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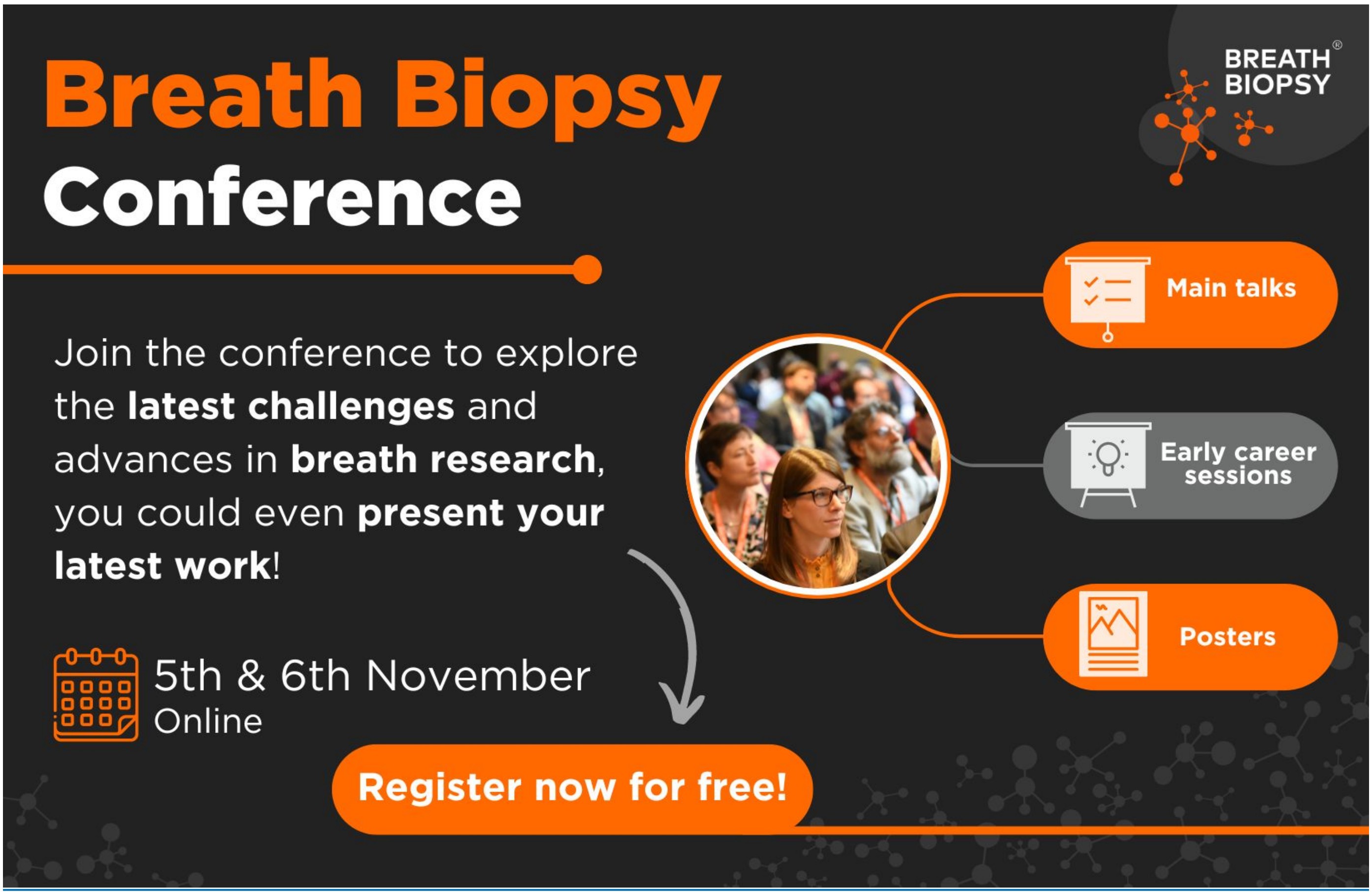

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LETTER

Detecting climate milestones on the path to climate stabilization

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Supplementary material for this article is available online

Abstract

The era of anthropogenic climate change can be described by defined climate milestones. These milestones mark changes in the historic trajectory of change, and include peak greenhouse gas emissions, peak greenhouse gas concentration, deceleration of warming, net-zero emissions, and a transition to global cooling. However, given internal variability in the Earth system and measurement uncertainty, definitively saying that a milestone has passed requires rigour. Here CMIP6 simulations of peak-and-decline scenarios are used to examine the time needed to robustly detect three climate milestones: (1) the slowdown of global warming; (2) the end of global surface temperature increase; and (3) peak concentration of CO_2. It is estimated that it will take 40 to 60 years after a simulated slowdown in warming rate, to robustly detect ($>95\%$ change) the signal in the global average temperature record. Detecting when warming has stopped will also be difficult and it takes until the mid 22nd century to have enough data to conclude warming has stopped. Detecting that CO_2 concentration has peaked is far easier and a drop in CO_2 concentration of 3 ppm is consistent with a greater than 99% chance that CO_2 has peaked in all scenarios examined. Thus it is likely that as the rate of CO_2 emissions is reduced, and net-zero emissions is approached, interpreting the global temperature record will become difficult—with a high potential to create confusion amongst policy makers and the general public.

1. Introduction

The Paris Agreement commits nations to hold the change in global average temperatures well below 2 °C relative to the pre-industrial climate and to pursue efforts to limit warming to 1.5 °C relative to preindustrial levels [1]. It therefore sets global annual mean near-surface temperature change (hereafter global average temperature change) as a paramount indicator for global climate policy. Importantly, the Paris Agreement text is susceptible to both the understanding that global average temperature rise should be kept below 1.5 °C at any point in time and the understanding that it should return to below 1.5 °C after a potential overshoot that remains well below 2 °C at all times [2, 3]. However, both cases require global average temperature rise to be halted. Scientific efforts have established that halting global average surface temperature increase requires near zero emissions of CO_2 [e.g.][4–8], and a gradual reduction of non-CO_2 forcing [9]. These scientific evaluations have informed the proliferation of national net-zero goals that many nations have now committed to [10–13]. However the path to global climate stabilization is a long one and even the most mitigation-intense future scenarios do not forecast reaching global net-zero greenhouse gas emissions until the 2060s CE [14–16]. Thus it is useful to define milestones on this path, informed by the primary cause of climate change (emissions of greenhouse gases and aerosols) and by the principle metric of climate change—change in global average near-surface temperature. Climate

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milestones act as progress indictors on the path to climate stabilization. As the project of climate stabilization is likely to take longer than the lifetimes of most living adults [17] climate milestones are needed to mark progress towards that ultimate goal.

