Future climate change hotspots under different 21st century warming scenarios

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Abstract

Identifying climate change hotspot regions is critical for planning effective mitigation and adaptation activities. We use standard Euclidean distance (SED) to calculate integrated changes in precipitation and temperature means, interannual variability, and extremes between different future warming levels and a baseline period (1995–2014) using the Coupled Model Intercomparison Project Phase 6 (CMIP6) climate model ensemble. We find consistent hotspots in the Amazon, central and western Africa, Indonesia and the Tibetan Plateau at warming levels of 1.5 °C, 2 °C and 3 °C for all scenarios explored; the Arctic, Central America and southern Africa emerge as hotspots at 4 °C warming and at the end of the 21st century under two Shared Socioeconomic Pathways scenarios, SSP3-7.0 and SSP5-8.5. CMIP6 models show higher SED values than CMIP5, suggesting stronger aggregated effects of climate change under the new scenarios. Hotspot time of emergence (TOE) is further investigated; TOE is defined as the year when the climate change signal first exceeds the noise of natural variability in 21st century projections. The results indicate that TOEs for warming would occur over all primary hotspots, with the earliest occurring in the Arctic and Indonesia. For precipitation, TOEs occur before 2100 in the Arctic, the Tibetan Plateau and Central America. Results using a geographical detector model show that patterns of SED are shaped by extreme hot and dry occurrences at low-to-medium warming, while precipitation and temperature means and extreme precipitation occurrences are the dominant influences under the high emission scenario and at high warming levels.

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1. Introduction

The recent unprecedented rate of global warming will have potentially profound effects on both natural ecosystems and human societies, for example, by promoting natural hazards growth (Kumar & Mishra, 2020; Wahl et al., 2015), accelerating the hydrologic cycle (Giorgi et al., 2019) and carbon cycle (Gao et al., 2021; Lu et al., 2021), reducing food security (Fujimori et al., 2019; Tai et al., 2014), and facilitating the geographic expansion of many infectious diseases (Liang & Gong, 2017; Waits et al., 2018), resulting in serious economic losses and a range of adverse health effects (Dottori et al., 2018; Sun et al., 2019; Surendran Nair et al., 2020; Watts et al., 2020).

In late 2015, the 21st Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) resolved to restrict the increase in global mean surface temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit this even further, to 1.5 °C (UNFCCC, 2015). It nevertheless has to be recognized that if the current trajectory of greenhouse emissions continues, it will be difficult to achieve a 2 °C (or more aggressive) temperature target, requiring transformational changes across all areas of modern society (Sanford et al., 2014; Schellnhuber et al., 2016). Recent studies have shown that the likely range of global temperature increase will be 2.0–4.9 °C (Raftery et al., 2017), and thus, warming levels of 1.5 °C, 2 °C, 3 °C and 4 °C are important milestones not only for mitigation but also for understanding the expected impacts of climate change.

Regional climates are the complex result of various processes that vary strongly by
geographical location, and therefore they respond differently to changes in global-scale influences (IPCC, 2013). There is increasing interest in measuring the regional responses to climate change to understand how these may vary for different levels of global warming. Prior research has shown that both observed and projected changes in surface temperatures and precipitation exhibit large regional variations, and spatial features of precipitation changes are even more regionally variable than changes in temperature (Adler & Gu, 2015; Chen et al., 2020; Contractor et al., 2020; Dunn et al., 2020; Feng et al., 2014; Gao et al., 2020). To facilitate decision-making on mitigation and adaptation strategies and formulate warming targets to avoid unacceptable climate change, it is necessary to understand and quantify potential spatial heterogeneity in the climate change response. A region whose climate is especially responsive to global warming is typically referred to as a climate change hotspot (Giorgi, 2006); hotspots are exposed to greater risk than other regions, compounding the challenges they experience. Therefore, finding hotspots and understanding the mechanisms of response enhancement are crucial steps toward understanding, adapting to, and avoiding the risks of future climate change.

