as documented by the background correlation coefficients and their future changes having the same sign. In other words, in these regions we see stronger ENSO teleconnections under future global warming, which in turn could translate to increased predictability of climate in the regions on seasonal to interannual timescales, but also stronger impacts. In contrast, decreased precipitation co-variance with ENSO is found for North America over the Pacific Northwest as well as much of the Southern

300 U.S. and Mexico, as well as over Columbia/Venezuela, Bangladesh/Myanmar, parts of eastern Australia, and parts of eastern Siberia. Taken together, the global pattern of ENSO/precipitation co-variance changes (**Fig. 4d**) is due to a combination of simulated weakening of ENSO SST variability (**Fig. 4a**) and eastward expansion of the region of maximum convective activity in the equatorial Pacific (**Fig. 4b**) (analysis for the June-July August (JJA) season in shown in **fig. S6**), and likely other projected changes of the background atmospheric circulation.

305 **3.4 Forced Changes in Phenology of Net Ecosystem Production**

Finally, we illustrate how anthropogenic forcing impacts the phase of the seasonal cycle by focusing on the phenology of NEP in the Northern Hemisphere mid-to-high latitudes (over 50°N-80°N). This is motivated by ecological concerns that a shift to an earlier spring bloom, in particular over the land regions adjacent to the Arctic, can drive a phenological mismatch in ecological interactions between plants and animals (Renner and Zohner, 2018). For the seasonality/phenology analysis in the

310 upper panel of **Fig. 5**, and area-integral of daily-mean net ecosystem production (NEP), representing the difference between gross primary productivity and ecosystem respiration, is performed over the domain 50°N-80°N for each ensemble member separately. A total of 90 ensemble members are used, as daily-mean CLM5 output was not saved for the first 10 members, namely for 1001.001, 1021.002, 11041.003, 1061.004, 1081.005, 1101.006, 1121.007, 1141.008, 1161.009, and 1181.010.

315 Ensemble-mean NEP is integrated over the region in 5-year intervals (colors in **Fig. 5**, upper panel). We find an evolving amplitude of the seasonal cycle and of the growing season length (the interval during which NEP is positive, indicating net land uptake of carbon). This representation of forced changes in the non-sinusoidal seasonal cycle reveals that the growing season length is projected to increase by approximately three weeks, with the onset shifting two weeks earlier and termination

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shifting one week later. It also reveals a more than doubling of the amplitude of the seasonal cycle as a forced response. This
represents an increase in the "breathing" of the terrestrial high-latitude biosphere. Information from individual ensemble
members in 20-year intervals regarding the timing of (i) first zero crossing, (ii) maximum NEP, (iii) second zero crossing, and
(iv) maximum negative NEP (**Fig. 5**, lower panel) reveals that interannual variability is in general smaller than the forced trend
evident in the ensemble mean in spring. This analysis indicates that for NEP aggregated over this region the phenological shift
as a decadal trend becomes emergent relative to estimates of the natural variability already within the first decades of the 21$^{st}$
century, a trend that is broadly consistent with observations (Zhu et al., 2016; Myers-Smith et al., 2020). Internal variability
in the date of the onset of the growing season decreases by 35% over the course of the simulations and decreases by 18% for
the date of the end of the growing season. The forced changes in growing season length are mostly attributable to changes in
the mean temperature (Lawrence et al., 2019; Lombardozzi et al., 2020). In contrast, the internal variability in the amplitude
of the seasonal maximum increases by 63% over the simulations, and the absolute amplitude of the seasonal minimum
increases by 22% over the course of the simulations.

## 4 Discussion

This study introduced a new, publicly available Large Ensemble of climate change simulations conducted with the global fully
coupled CESM2 model. This Large Ensemble (CESM2-LE) is unprecedented in terms of its combination of size (100
members), duration (1850-2100), and spatial resolution in the atmosphere and ocean (nominally 1° horizontally). As such, it
affords a unique opportunity to study not only forced changes in the mean state, but also forced changes in internal variability,
including higher-order statistical moments. Here we showcase aspects of the remarkable diversity of forced responses in
amplitude, frequency, patterns, co-variance, and seasonal characteristics of internal variability in CESM2-LE across a broad
suite of key physical and ecosystem quantities, spanning the atmosphere, land, cryosphere, and ocean. Importantly, and
contrary to conventional wisdom, the changes are not solely centered on the frequency of specific climate modes such as
ENSO and the Madden Julian Oscillation, but are instead broadly distributed over nearly all timescales (**Fig. 2**), in particular
for non-Gaussian distributed variables. The mechanistic underpinnings of the changes in variability go beyond amplification
or damping of major climate modes, and possibly include state-dependence of linear stabilities, non-linearities, rectification,
and changes in damping timescales and noise characteristics, many of which will be investigated in forthcoming studies
analyzing the breadth of the CESM2-LE output fields.