For greenhouse gases and aerosols a range of potential climate milestones can be defined, namely: peak emission, peak concentration, net-zero emission, and—at the limit and in certain circumstances—zero concentration. Whether a particular milestone makes sense for a gas or aerosol depends on whether it is naturally occurring or synthetic, and its lifetime in the atmosphere. For some greenhouse gases key milestones have already passed. For example CFC-11, which was banned by the Montreal Protocol due to its effect on stratospheric ozone [18], had peak emissions sometime in the late 1980s and reached a peak concentration in 1993 at 269 pptv [19]. However for most greenhouse gases such milestones will have to be achieved in the future.

Climate milestones can also be defined for global temperature change. Narrowing our focus to peaking global average temperature increase, two milestones become notable: when the rate of warming has slowed, and when warming has stopped (equivalent to passing peak temperature). Due to the intrinsic inter-annual variability in estimated global average temperature change, assessing changes in the rate of temperature change requires rigour [20] as otherwise insights might not live up to statistical scrutiny. For example, this was repeatedly the case during the so-called 'global warming hiatus' of the 2010s [20, 21]. Thus for each climate milestone it is more important to quantify when such a milestone can be detected, rather than when such a milestone might retrospectively be assessed to have been passed.

There are a large number of climate milestones that can be defined and thus as a first exploration of the topic a narrower focus is needed. We have chosen to focus on two temperature milestones, and a single milestone in the evolution of a single greenhouse gas, CO_2, the main driver of global warming [22]. The milestones are: (1) the slowdown of global warming; (2) the end of global surface temperature increase; (3) peak concentration of CO_2. We probe two additional milestones in our supplementary material—peak emissions of CO_2 and net-zero CO_2 emissions. These two milestones are important for understanding CO_2 derived climate-milestones, but cannot be directly measured instrumentally and thus are far less amenable to existing techniques of statistical analysis. The three primary milestones will be explored using statistical methods developed to study the 'global warming hiatus'. Exploration of climate milestones for other greenhouse gases and aerosols are important next steps, but are left as research opportunities for teams that are experts on the intricacies of the sources, sinks and biogeochemical cycling governing these gases and aerosols.

2. Methods

2.1. Global temperature milestones

While the so called 'global warming hiatus', that became a subject of scientific interest in the 2010s, turned out to be an outcome of expected natural climate variation [20, 21], intense study of the phenomenon lead to development of improved statistical tools for examining changes in the rate of global average temperature change [e.g.][20]. One of the most robust methods developed in this period is the Monte–Carlo based method developed by Rahmstorf *et al* [20], which we use here as the basis of our analysis of global average temperature change. Monte–Carlo methods use large numbers of simulations with randomized parameter values to approximate the potential behaviours of complex systems [23], and are particularly useful for quantifying low probability events [23]. The method of Rahmstorf *et al* [20] essentially applies a simple signal and noise model, where the signal is taken as the linear trend in global average temperature from 1972 to 2014 CE, and the noise is taken as white noise with a standard deviation of the residuals from the 1972 to 2014 CE trend fitting [20]. Note that white noise is simply normally distributed values with no autocorrelation [24]. Monte–Carlo simulations of randomly generated noise were then produced and added to the signal from the 1972 to 2014 trend, to examine whether the temperature trends of the hiatus period, defined as either 2000 to 2012 CE or 2001 to 2014 CE, are anomalous to the degree of reaching some reasonable metric of significance [20].

Here we modify the method of Rahmstorf *et al* [20] to examine our three primary climate change milestones: when global warming has slowed, when global warming has stopped, and when CO_2 has reached a peak. For the two temperature milestones we use projections of global average temperature change from the Climate Model Intercomparison Project phase 6 (CMIP6), taking the global averages from the *CMIP6 Data Viewer* database [25].

2.1.1. Global warming slowdown

For the global warming slowdown milestone we examine the four ScenarioMIP scenarios that were designed to have temperature peaks in the 21st century [26] as well as the historical simulations conducted for CMIP6. These scenarios are SSP1-1.9, SSP1-2.6, SSP4-3.4, and SSP5-3.4-over, where the number following SSP denotes the Shared Socioeconomic Pathway on which the scenario is based, and the following values the intended end-of-century radiative forcing of the scenario. We use 1970 to 2020 CE as our baseline warming period from which we derive the historical warming rate, which we take to be our signal. The signal is derived independently for each of the climate model simulations in the CMIP6 archive for each SSP scenario. Additionally we examine SSP2-4.5, which was not designed to reach a peak temperature in the 21st century, but does reach peak emissions, as a check on our method. Table 1 gives the number of models and number of simulations available for each SSP in the CMIP6 archive.