Previous studies have quantified global hotspots in aggregations of multidimensional climate change using, for instance, projections from the Coupled Model Intercomparison Project Phase 3 (CMIP3) (Diffenbaugh et al., 2008; Giorgi, 2006) and Phase 5 (CMIP5) (Diffenbaugh & Giorgi, 2012; Gu et al., 2014; Torres & Mareng, 2013; Xu et al., 2019), as well as observations (Turco et al., 2015). Other
climate-related hotspot identification studies have focused on, for example, drought hotspots (Dosio et al., 2020; Prudhomme et al., 2014), multisectoral hotspots (Byers et al., 2018; Piontek et al., 2014) and hotspots for compound events (Ridder et al., 2020). CMIP6 now offers the most recent state-of-the-art climate model experiments (Eyring et al., 2016); it aims to improve climate change projections by using better parameterization and process representation. CMIP6 has developed a new set of Shared Socioeconomic Pathways (SSP) scenarios for greenhouse gas concentrations (O’Neill et al., 2016). These scenarios relate newer socioeconomic scenarios to the Representative Concentration Pathways (RCPs) first adopted in CMIP5 and cover wider ranges of warming responses than the RCPs (Taylor et al., 2012; Tebaldi et al., 2020; Tokarska et al., 2020). Some skill assessments on the performance of CMIP6 in simulating temperature (Fan et al., 2020; Li et al., 2020), precipitation (Rivera & Arnould, 2020; Srivastava et al., 2020) and other variables (Jian et al., 2020; Krishnan & Bhaskaran, 2020; Vignesh et al., 2020) have been made, and the results enhance confidence in the fidelity of future climate projections based on CMIP6 ensembles.

It is not clear how climate will change and where climate change hotspots would be under these new scenarios. To address this gap, we employ statistical measures of aggregate climate change to identify regional climate change hotspots over the global land surface under global warming of 1.5 °C, 2 °C, 3 °C and 4 °C above pre-industrial levels in CMIP6 projections. Hotspots will show a more serious response to climate change than other regions with the increase of greenhouse gas emissions. This raises a
key question about the timing of significant climate change happening in hotspot regions in the 21st century. Trying to answer this question, we further explore when the climate change signal will emerge from natural climate variability in identified climate change hotspots and their dependence on the SSP scenarios. Moreover, the contributions of each climate variable to the hotspot index have not been well quantified under different warming levels and new scenarios. Accordingly, here we use a geographical detector model (GDM) to obtain an order-of-magnitude estimate of driving factors of climate change hotspots. Section 2 describes the model and experiments used, as well as the methods employed for identifying hotspots and detecting driver factors. Major results are presented in section 3 and discussed in section 4. Concluding remarks and some perspectives regarding future studies are presented in section 5.

2. Materials and Methods

2.1 Climate model ensemble

Simulations of monthly mean precipitation and surface temperature from 24 global climate models (GCMs) were retrieved from the CMIP6 archive (https://esgf-node.llnl.gov/search/cmip6/). We focus on the historical CMIP6 experiments (1850–2014) and four future scenarios from the SSPs (2015–2099). The four SSPs assume increases in radiative forcing of 2.6 W/m² (SSP1-2.6; low-forcing pathway), 4.5 W/m² (SSP2-4.5; medium-forcing pathway), 7.0 W/m² (SSP3-7.0; medium- to high-forcing
pathway) and 8.5 W/m² (SSP5-8.5; high-forcing pathway) by the year 2100 (O’Neill et al., 2016). Changes in future characteristics are established using differences between the different warming levels of the SSPs’ output and the 1995–2014 historical output. To reduce the impact of internal variability on hotspot identification, we use as many members of each model as possible, including 163 historical realizations, 66 SSP1-2.6 realizations, 69 SSP2-4.5 realizations, 74 SSP3-7.0 realizations and 69 SSP5-8.5 realizations in total (see Supplementary Information Table S1). We converted CMIP model data to a common 1° × 1° grid using bilinear interpolation to facilitate the calculation of multi-model means.