If the ubiquitous changes in variance across temporal and spatial scales described here are realized in the real world, they will
have a number of important implications for informing adaptation strategies and assessing potential impacts. This holds for
water resource management and agriculture, fisheries, and occurrence of wildfires. Forced changes in phenology and phasing
of the seasonal cycle for ecosystem productivity pose risks of mismatches with trophic level interactions and energy transfers.
The ubiquity of such changes in variability also points to the importance of moving beyond the assumption of stationary
variability in detection and attribution studies of climate change (Hegerl et al., 2007), and underscores the necessity of
recalibrating climate-economy models (Diaz and Moore, 2017) to account for an entirely different probability distribution for
variability (**Fig. 2**, **fig. S5**) than what is currently used when projecting future climate change scenarios. The non-stationary
nature of climate noise under anthropogenic forcing (**Fig. 2**) and the evolving teleconnections patterns (**Fig. 4**) also have
implications for seasonal to multi-year climate predictability.

Although our analysis of the CESM2-LE has revealed a broad range of forced changes in variance across physical scales and
Earth system variables, it nevertheless should be emphasized that model-uncertainty has not been considered here. There is
already evidence for the narrower case of interannual variability in surface temperature and precipitation that model uncertainty

360     in forced changes exhibits pronounced differences between models (Maher et al., 2021) (their Supplementary Figures 7 and 8). Thus it is our hope that our work will motivate further investigations of forced change in Earth system variance across a broad range of timescales under existing archives of large ensemble simulations (Deser et al., 2020; Schlunegger et al., 2020).

        Taken together, our analysis reveals an Earth system which is far more sensitive in its statistical characteristics to
365     anthropogenic forcing than previously recognized. Although only a small fraction of such forced changes could be documented in this study, we expect that the diagnostic ensemble analysis tools applied here, along with the open access to our datasets, will inspire further investigations into the non-stationarity of Earth system processes in the presence of anthropogenic forcing.

**Code Availability**

Analysis code is available from the authors by request. The python wavelet software used for Fig. 3 was provided by Evgeniya Predybaylo (Torrence and Compo, 1998) and is available at http://atoc.colorado.edu/research/wavelets/.

**Data Availability**

The CESM2-LE model output is available through:

https://www.cesm.ucar.edu/projects/community-projects/LENS2/data-sets.html

**Author Contributions**

The CESM2-LE projected was initiated by KBR., A.T., G.D. and C.D. The scientific framing of this manuscript was developed by K.B.R., A.T., J.-E. K., R.Y. K.S., S.-S. L. and M.F.S. Analyses and scientific post-processing were performed by R.Y., J.-E.K., K.S., L.H., T.B., and W. K. The CESM2-LE model runs were set up, performed, and extracted through a joint effort by the team of S.-S.L., N.R., and J.E. The initialization procedure for the model was developed through the joint efforts of C.D., G.D., I.S., W.K., S.G.Y., and N.R. All authors discussed the results and contributed to the writing of the manuscript.

**Competing Interests**

The authors declare that they have no conflict of interest.

420   **Figure 1: Annual mean evolution of global fields over 1850-2100 for 100 ensemble members.** For model fields, bold lines represent ensemble means, and dark and light shading represent one standard deviation (SD) and two SD variability. Observational data are shown in red when appropriate. Portions of the figure with light-blue background shading indicate the historical period (1850-2014) while portions with light-red background shading indicate the projection period (2015-2100). (a) Top of atmosphere radiative balance (W m$^{-2}$) along with the CERES-EBAF product (Loeb et al., 2018), (b) anomalies of