We derive our noise model from the pre-industrial control simulations. These simulations are detrended to correct for drift [27] and global average temperature anomalies are taken as characterizing the internal variability. Rahmstorf *et al* [20] notes that residuals in global average temperature records are serially autocorrelated but ignored the autocorrelation and used a white-noise noise model, as inclusion of a more complex noise model would make the 'global warming hiatus' less statistically significant [20], and thus be counterproductive to showing that the 'global warming hiatus' did not reach any reasonable threshold of significance. Here however, we are examining the reverse question and hence ignoring the autocorrelation will create an underestimate in the amount of time needed to detect a change in warming trend, and underestimate uncertainty [28]. Thus we must include a more complex noise model for this study. The next simplest noise models after white noise are coloured noise models [24]. Coloured noise either has more power in the high frequency range (blue noise), or more power in the low frequency range (pink, red, and brown noise) [e.g.][24]. Figure 1 shows a fast Fourier transform of global average temperature from the drift corrected pre-industrial control simulation from ACCESS-ESM-1-5. The figure clearly shows that there is more low frequency power than higher frequency in global temperature trends. Consistent with frequency distribution of noise in the simulated global average temperatures, the pre-industrial control simulations in the CMIP6 archive have lag-1-year autocorrelations of 0.22 to 0.77, with a median of 0.56.

Coloured noise models use a power law relationship to approximate the change in power with frequency [24]:

$$P = \frac{1}{f^{\alpha}} \tag{1}$$

where P is power, f is frequency, and α controls the colour of the noise. $\alpha = -1$ is blue noise, $\alpha = 0$ is white noise, $\alpha = 1$ is pink noise, and $\alpha = 2$ is brown noise, which is equivalent to a random walk [e.g.][24]. Fitting the power law relation to all available pre-industrial control simulations resulted in α values ranging from 0.76 to 0.89 with a median of 0.85. Test simulations within this range of α values resulted in a ± 0.5 year difference in estimated temperature climate milestone dates. Therefore our simulations for each climate model all use a noise model

Table 1. Number of models and number of simulations in the CMIP6 archive for each scenario designed to have peak temperatures in the 21st century. The number of simulations is higher than the number of models since some modelling groups conduct multiple ensemble members for each scenario. SSP2-4.5 is separated as it is not a temperature overshoot scenario.

Scenario label	Number of climate models	Number of simulations
SSP1-1.9	10	76
SSP1-2.6	34	190
SSP4-3.4	8	22
SSP5-3.4-over	8	19
SSP2-4.5	17	143

with an α value of 0.85. Sensitivity tests with white-noise were also conducted to examine our choice of using a more complex noise model than uncorrelated Gaussian noise. Noise time-series were generated using the python package *colorednoise* with the function *powerlaw_psd_gaussian*. Standard deviations were taken from the residuals to the linear fit from the signal model (1970 to 2020 CE global average temperature) for each climate model.

Monte–Carlo simulations were conducted for each climate model simulation available, where the signal model and 10 000 randomly generated noise models were combined to create emulated global temperature change time-series. Trends were then computed from these time series ranging from 3 years to 80 years to form a distribution of possible trends consistent with continued warming at the historical rate, of each length of time.

To examine the global warming slowdown milestone for each climate model simulation available, trends were computed starting from the estimated year of peak CO_2 emissions in that scenario. The computed trend is compared to the distribution of trends from the Monte–Carlo simulations to assess the probability that the computed trend is compatible with continued warming at the 1970 to 2020 CE rate. The year of peak fossil fuel CO_2 emission is assumed to be a constant for each scenario and is taken as the mean value from CMIP6 Earth System Models (ESMs) [15]. For example, in SSP1-1.9 the mean year of peak emission was 2020 (table 2). So the first computed trend is 2020 to 2022, which is compared to all Monte–Carlo simulated 3 year trends, then a trend is computed from 2020 to 2023 which is compared to all 4 year trends, ext. until the end of the simulation in the year 2100. All peak emission estimates are from Liddicoat *et al* [15] and are shown in table 2.

A limitation of this method is that it requires an assumed start date. We chose the year of diagnosed peak fossil fuel emissions because ESM simulations [8, 29], and theory [30] suggest that the rate of warming should be proportional to the rate of emissions of CO_2. Hence the year of peak CO_2 emissions is our

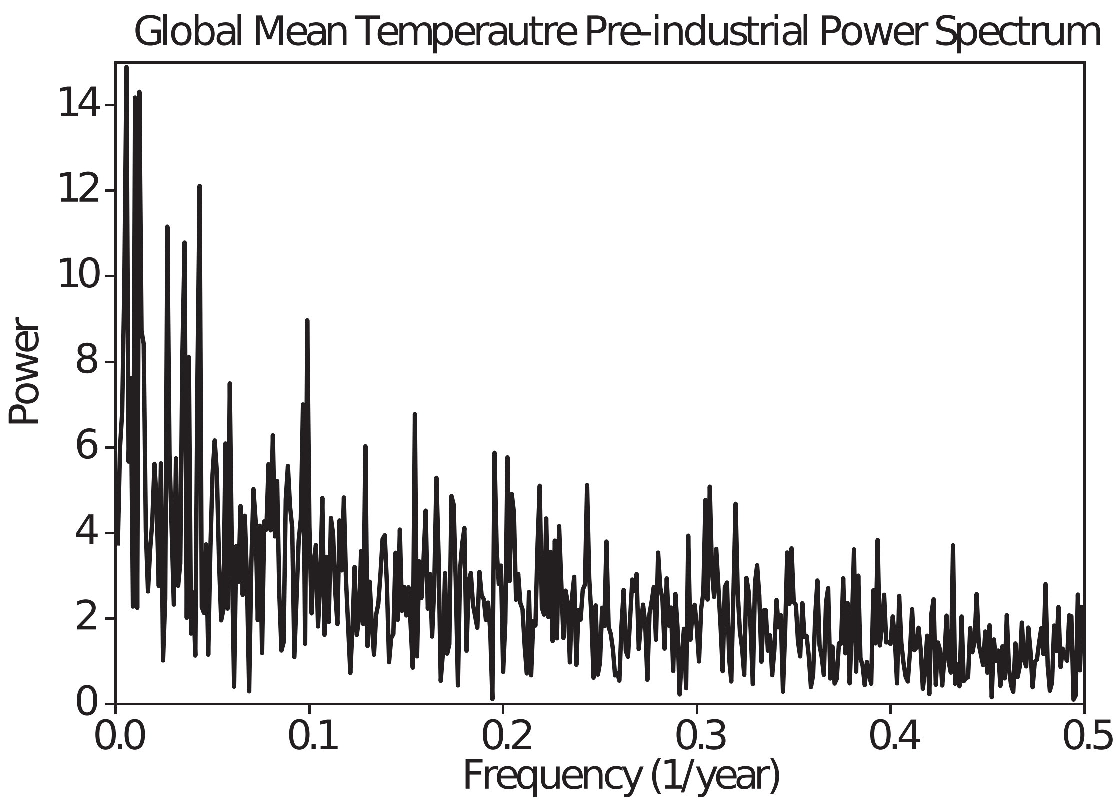

Figure 1. Power spectrum of drift-corrected Pre-industrial control simulation for climate model ACCESS-ESM-1-5. Note that there is more power at lower frequency consistent with a system in between true uncorrelated randomness and a random walk.