2.2 Identifying warming periods

Following the methodology of Dosio & Fischer (2018), in this study, we focus on 1.5 °C, 2 °C, 3 °C and 4 °C global warming relative to preindustrial levels of 1881–1900 by applying time-slicing. More precisely, we define time windows using a particular year as a center year for a 20-year warming level time slice for multi-model means. To define the periods for the different global warming levels, we analyzed past observed and future projected temperatures. We selected the 20-year period from 1995 to 2014 (inclusive) as a reference, as it represents the present climate in the CMIP6 historical simulations. We use observed annual mean global temperature data from the GISS Surface Temperature Analysis (GISTEMP v4) dataset from NASA’s Goddard Institute for Space Studies (Hansen et al., 2010). After applying a 20-year running mean
to these data, we estimate that global warming in the reference period is 0.8 °C warmer than the preindustrial level. The resulting mean global warming compared to the reference period corresponds to 0.7 °C in a 1.5 °C world, 1.2 °C in a 2 °C world, 2.2 °C in a 3 °C world and 3.2 °C in a 4 °C world. For the multi-model means, the different warming level periods are defined as the 20-year period centered around the year when the 1.5 °C, 2 °C, 3 °C or 4 °C warming is first reached (Table S2).

2.3 Hotspot identification

Our hotspot identification framework is based on the approach used by Diffenbaugh & Giorgi (2012). They use a standard Euclidean distance (SED) to quantify the total change in multi-dimensional climate space between the future and present periods in the CMIP5 climate model ensemble. In our study, we selected seven climate indicators from each of four seasons (December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON)) to quantify global climate change hotspots in the CMIP6 ensemble, including the mean, variability and extreme values of temperature and precipitation. The SED (unitless) was computed by aggregating the changes in selected climate indicators between future warming levels (1.5 °C, 2 °C, 3 °C, 4 °C and 2080–2099) and the “present” period (1995–2014) within the CMIP6 historical simulations (the spatial patterns of the climatological mean climate indicators during the base period are shown in Figure S1). Only land grid cells were considered in our analysis, and Antarctica was
excluded. At each land grid point, the total SED was calculated as

$$S_{ED_{tot}} = \sqrt{\sum_v S_{ED_v}}$$  \hspace{1cm} (1)

for

$$S_{ED_v} = (x_{fv} - x_{pv})^2 / (max[abs(x_{fv} - x_{pv})]_{ij})^2$$  \hspace{1cm} (2)

Where $x_{fv}$ denotes the value of climate indicator $v$ under future warming levels, $x_{pv}$ denotes the value of variable $v$ in the “present” period, and $max[abs(x_{fv} - x_{pv})]_{ij}$ denotes the maximum absolute value of land-grid-point change in climate indicator $v$ over all land grid points $ij$ (for longitudes $i \in [0, 360]$ and latitudes $j \in [0, 180]$) in the period 2080–2099 under SSP5-8.5, which is used to normalize the SED metric to facilitate intercomparison among different regions and periods. The $S_{ED_v}$ involves seven climate change indicators: absolute change in mean surface temperature ($\Delta T$), fractional change in mean precipitation ($\Delta P$), fractional change in interannual standard deviation of detrended surface temperature ($\Delta T_{var}$), fractional change in the interannual coefficient of variation of detrended precipitation ($\Delta P_{var}$), frequency of years above the baseline (1995–2014) maximum surface temperature ($\Delta Hot$), frequency of years below the baseline minimum precipitation ($\Delta Dry$) and frequency of years above the baseline maximum precipitation ($\Delta Wet$). The climate indicators are first calculated according to each realization of each model, then the model mean climate indicators are calculated across all realizations of that model, and finally the multi-model mean is calculated, yielding the ensemble mean of the 28 climate indicators. More detailed calculations are provided in the Supplementary Information. We defined hotspot identification
“robustness” using inter-model standard deviation of the total SED.