425   the global mean precipitation (mm day$^{-1}$) increasing 5.4% between the 1850s and the 2090s, compared with the Global Precipitation Climatology Project (GPCP) (Adler et al., 2003; Adler et al., 2012), (c) anomalies of global mean surface temperature, increasing by 4.4°C between the 1850s and 2090s, along with HadCRUT4 (Morice et al., 2012) anomalies over 1950-2019, (d) anomalies of ocean heat content integrated over the upper 1500m, along with an observation-based product (Ishii et al., 2017), (e) anomalies of sea ice extent for the Arctic (black) and Southern Ocean (blue), with observed sea ice

430   extent over 1979-2020 (Fetterer et al., 2017), and with the vertical scales of the anomaly plots offset to facilitate comparison, (f) Atlantic Meridional Overturning Circulation (AMOC) transport anomalies at 26.5°N, with RAPID array observations (Frajka-Williams et al., 2019), (g) globally-integrated net primary productivity (NPP) over the ocean (blue; increase of 2.7% between the 1850s and 2090s), and over land (green), and (h) globally-integrated net $CO_2$ fluxes over the ocean (solid blue) and integrated net $CO_2$ flux (net biome production, or NBP, including fire and land-use change) over land (green) with all

435   quantities in (g) and (h) in units of PgC yr$^{-1}$. For each case, where observational products are included, anomalies are calculated with respect to the period spanned by the observations. For anomaly fields, printed numbers represent the absolute mean of the ensemble mean of CESM2-LE (black or blue numbers) and the observational product (red numbers).
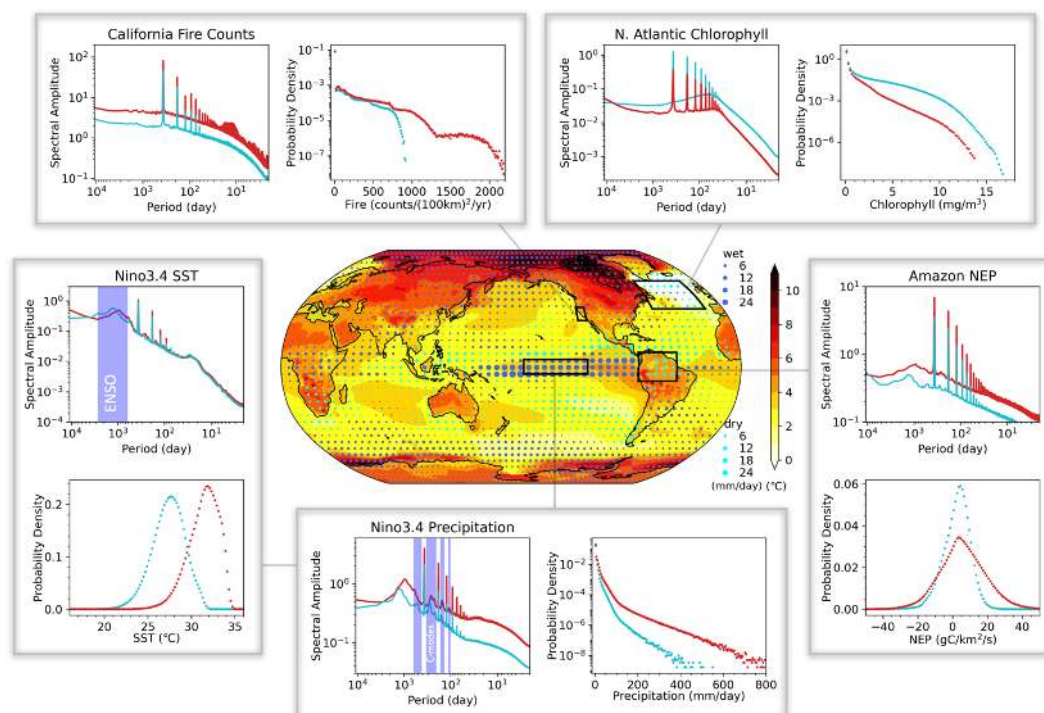
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**Figure 2: Changes in the Fourier amplitude spectrum of historical (1960-1989) to future (2070-2099) climate variability in CESM2-LE.** The center map shows historical-to-future changes in surface temperature (shaded, °C) and precipitation (solid blue dots, mm day$^{-1}$). Each pairing of panels shows historical (cyan) and future (red) spectra and PDFs for five different variables over four different regions. The spectra are considered over the respective periods, 1960-1989 (historical) and 2070-