prior for the inflection point to a decelerating warming rate, with the date of peak fossil fuel emissions a proxy for the date of peak overall CO_2 emissions [15]. A sensitivity test for SSP1-1.9 was conducted by selected baseline year in a 40 year window surrounding the year of peak fossil fuel CO_2 emissions to examine the sensitivity of our results to our choice of a prior. The results of this sensitivity test are shown in supplementary material section S1.

2.1.2. The end of warming

To determine whether global warming has stopped is very similar to determining whether global warming has slowed. Essentially, the only difference is that the signal is zero instead of a linear trend. The noise model remains the same, as does the method of examining ever longer trends from a fixed starting point. Again the fixed starting point for each SSP needs to be based on some outside prior expectation. The logical starting point is thus when net-zero CO_2 emissions is reached, as the expected warming following zero CO_2 emissions is zero, with a substantial uncertainty range [7, 31]. However in the four SSP scenarios designed to have temperature peaks in the 21st century, net-zero is expected towards the end of the century (between 2058 and 2091 CE in existing ESM simulations) [15]. Thus for the great majority of simulations it will thus be challenging to detect the end of warming by the end of the simulations in 2100 CE. To get around this problem we focus on the simulations of SSP1-2.6 that were extended to the year 2300 CE. There are 16 such simulations conducted by 5 climate models in the CMIP6 archive. All net-zero fossil fuel emission date estimates are from Liddicoat *et al* [15] and are shown in table 2. Notably these net-zero dates, computed from diagnosed emissions, are different from the net-zero dates from the original emissions pathways provided as data for the SSPs. The inconsistency is created by differences between the internally simulated carbon-cycle of each ESM and the carbon-cycle of the climate emulators used to convert SSP emissions into CO_2 concentration pathways [26]. By choosing net-zero dates from diagnosed emissions we are prioritizing the internal consistency of the ESM carbon cycles and ESM generated global temperatures. Note that detecting the date of net-zero is also challenging (see discussion in supplementary materials section S2) meaning any implementation of our method with observed data in the late 21st century will be subject to uncertainty over the appropriate starting date.

2.1.3. Temperature metric caveat

Note that we are using globally averaged near-surface air temperature (CMIP6 *tas* variable), not a combined partially masked, sea-surface temperature, land-air temperature analogous to the observational global temperature change records [21, 32]. Thus our results represent the time necessary to detect a change in warming rate if one has perfect knowledge of global

Table 2. Estimated year of peak fossil fuel CO_2 emissions, net-zero fossil fuel CO_2 emissions, and peak CO_2 concentration for each scenario. Emission estimates are from Liddicoat *et al* [15], peak CO_2 concentration is prescribed by the scenarios [33], and are taken from the SSP extension scenarios published by Meinshausen *et al* [34]. SSP2-4.5 is separated as it is not a temperature overshoot scenario. FF is Fossil Fuels.

Scenario label	Peak FF CO_2 emission (year CE)	Net-zero FF CO_2 emission (year CE)	Peak CO_2 concentration (year CE)
SSP1-1.9	2020	2065	2040
SSP1-2.6	2023	2081	2063
SSP4-3.4	2022	2084	2078
SSP5-3.4-over	2041	2072	2061
SSP2-4.5	2045	—	2211

surface air temperature. However using the global near-surface air temperature avoids the necessity of making assumptions about the future condition of the global temperature observation network. Therefore our results should be interpreted as an estimate of the minimum amount of time it would take to detect these temperature climate milestones.

2.2. Peak CO_2 concentration

To examine peak CO_2 concentration we again modify the method by Rahmstorf *et al* [20]. However, for peak CO_2 concentration we are less confident in ESM simulations, as preindustrial control simulations show an enormous inter-model range in simulated inter-annual variability in CO_2 concentration [35]. Instead we rely both on ESM results and the instrumental record of atmospheric CO_2 concentration. While CO_2 concentration is now monitored at many locations around the world, the longest nearly continuous record is from Mauna Loa [36]. Examining the record from this single site, has shown the unambiguous rise in CO_2 concentration for the past 65 years [36]. Consequently the Mauna Loa record (called the Keeling curve) will likely be key in determining when CO_2 concentration has peaked. Thus we examine both the instrumental record from, and ESM outputs for, this location.

For our CO_2 concentration signal model we use the prescribed northern hemisphere CO_2 concentration pathways from the four peak and decline SSP scenarios (SSP1-1.9, SSP1-2.6, SSP4-3.4, and SSP5-3.4-over) [34]. One of our noise models is derived from the Keeling curve by removing the quadratic trend in CO_2 concentration, the other noise model is derived from ESMs which conducted pre-industrial control simulations in emissions-driven configuration. Figure 2(a) shows the Keeling curve and the quadratic fit, which is remarkably close. The residuals relative to the statistical fit are shown in figure 2(b), and their fast-Fourier transform in figure 2(c). The CO_2 errors show strong autocorrelation of 0.81 and are consistent with pink noise with a fitted α of 0.68, and a standard deviation of 0.717 ppmv. Notably the signal to noise ratio in the Keeling curve is so high that a year-on-year decline in CO_2 concentration has never been recorded.