2.4 Calculation of time of emergence (TOE)

We are also interested in the timing of when the anthropogenic climate change signal emerges from the underlying variability and uncertainty noise in regions identified as future climate change hotspots. This concept, referred to as “time of emergence” (TOE), can help guide the prioritization and timing of climate change adaptation actions (Giorgi & Bi, 2009; Nguyen et al., 2018). The TOE is the ratio between the signal of mean precipitation and mean temperature change and the estimated natural variability, uncertainty and noise in hotspots projected for the 21st century. We define the signal as the ensemble mean precipitation (or temperature) change using a 20-year running window of the difference with respect to the base period (1995–2014). The noise is estimated by adding the variance of each model relative to the multi-model ensemble mean (inter-model component) to the variance of each model relative to its own ensemble mean (internal variability).

The TOE is defined as the year the signal-to-noise ratio (SNR) exceeds a particular threshold and remains above that threshold value. We use SNR > 1 or SNR < −1 to indicate that a climate signal has emerged from the noise of natural variability, while SNR > 2 or SNR < −2 indicates that a statistically significant signal emerges that exceeds the 95% confidence interval of the natural variability (Barrow & Sauchyn, 2019; de Elía et al., 2013).
2.5 Detecting the driving factors

To detect the driving factors behind the emergence of climate change hotspots, we employed a geographical detector model (GDM) (Wang et al., 2010; Wang et al., 2016) to quantify the contribution of each climatic factor to multi-dimensional aggregate climate changes (SED changes under different SSPs and warming levels) based on spatially stratified heterogeneity. The GDM method has been extensively applied in the fields of health, ecology, geography, and atmospheric studies (Hu et al., 2020; Luo et al., 2016; Yin et al., 2019; Zhao et al., 2020) and shows good performance. Here we introduce the method briefly within our present context; a more detailed description of the GDM method can be found in Wang et al. (2016). The GDM method proposes a $q$-statistic value to measure the magnitude of the influencing power of a single factor and to test its significance. In this context, we calculated the $q$ values for the seven climate indicators (seasonal indicators were summed to calculate the annual values) listed in Section 2.3 to quantify the climatic factors that determine hotspot distribution. Usually, the value of $q_x$ is within the range $[0,1]$; $q_x = 0$ represents when spatial stratification of heterogeneity is not significant, and when the value of $q_x$ tends towards 1, this indicates that the climatic factor $x$ is more strongly associated with the distribution of SED. The $q$-statistic is defined as follows:

$$q_x = 1 - \frac{\sum_{i=1}^{m} N_i \sigma_i^2}{N \sigma^2}$$

where $q_x$ is the power of climatic factor $x$ as a determinant ($i = 1, \ldots, m$ is the stratum
of SED for climatic factor $x$); $N_i$ and $N$ are the number of total samples in the $i$th stratum and the entire area, respectively; $\sigma_i^2$ is the variance of SED in the $i$th stratum and $\sigma^2$ is the global variance of SED in the entire area.

3. **Results**

3.1 **Distribution of climate change hotspots**

We investigate future climate hotspots by calculating the multi-model ensemble aggregate change in seasonal temperature and precipitation for the periods of specific warming levels relative to 1995–2014 under each emission scenario (Figure 1). For the warming levels of 1.5 °C, 2 °C and 3 °C, the overall spatial patterns of SED are generally consistent across the four SSP scenarios, and the SED values increase slightly with the increases of greenhouse gas emissions for the same warming level. Areas in central and western Africa, the Tibetan Plateau, the Amazon and in Indonesia under four scenarios were identified as hotspot regions. For the 4 °C warming level, the spatial patterns of SED start to change under both the SSP3-7.0 and SSP5-8.5 scenarios. Specifically, areas of the Arctic, Central America and southern Africa emerge as hotspot regions. In addition, the Tibetan Plateau, Indonesia, central and western Africa and the Amazon are still climate change hotspots, and the hotspot areas of the Amazon tend to expand. By the end of the 21st century, the SED distribution across different scenarios is quite different. Under the SSP5-8.5 scenario, we see that the distribution of hotspots is the same as that appearing at 4 °C but with higher values of aggregate climate change.
We also find that the spatial heterogeneity of SED distribution under SSP5-8.5 becomes smaller over the global land, which indicates that every region will be confronted with the risks of climate change under the high-emission scenario.