445  2099 (future), thereby including the trend, and PDFs are considered for all days over 1980-1989 and 2090-2099 to minimize the impact of the trend. From upper-left clockwise, each pair of panels shows the historical (blue) and future (red) members of fire occurrences in California (32°N-41°N, 125°W-118°W, land only), surface chlorophyll concentrations in the North Atlantic subpolar gyre (40°N-60°N, 60°W-15°W), net ecosystem production (NEP) in the Amazon (10°S-10°N, 80°W-50°W, land only), precipitation over the Niño3.4 regions (5°S-5°N, 170°W-120°W), and sea surface temperature (SST) over the

450  Niño3.4 region. The spectra are calculated for daily timeseries at individual grid points including both forced responses and internal variability and using 30-year intervals. Subsequently the spectra are averaged over the grid points in each region. Sharp spectral peaks are associated with the annual cycle and its non-sinusoidal components, which generate high-order harmonics. Shaded areas for spectra of precipitation and temperature in the Niño3.4 region correspond to the timescales of the El Niño-Southern Oscillation (ENSO) and ENSO-annual cycle combination modes (Stuecker et al., 2013) (C-modes). Spectra

455  are shown as amplitude, with the units being the same as the x-axes for the PDFs. PDFs of positive-definite variables (California fire counts, N. Atlantic surface chlorophyll, and Niño3.4 precipitation) are shown with logarithmic y-axes. The fields in the center panel are presented in more detail in **fig. S4**, except that there 2m reference temperature is used rather than surface temperature. A suite of complementary spectral and PDF analyses to those shown here are presented in **fig. S5**.
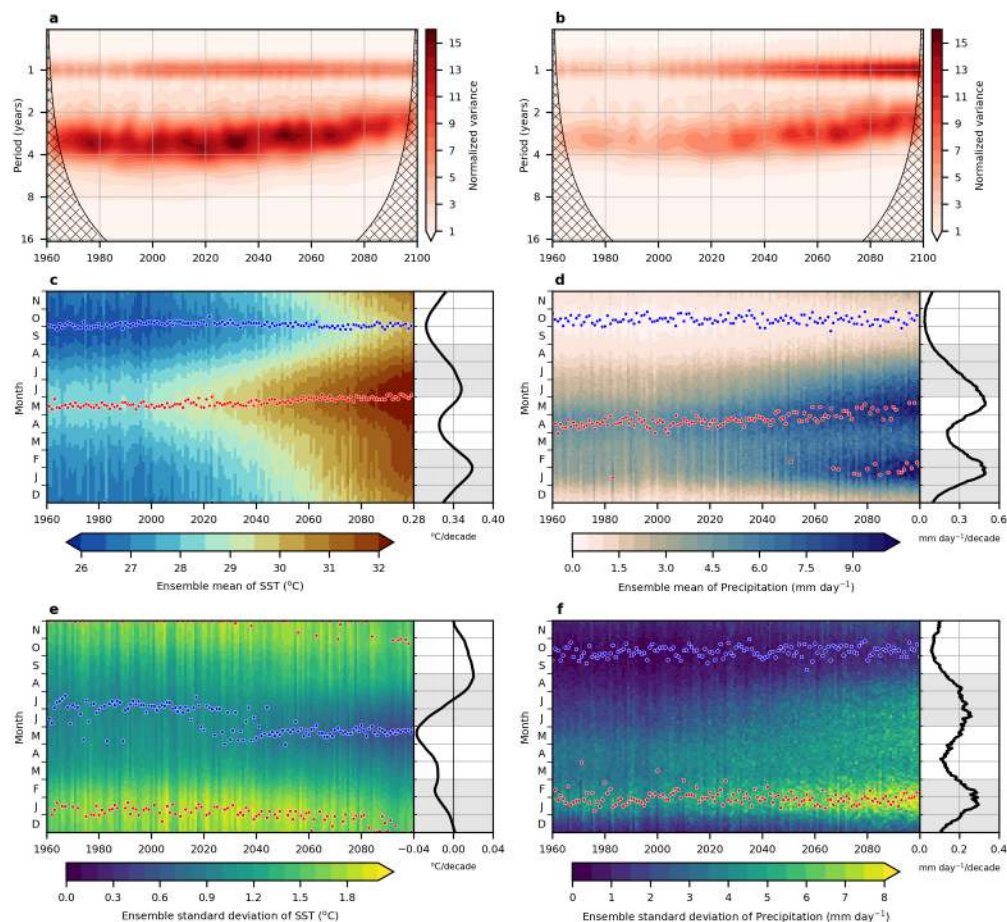