Nine ESMs conducted pre-industrial control simulations in emissions-driven configuration (CMIP6 experiment esm-piControl). These models have 1 year lag autocorrelation values of 0.83 [0.75 to 0.95] (median [min to max]), and a standard deviation of 0.788 [0.318 to 1.54] ppmv. The fitted α values are 0.87 [0.84 to 0.92]. We use the median ESM values of standard deviation and α for our noise model parameters. Given how similar the median ESM values and the values derived from the observational record are, we do not expect the results of the two noise models to vary substantially. Again we simulate noise using the python package *colorednoise* with the function *powerlaw_psd_gaussian*. 100 000 simulations are done for each scenario.

We quantify whether CO_2 concentrations have reached their absolute peak by computing the drop in CO_2 concentrations relative to local peaks in the record. That is, we are looking to answer the question 'how far does CO_2 concentration need to drop from the last peak to be sure another record peak will not occur'? To quantify this answer for each scenario, we examine the period of time between the first local peak in CO_2 concentration and the ultimate peak in CO_2 concentration in each of the 100 000 emulated CO_2 pathways. We then compute the largest drop in CO_2 concentration between each local peak and the next local minimum. The distribution of these drops after local peaks is used to quantify what magnitude of CO_2 concentration drop is no-longer consistent with the last peak being a local peak. This method is illustrated in figure 3. The method used here implicitly assumes a relatively smooth change in emission rates with annual changes within the historically observed range.

3. Results

3.1. Global temperature milestones

Figure 4 shows the probability that the rate of global warming has slowed for each of the four peak-and-decline scenarios and each individual model simulation, figure 5 shows the same for SSP2-4.5. Despite substantial variability, all simulations show increasing probability that warming has slowed, relative to the 1970 to 2020 period, as the 21st century progresses (figure 4). To compute a central estimate for the global warming slowdown climate milestone we take the mean of all ensemble members for each individual climate model, then take the median of these means for all of the climate models. This procedure prevents models with many ensemble members from dominating the central estimate. These central estimates and the full ensemble range are shown in table 3 for three common significance thresholds, 95%, 99% and

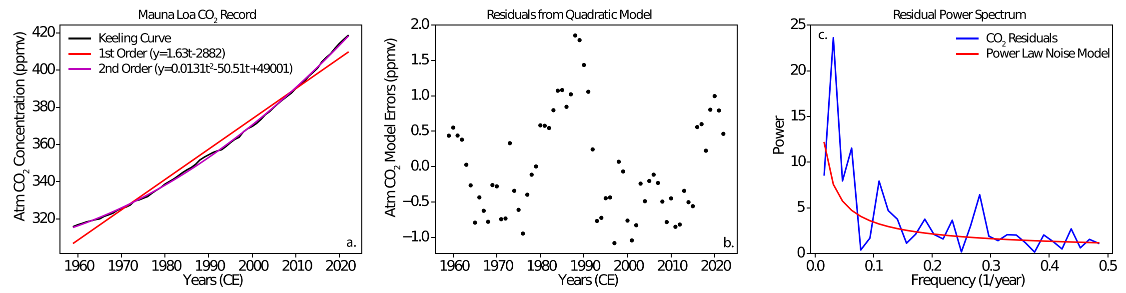

Figure 2. (a) Annual atmospheric CO_2 concentration record from Mauna Loa, often called the Keeling Curve, as well as a linear and quadratic fit to the curve. (b) Deviations from the quadratic fit. (c) Power-spectrum of residuals as well as the fit of the power-law model (basis for modelling coloured noise). Note that the residuals have more power at lower frequency consistent with systems in between uncorrelated random errors (white noise) and a random walk (brown noise).

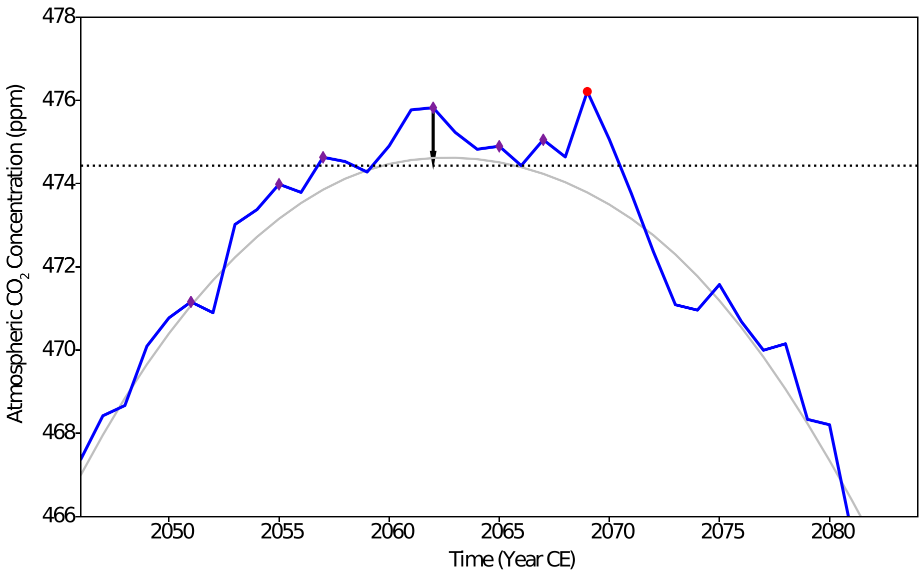

Figure 3. Illustration of the method used to detect true peak in atmospheric CO_2 concentration. Blue line is the emulated annual average CO_2 concentration produced by adding randomly generated noise to an underlying CO_2 pathway (shown in grey line). Purple diamonds mark local CO_2 peaks, red circle marks the ultimate peak in CO_2 concentration. Arrow dropping to dotted line shows the largest drop in CO_2 concentration between each local peak and the next local minimum. Exceeding this depth is the metric used to quantify if the ultimate peak has passed. Note that to illustrate the method better an example was selected with many local peaks and large drop in CO_2 before the ultimate peak, most emulated pathways have much smaller concentration drops after local peaks.