<Figure 1>

In addition to the above climate change hotspots, we also find some areas that consistently exhibit low SED values, suggesting that those regions exhibit relatively small aggregate response to global warming and could face lower risk of climate-related stresses relative to other global land areas. Areas with small SED values include, for instance, northern Europe, southern Greenland, the eastern United States, southern South America and the Indian Peninsula. Even still, these regions are affected by some single climate factors, which are analyzed in the discussion section.

Analysis of SED patterns reveals robust hotspot regions under different future forcings and different warming levels. However, different models produce somewhat different changes in the climate in response to the same radiative forcing (Hawkins & Sutton, 2011). Therefore, we next assess the inter-model uncertainty in the SED metric to assess whether hotspot identification is robust among multiple models (Figure 2). Overall, the hotspot regions that have been identified show a small inter-model standard deviation (STD) except for in the Amazon; that is, the CMIP6 models agree reasonably well on the locations of climate change hotspots. Moreover, the STD of inter-model
SED values decreases with the increase of global warming magnitude, and the inter-model uncertainty also tends to decrease from SSP1-2.6 to SSP5-8.5 at each warming level; this indicates that the model responses to the high-emission scenario at the end of the 21st century are more consistent and hotspot identification is more robust for this situation. However, some special cases should be noted. For example, the inter-model uncertainty of Indonesia is the largest at the 2 °C warming level under the SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios, while for the SSP1-2.6 scenario, the inter-model uncertainty in Indonesia is the strongest at the end of the 21st century. Among all warming levels and emission scenarios, CMIP6 models consistently show the greatest uncertainty in the Amazon region. We suspect that a possible reason for this uncertainty is the large SED in the Amazon region that is due to the large values of most climate indicators ($\Delta T$, $\Delta P$, $\Delta T_{var}$, $\Delta P_{var}$ and $\Delta Dry$), resulting in large order-of-magnitude differences among the CMIP models. On the other hand, the current results show that the CMIP models generally perform poorly in simulating Amazonian temperature and precipitation, a problem that arises from the models’ diverse sea surface temperature responses and soil moisture feedbacks and generates considerable uncertainty in model projections (Chai et al., 2021; Joetzjer et al., 2013). Central and western Africa, which is a persistent hotspot identified by the CMIP6 models, always shows smaller magnitudes of inter-model uncertainty relative to other regions of the globe.

< Figure 2 >
3.2 Time of emergence (TOE) of hotspots

In the previous section, we focused on the absolute magnitude of future climate change, and on that basis, we also identified hotspot regions under specific levels of warming. However, the emergence of signals in anthropogenic climate change is obscured by the natural climate variability. Defining when a climate change signal is evident beyond natural variability is important for climate change adaptation of different societal and ecosystem sectors, especially for hotspot regions. To this end, in this subsection we estimate when temperature and precipitation change signals will be detectable in seven hotspot regions by calculating the TOEs based on area-averaged temperature and precipitation from the CMIP6 ensembles.