**Figure 3: Changes in the dominant frequencies and seasonal variance of sea surface temperature (SST, left) and precipitation (right), in the Niño3.4 region (5°S-5°N, 170°W-120°W).** (Top) The wavelet power spectra of Niño3.4 (a) SST and (b) precipitation using a Morlet wavelet, normalized by $\bar{\sigma}^{-2}$, where $\bar{\sigma}$ is the ensemble mean standard deviation of the respective Niño3.4 time series (Torrence and Compo, 1998). The y-axis shows the equivalent Fourier period in years. The hatching indicates regions where the wavelet spectrum is not trustworthy due to edge effects. Prior to calculating the wavelet spectra, the time series were detrended by subtracting the ensemble-mean annual means, which were linearly interpolated to a monthly timestep. (Middle) The ensemble-mean of Niño3.4 (c) SST and (d) precipitation indicated for each day (ordinate) and year (abscissa) using daily output. The red/blue dots indicate the maximum/minimum daily values of each year. The black line to the right in panels (c)-(f) indicates the linear trend over 1960-2100. (bottom) Same as for (c) and (d), but for the cross-ensemble standard deviations of (e) SST and (f) precipitation.
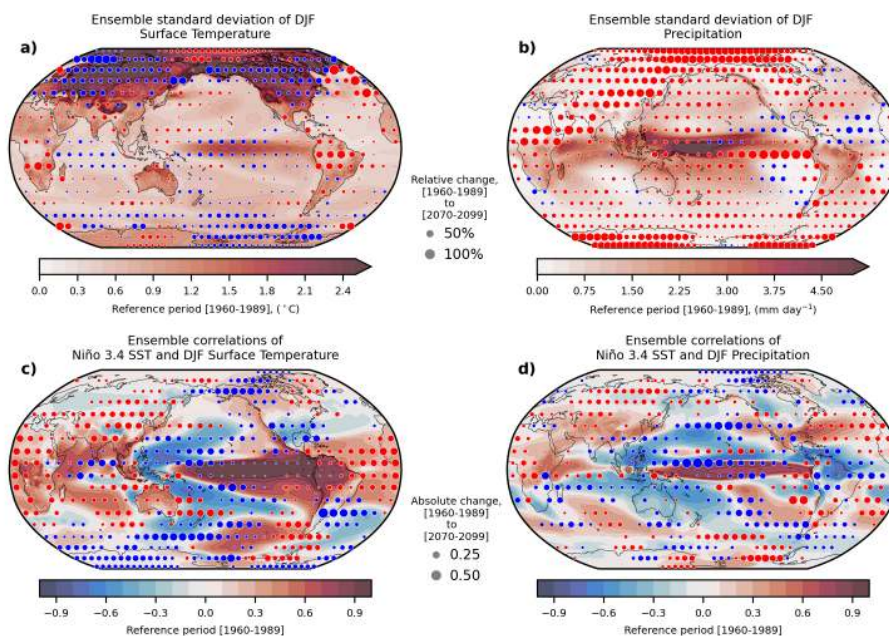
**Figure 4: Changes in the patterns of interannual variability and Niño3.4 correlation coefficients of December-January-February (DJF) surface temperature and precipitation.** (Top) Color shading shows the time-averaged absolute cross-ensemble standard deviation of the DJF seasonal mean surface temperature (a) and precipitation (b) for the period 1960-1989.
475 Circles show the relative changes in the standard deviations between 2070-2099 and 1960-1989, where insignificant change ($p \geq 0.05$) has been removed. Statistical significance of the changes (circles) was determined based on the $p$-values of the two-sample Welch's $t$-tests for the equality of temporal means of the ensemble standard deviations, with the equivalent sample sizes adjusted to account for serial correlations (Methods). (Bottom) Color shading shows ensemble-wise correlations of the Niño3.4 index with surface temperature (c) and precipitation (d) anomalies for DJF, averaged over the period 1960-1989.