99.9% certainty for the peak-and-decline scenarios. While the selection of any significance threshold is philosophically contentious [37] and ultimately must be a subjective judgment based on expert assessment, for the system under consideration the differences are relatively minor, as the difference between a 1 in 20 chance and a 1 in 1000 chance of being in error is only about a decade of data (table 3). Note that the dates given for any of the significance thresholds will tend to be later than the dates given by the best estimate from a multi-model average, which would roughly correspond to a 50% threshold. For each significance threshold we give the central estimate and the full range from all climate model simulations. The range is used due to the small number of climate models available for most scenarios (see table 1).

A 99% chance of having detected a slowdown in warming rate occurs in 2063 [2032 to 2083] CE for SSP1-1.9, in 2064 [2035 to ⩾2100] CE for SSP1-2.6, in 2085 [2056 to ⩾2100] CE for SSP4-3.4, and in 2077 [2058 to 2095] CE for SSP5-3.4-over. In all cases the central estimates for when the climate milestone can be detected occur decades (41 to 63 years) following the theoretically expected time of slowdown, i.e. after peak fossil fuel emissions. Considering the full ensemble range a 99% chance of detection could occur within two decades of peak fossil fuel emissions, or not until sometime in the 22nd century.

The median detection of slowdown for SSP2-4.5 does not reach any of our chosen significance thresholds during the 21st century, despite peak CO_2 fossil fuel emissions occurring in 2045 CE. However the 90% certainty threshold is reached in 2090 [2057 to ⩾2100] CE. Thus in scenarios that do not rapidly transition from peak emissions to net-zero emissions,

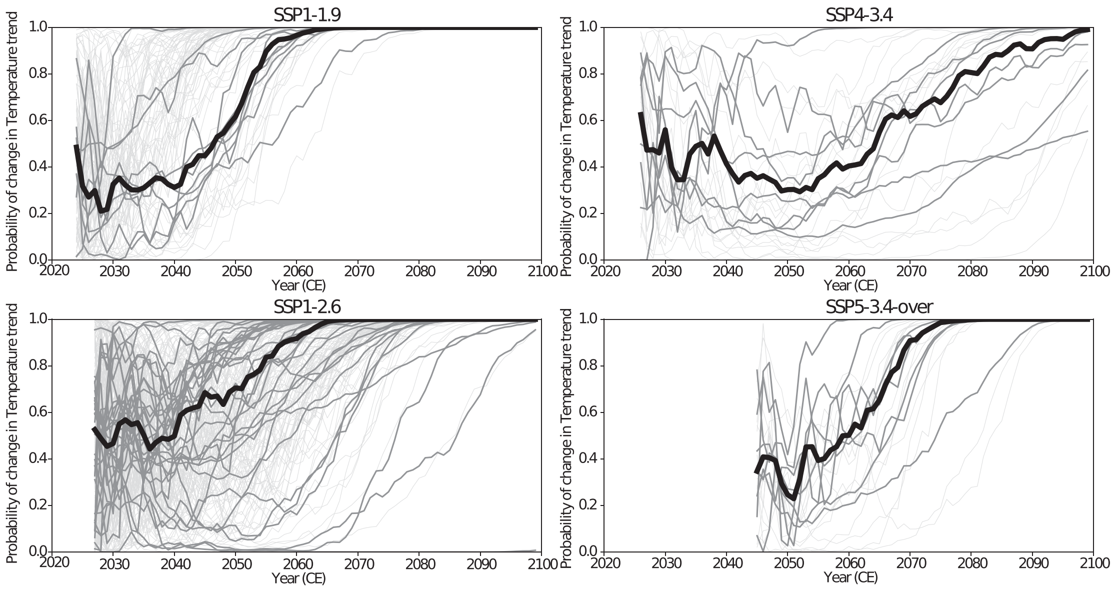

Figure 4. Probability that a slowdown is global warming has been detected for each of the four peak-and-decline SSP scenarios. Light grey lines are individual climate model simulations, darker grey are ensemble means for each climate model, and the thick black line is the median of all of the model ensemble means (such that each climate model gets one vote in the median).

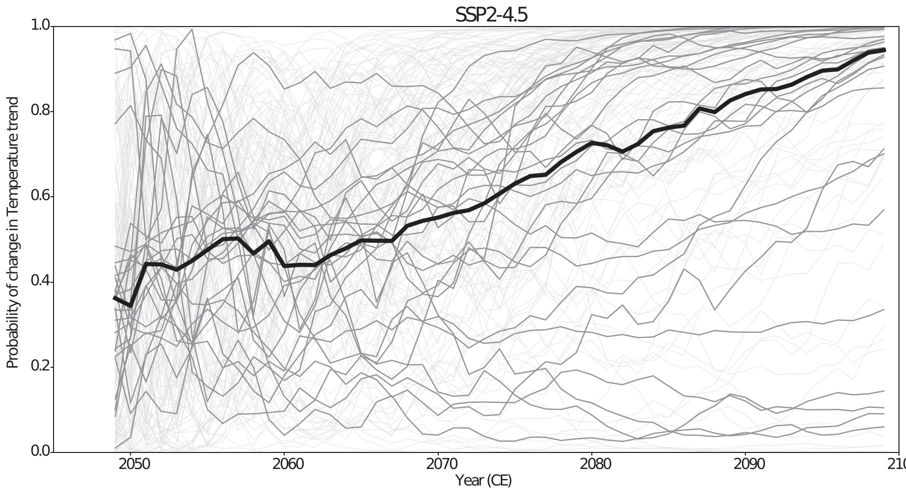

Figure 5. Probability that a slowdown is global warming has been detected for SSP2-4.5. Light grey lines are individual climate model simulations, darker grey are ensemble means for each climate model, and the thick black line is the median of all of the model ensemble means (such that each climate model gets one vote in the median).