Figure 3 shows changes in the SNR for temperature over time for the global land and seven major hotspot regions. In general, the spatial pattern of TOE for annual temperature shows that almost all global land grid cells exhibit a warming signal that is clearly outside the range of natural variability by 2100 under SSP5-8.5. More specifically, the earliest TOE occurs in the tropical regions before 2040. The high latitudes of the northern hemisphere exhibit relatively early warming signal emergence before 2050, excluding Greenland (where TOE is around 2060). For extra-tropical regions, TOE for warming occurs after 2060, showing the latest emergence over the global land.
We next investigated the differences in the timing of emergence among the seven hotspot regions (the surrounding seven panels in Figure 3). First, we found similar behavior for all seven regions—that is, the timing of annual warming TOE would move forward with an increase in radiative forcing. In the cases of the medium- and high-emission scenarios (SSP2-4.5, SSP3-7.0 and SSP5-8.5), the SNRs of the seven hotspots exhibit a continuous increase during the 21st century, while under the low-emission scenario, SSP1-2.6, the SNR begins to decrease slightly around 2080. In addition, for the SSP3-7.0 and SSP5-8.5 scenarios, the TOE appeared not only for SNR > 1 but also for SNR > 2, indicating that a significant signal emerges from the internal variability in high-emission scenarios.

Over the western Arctic (WARC), eastern Arctic (EARC) and Indonesia (IDN) regions, the TOE for SNR > 1 occurs around 2040 in all four scenarios, which is earlier than in the other four hotspot regions. Furthermore, WARC experiences the earliest emergence among all the hotspots: SNR > 1 emerges in 2037 under the SSP5-8.5 scenario, while in other scenarios, it emerges in 2041. The Central America (CAM), central and western Africa (CWAF) and Amazon Basin (AMZ) regions show later TOEs—around 2050—than the above three hotspots. By contrast, over the Tibetan Plateau (TP), the TOE of annual warming appears the latest among the seven hotspots, yielding a TOE > 2055, while the TOE for SNR > 2 occurs at about 2085 for the SSP5-
8.5 scenario. For the SSP2-4.5 and SSP3-7.0 scenarios, the TOE of TP would occur after 2060. In all these hotspot regions, and especially in the Arctic, adaptation plans need to focus on reducing the impacts of temperature.

In most regions over the global land surface, the TOE for the annual mean precipitation signal tends to be later than the TOE for annual mean temperatures signals, occurring towards the end of the 21st century or even beyond (Figure 4). As several previous studies have noted, a possible reason may be that the internal variability associated with precipitation is quite large compared to the variability of temperature (Akhter et al., 2018; Hawkins & Sutton, 2012). For the precipitation signal, the TOE under the SSP5-8.5 scenario occurs earliest over the high latitudes of the northern hemisphere, emerging around 2030 or in some cases earlier. Other regions with a TOE for the precipitation signal under SSP5-8.5 occurring during the mid-21st century include parts of the tropics, certain subtropical regions in the southern hemisphere, the Mediterranean, and central and eastern China.

< Figure 4 >

Two hotspot regions (CAM and AMZ) exhibit negative SNR under all four future scenarios due to their negative precipitation change signals. For CAM, we found that the TOE for SNR < −1 occurs around 2065 in the SSP3-7.0 and SSP5-8.5 scenarios; however, the TOE for SNR < −1 in AMZ does not appear until the end of the 21st
century. The SNR shows positive values and generally strengthens over time in WARC, EARC, TP, CWAF and IDN under all future emission scenarios except SSP1-2.6. TOEs for SNR > 1 in the two Arctic regions are before 2035, and these regions exhibit TOEs of SNR > 2 in the middle and late decades of the 21st century under SSP5-8.5, SSP3-7.0 and SSP2-4.5. For SSP1-2.6, the SNR exceeds 1 for the first time around 2055 and remains around 1 in these two regions, which indicates that the precipitation change signal is relatively weak under this scenario. For the TP region, the TOE is delayed by several decades, with TOE for SNR > 1 occurring after 2070 under the medium- and high-emission scenarios. From the above results, we can see that the anthropogenic signals in the regions WARC, EARC, TP and CAM are easier to detect than in the other three hotspot regions. Also, we can see that the significant delays in TOEs that would result from achieving the lower emission scenario would be of great significance for mitigating the effects of climate change, especially for the CAM region, which is expected to experience a decreasing precipitation trend in the future.