480 Circles show the absolute change in correlations between 2070-2099 and 1960-1989, where statistically insignificant changes ($p \geq 0.05$) have been removed. The Niño3.4 index for ENSO is the spatial average of sea surface temperature within 5°S-5°N, 170°W-120°W. Statistical significance of the changes (circles) was determined based on the $p$-values of two-sample Student's $t$-test of the Fisher $z$-transformed correlation coefficients (Timmermann et al., 2014). Note that the $t$-test treats the ensemble standard deviations and correlations as stationary and serially uncorrelated with either of the two periods. For all four panels,
485 the circles represent subsampled fields at 10° intervals over the global domain. The corresponding analysis for June-July-August (JJA) is presented in **fig. S6**.
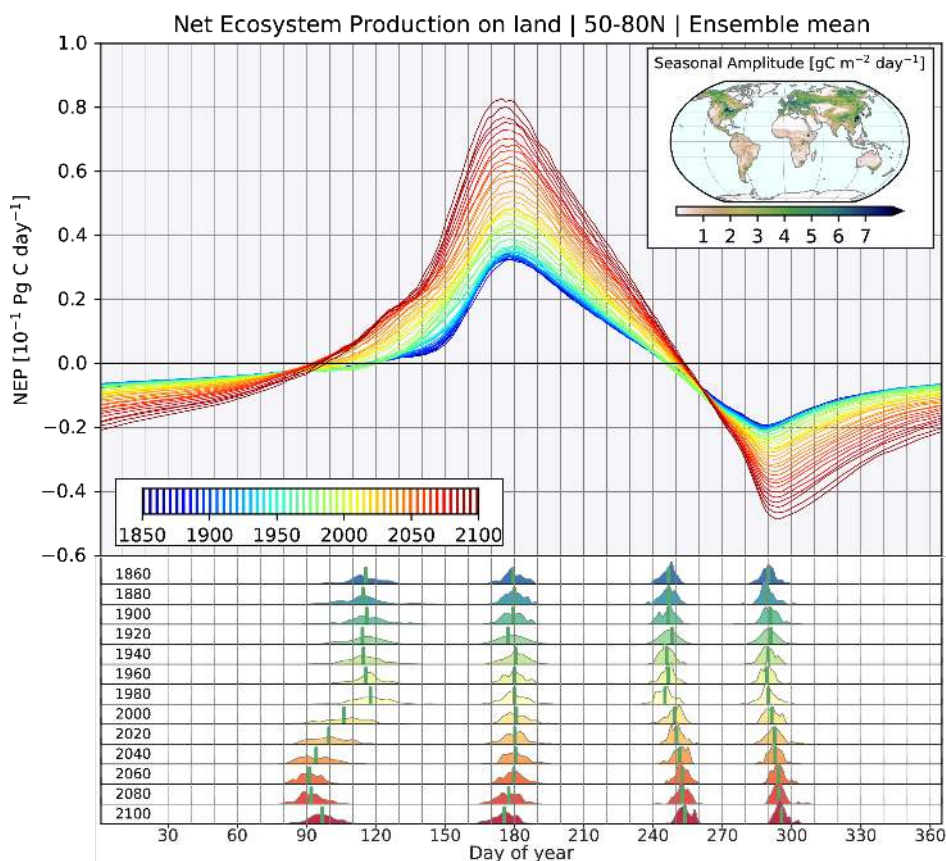
**Figure 5: Expansion of growing season length, or equivalently the carbon uptake period, over 50°N-80°N (shown here for all 90 members for which daily-mean land output was saved).** Upper panel: Evolution of ensemble mean seasonal cycle
490 (one line for every five years, color-coded) of integrated net ecosystem productivity (NEP), with positive values indicating net terrestrial carbon uptake and negative values indicating loss of carbon from the aggregated land region. The first zero crossing marks the start of the growing seasons, and the second zero crossing marks the end of the growing seasons; Lower panel: Histograms of first occurrence of zero crossing, peak, second zero crossing, and minimum as a function of the day of year. The horizontal axis for both panels is a climatological calendar year, and aggregation is done across 90 members. The
495 histograms represent model output sampled at 20-year intervals. The inlay map (upper right) shows the ensemble mean amplitude of the seasonal cycle of NEP averaged over 1960-1989 (gC m$^{-2}$ day$^{-1}$).

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