Table 3. Common Era year of detection of a slowdown in global warming for three common choices of significance threshold. Central estimates are the median of the mean of all ensemble members for each individual climate model. Ranges are ranges of all ensemble members from all climate models.

Scenario label	95%	99%	99.9%
SSP1-1.9	2058.0 [2032 to 2075]	2063.5 [2032 to 2085]	2068.0 [2041 to 2093]
SSP1-2.6	2061.0 [2035 to ⩾2100]	2064.5 [2035 to ⩾2100]	2068.5 [2042 to ⩾2100]
SSP4-3.4	2080.0 [2029 to 2097]	2085.5 [2056 to ⩾2100]	2089.5 [2065 to ⩾2100]
SSP5-3.4-over	2072 [2057 to 2097]	2077.0 [2058 to 2095]	2081.0 [2062 to ⩾2100]

a very long time is likely needed to detect a slowdown in warming rate.

One climate model, CanESM5 conducted 50 member ensembles for both SSP1-1.9 and SSP1-2.6. This large ensemble allows us to isolate the part of the variability that is inherent to the simulated climate system from that which is due to differing model physics, parameterizations, and structural assumptions in model design. In CanESM5 the mean number of years since peak global CO_2 emissions needed to detect a global warming slowdown was 25.5 years with a range of 17 to 37 years for SSP1-1.9, and 31.5

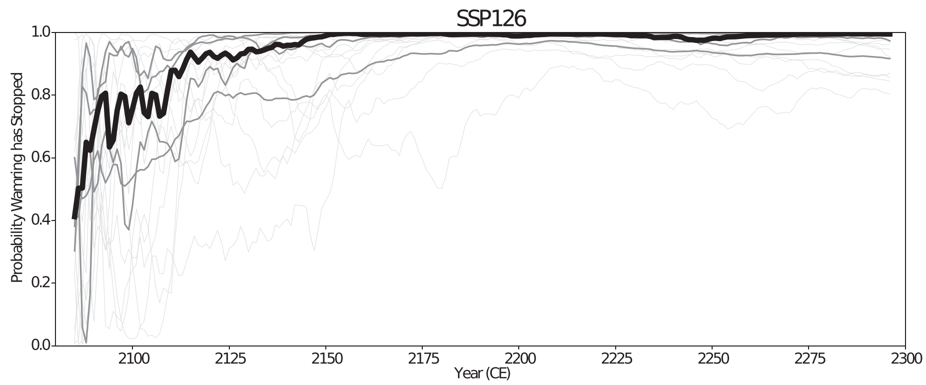

Figure 6. Probability that global warming has stopped for SSP1-2.6. Light grey lines are individual climate model simulations, darker grey are ensemble means for each climate model, and the thick black line is the median of all of the model ensemble means (such that each climate model gets one vote in the median).

Table 4. Results of Monte–Carlo simulations of SSP scenario derived CO_2 pathways with noise. Values shown for parameters derived from Keeling Curve, values for ESMs are very similar.

Scenario label	Prescribed peak (years CE)	First local CO_2 peak (years CE)	CO_2 drop for 99% chance of peak (ppm)	Lag from peak to detection (years)
SSP1-1.9	2040	2032 ± 6.9	-2.7	8.4 ± 3.5
SSP1-2.6	2063	2046 ± 10.7	-2.9	9.3 ± 4.0
SSP4-3.4	2078	2051 ± 14.5	-2.9	8.0 ± 2.9
SSP5-3.4-over	2061	2058 ± 3.2	-2.2	3.5 ± 2.0

years with a range of 11 to 43 years for SSP1-2.6. Thus there is a 20 to 30 year range in detection time of global warming slowdown, just from internal climate variability as simulated by CanESM5.

As a sensitivity test the Monte–Carlo analysis was repeated for SSP1-1.9 with a white-noise model instead of the light pink noise derived from simulated climate variability. This test gave the central estimate of 2056 CE for a 99% chance of detecting a slowdown in global warming, with a range of 2032 to 2070 CE (compared to 2063 [2032 to 2083] with pink-noise). Thus, although the autocorrelation in global mean near-surface temperature is an important feature of the system, ignoring it does not fundamentally change our core result that detecting a slowdown in global warming will take decades following a slow-down in emissions rate.

Figure 6 shows the probability that global warming has stopped for the climate models that conducted extensions of the SSP1-2.6 scenario to the year 2300. The figures show that while most model simulations suggest a high degree of certainty that warming has stopped by the mid 22nd century, in some simulations it is unclear if warming has stopped even by the beginning of the 24th century. The central estimate for a 95% chance of detecting that global warming has stopped is 2136 CE with an ensemble range of 2092 to $\geqslant$2300 CE, while the central estimate for a 99% chance of detecting that global warming has stopped is 2150 CE with a range of 2092 to $\geqslant$2300 CE. The 99.9% threshold is not reached by most of the ensemble members by the end of the simulations in year 2300 CE.

3.2. Peak CO_2 concentration

As the rate of CO_2 concentration increase declines, eventually the signal-to-noise ratio will drop below one and local annual peaks and dips in concentration will likely become a characteristic of the CO_2 record. The method described in section 2.2 was intended to capture such behaviour, assuming that internal variability of CO_2 concentration does not change in the future. Table 4 shows the results of the Monte–Carlo simulations using parameters derived from the Keeling curve. The simulations suggest that the first local peak of CO_2 concentration will occur a decade or two before the prescribed peak in the SSP scenario. For example, in SSP1-1.9 the first local peak is projected to occur in 2032$\pm$6.9 years CE, compared to a peak in 2040 CE in the underlying SSP scenario (used as the signal model), while in SSP1-2.6 the first local peak is projected to occur in 2046$\pm$10.7 years CE, compared to a peak in 2063 CE in the underlying SSP scenario.