4. Discussion

Based on simulation results from the 24 climate models from CMIP6, we have investigated climate change hotspots and estimated the TOE of annual temperature and precipitation signals for climate change under different emission scenarios and warming levels. Our results are basically consistent with hotspots previously identified using CMIP5 models (Diffenbaugh & Giorgi, 2012) and observations (Turco et al.,...
2015), indicating the robustness of results from the CMIP models and the persistence of observed and modeled hotspot regions over time. However, the SED values calculated from the CMIP6 models are larger than those calculated from the CMIP5 models, suggesting that the aggregated effects of climate change are more serious under the new CMIP6 scenarios that consider social and economic factors. A possible reason is that the magnitude of the warming in CMIP6 is higher than in CMIP5 for corresponding periods. In addition, besides in southern South America and the Indian Peninsula, where relatively small responses to global warming were found in CMIP5 as well (Diffenbaugh & Giorgi, 2012), we also found that the regions of northern Europe, southern Greenland and the eastern United States exhibit relatively small SED values in the CMIP6 projections.

Although our results for hotspot identification are robust, it should be noted that the assessment of climate change hotspots is highly influenced by our choice of climate variables. In this study, we mainly focus on aggregations of multidimensional climate change for two basic climate variables (temperature and precipitation), which play a crucial role in many fields and have often been used to identify climate change hotspots in previous studies (Torres & Marengo, 2013; Xu et al., 2019). In addition, the SED values may vary depending on the number of years selected for the reference and future periods (a period of 20 years is used in our study). Nevertheless, Turco et al. (2015) investigated the influence of selecting 20-year and 30-year subperiods on the distribution of hotspots and found that most of the hotspot regions were persistent for

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these two time scales. A likely reason is that the key indicators of the hotspots are large enough to mask the natural internal variability. Our hotspot identification results are based on the global scale; however, it should be noted that if the continental scale or other smaller regional scales are considered, other hotspots will be identified according to the region selected.

To detect the driving climatic factors that determine the emergence of climate change hotspots, we first determined the strength of the significant climatic indicators influencing multi-dimensional aggregate climate changes under different SSPs and warming levels. Then we assessed the potential implications of the changes in precipitation and temperature statistics for each hotspot region in detail. Figure 5 shows rose diagrams with the relative contributions of seven temperature and precipitation indicators to the spatial distribution of SED using the geographical detector technique.

As shown in Figure 5, the determinant ($q$) values for the seven climate indicators show similar rankings for warming at 1.5 °C, 2 °C, 3 °C and 4 °C relative to preindustrial levels. The results indicate that frequency of years above the baseline maximum surface temperature ($\Delta$Hot), which had the highest $q$ values, can predominantly explain the spatial heterogeneity of SED statistics, followed by the frequency of years below the baseline minimum precipitation ($\Delta$Dry). The frequency of years above the baseline maximum precipitation ($\Delta$Wet) and interannual standard deviation of temperature ($\Delta$Tvar) proved to have a weak explanatory influence.
As global warming develops over time, the relative importance of the dominant factors that affect the spatial distribution of SED differ at the end of the 21st century under SSP3-7.0 and SSP5-8.5. In this case, although the \( p \) value of \( \Delta Hot \) is still the largest under SSP3-7.0 scenario, the change in mean surface temperature (\( \Delta T \)), \( \Delta Wet \) and the change in mean precipitation (\( \Delta P \)) were found to have a strong influence on SED statistics. For SSP5-8.5, the changes in \( \Delta T \), \( \Delta P \), \( \Delta Wet \) and \( \Delta Dry \) are the dominant factors affecting the distribution of SED. However, we highlight the sharp drop in the contribution of \( \Delta Hot \) (\( q = 0.010 \)) under SSP5-8.5; a possible reason for this drop is that the frequency of extreme hot conditions will accelerate equally over most parts of the global land under the high level of global warming associated with this scenario, while the spatial heterogeneity of extreme hot occurrences is relatively larger when warming at 1.5 °C, 2 °C, 3 °C and 4 °C and under the low and medium emissions scenario (SSP1-2.6 and SSP2-4.5) at the end of the 21st century. Furthermore, the \( q \) values for \( \Delta Hot \) begin to decrease measurably when warming approaches 4 °C, but extreme hot occurrences are still the leading factor. It is important to note that the decrease in the contribution of \( \Delta Hot \) only means that its relative impact on the spatial pattern of SED weakens as the overall level of warming increases globally. Another way to look at this is that it shows that the risk of extreme hot occurrences in most land regions over the globe will be largest under the highest level of global warming.