A question we wish to explore with the Monte–Carlo simulations is: how far does CO_2 concentration need to drop from the last peak to be sure another record peak will not occur merely because of internal variability? To quantify this we compute the maximum drop in CO_2 concentration between local concentration peaks and minimums before the absolute peak in each simulation. A drop in CO_2 uncharacteristic of this range is interpreted as indicating that the last peak was the absolute peak in CO_2 concentration. We present results computed using parameters derived from the observed Keeling Curve in text with values from ESM derived parameters in parenthesis. For SSP1-1.9 a drop of −2.7 ppm (−2.6 ppm) relative to the last peak gives a 99% chance that the last peak was the absolute peak. For SSP1-2.6 this value is −2.9 ppm (−2.8 ppm), for SSP4-3.4 this value is −2.9 ppm (−2.7 ppm), and for SSP5-3.4 this value is −2.2 ppm (−2.0 ppm). Thus the drop in CO_2 concentration consistent with the last peak being the absolute peak does not have a strong dependence on scenario followed. Similarly in three of the scenarios the 99% probability threshold is reached in a similar amount of time. For SSP1-1.9 the 99% probability threshold is reached 8.4±3.5 years (7.7±3.7 years) after the absolute peak in CO_2, for SSP1-2.6 the 99% probability threshold is reached 9.3±4.0 years (9.5±4.1 years) after the absolute peak, and for SSP4-3.4 the 99% probability threshold is reached 8.0±2.9 years (7.9±3.1 years) after the absolute peak. The exception is SSP5-3.4 where the 99% probability threshold is reached just 3.5±2.0 years (4.1±2.1 years) after the peak. These variations between scenarios can be explained by the steepness of CO_2 emissions reductions assumed in the underlying scenarios. These insights, however, allow us to say with good confidence that a drop of 3 ppm from peak CO_2 concentration indicates that the absolute peak concentration is in the past, and that we are likely to know we have passed the absolute peak within a decade of its occurrence.

4. Discussion

For examining temperature and CO_2 concentration climate milestones we have used a second order statistical model to simulate noise. While we argue this is a better approach than ignoring serial autocorrelation in global temperature [e.g.][20] and CO_2 concentration records, simple coloured noise models are imperfect—underestimating low-frequency noise and overestimating high frequency noise for global temperature. A way to circumvent such problems without having to develop ever more sophisticated statistical models of dynamic models is simply to conduct a very long pre-industrial control simulation with a full complexity climate model. A 10 000 year pre-industrial control simulation would be sufficient to carry out an analysis similar to that outlined in section 2.1.1. To build a noise model capable of capturing the natural variability in global average temperatures, random volcanic eruptions would also need to be incorporated into a modified pre-industrial control simulation. Such a modelling effort could be organized through Long Run MIP (www.longrunmip.org/), an effort that has collected transient simulations of the required length. However, even with incorporating random volcanic eruptions such simulations will remain limited by the processes not included in contemporary ESMs which may affect the noise signal in the future (for example ice-sheet collapse).

For assessing peak CO_2 concentration we have assumed the noise variability in the future will be the same as that observed between 1959 and 2022 or the median value from ESM pre-industrial control simulations (which happen to be close in value). However, studies of the variability in the annual growth rate of CO_2 concentration have shown that one of the strongest influences on the growth rate is the annual extent and intensity of wildfires [e.g.][38]. As the future fire-dynamics are strongly tied to magnitude of climate change [e.g.][39] our key assumption may be weak, and detecting peak CO_2 concentrations might in practice be harder. Improvements in Earth systems models may provide improved assessment of peak-CO_2, but such models would require high-fidelity fire dynamics, a challenging field of ESM development [40], and likely one of the sources of the large range in ESM simulation of pre-industrial CO_2 variability [35].

As long as global CO_2 emissions are not declining, our insights will have no particular policy relevance. However, once global emissions begin to be reduced, both government and other science communicators will have to explain which milestones are expected to be reached by when, and in which sequence. For example, peak CO_2-concentration occurs 6 to 18 years before net-zero fossil fuel emissions, which is our prior for when global temperature is expected to stop increasing. Besides the challenge in communicating the expected sequence of climate milestones, our results suggest that another challenge will be to explain the long period of time needed to establish with certainty from surface temperature observations that global warming has peaked. Hence, looking at surface temperature observations alone provides no simple solution to this science communication problem and combining multiple independent lines of evidence emerges as a potential avenue for tracking progress towards climate milestone detection and reduce these uncertainties.

5. Conclusions

Here we have examined three climate milestones on the pathway to climate stabilization focused on global average temperature change and atmospheric CO_2 concentration. Our results suggest that detecting global temperature milestones only from near-surface temperature data will be difficult, even under aggressive future mitigation scenarios. We estimate that it will take 40 to 60 years after a slowdown in warming rate, to robustly detect the signal in the global average temperature record. Detecting when warming has stopped will also be difficult and for the one peak-and-decline scenario that has model simulations extended to year 2300 CE, it takes until the mid 22nd century to have enough data to conclude warming has stopped when solely based on information provided by the observational temperature record. In some simulations it is unclear if warming has stopped (with greater than 95% certainty) even by the beginning of the 24th century. Detecting that CO_2 concentration has peaked is far easier and a drop in CO_2 concentration of 3 ppm is consistent with a greater than 99% chance that CO_2 has peaked in all scenarios examined. Such a drop is likely within only a decade of the absolute peak in CO_2 concentration, in scenarios with rapid mitigation of CO_2 emissions. The difficulty in detecting climate milestones has the potential to both obscure progress towards climate stabilization, and create uncertainty in the efficacy of mitigation methods, with potentially complex consequences for climate policy implementation. Overall it is sobering that even under aggressive mitigation scenarios a conclusive end to global warming is at the very outer edge of the living future, with only a small number of the very youngest children alive today likely to witness this climate milestone.

Data availability statement

All data used for this study is publicly available from CMIP6 Data Viewer https://cmip6.science.unimelb.edu.au/, Earth System Grid Federation https://esgf.llnl.gov/, or NOAA Global Monitoring Laboratory https://gml.noaa.gov/ccgg/trends/.

Python scripts used to process the data and conduct Monte–Carlo experiments are available as supplementary information.

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