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Taking the SSP5-8.5 scenario as an example, Figure 6 shows the normalized absolute annual changes in the seven temperature and precipitation indicators, which can provide the relative contributions of the indicators to each hotspot in detail. The normalized absolute changes of the 28 seasonal indicators at the time of 1.5 °C warming and the end of the 21st century are shown in the supplementary materials (Figures S2 and S3). Overall, the hotspot regions experience severe relative changes in several climate indicators (Figures 6, S2 and S3). The Amazon region, for example, exhibits relatively large changes in variability of both precipitation and temperature in all four seasons, in extreme dry occurrences in all four seasons, and in mean precipitation in JJA and SON. For areas in central and western Africa, Indonesia and Central America, the variability of precipitation, the high extreme hot and dry occurrences in all four seasons are the dominant factors that make this region a hotspot. The Tibetan Plateau shows strong changes in extreme hot and wet occurrences and in precipitation variability, especially in JJA, MAM and SON. For the Arctic, the key determinants making it a hotspot under high warming levels are the relatively large changes in DJF, MAM and SON mean temperatures and precipitations; in JJA and SON extreme hot seasons; and in extreme wet occurrences throughout the year. Furthermore, some regions with small SED values (i.e., not hotspots) also experience large changes in some climate indicators. For example, there is large precipitation variability in the Indian peninsula, which is cause for concern.
5. Conclusion

In this study, we conduct an integrated assessment of future climate change hotspots under different levels of global warming, considering the combined changes in climate means, variability and extremes for precipitation and temperature. The results show that the latest CMIP6 simulations identify robust hotspot regions of future climate changes, including the Amazon, central and western Africa, Indonesia and the Tibetan Plateau, at 1.5 °C, 2 °C and 3 °C warming levels under four future scenarios. As global warming progresses, areas of the Arctic, Central America and southern Africa emerge as hotspot regions under 4 °C warming and at the end of the 21st century under the SSP3-7.0 and SSP5-8.5 scenarios. In order to further analyze the robustness of hotspot identification, we estimate model uncertainty using the standard deviation of SED patterns for different models and find reasonable agreement on the locations of hotspots by CMIP6 models, except for the Amazon. Furthermore, our results provide time estimates for the emergence of mean temperature and precipitation change signals under the SSP5-8.5 scenario. For temperature, we identified TOEs during the 21st century for seven primary hotspot regions, with especially early emergence of hotspots in WARC, EARC and IDN. For precipitation, we identified TOEs during the 21st century in the regions WARC, EARC, TP and CAM, while the signal never exceeds noise during the 21st century in the other three hotspot regions. More attention is warranted for the CAM
region, especially, because of detectable precipitation reduction signals that may have notable consequences.

The patterns of the SED metric are shaped by the $\Delta Hot$ and $\Delta Dry$ variables for warming of 1.5 °C, 2 °C, 3 °C and 4 °C. At the end of the 21st century, $\Delta Hot$ and $\Delta Dry$ are still the dominant factors under SSP1-2.6 and SSP2-4.5, but the contribution from $\Delta Hot$ become weaker and weakest under SSP3-7.0 and SSP5-8.5, respectively. This indicates that the regional response of global warming is heterogeneous under low warming levels and low to medium emissions scenarios at the end of the 21st century. Conversely, by the end of this century, under a high emissions scenario, most global land regions will face the combined challenges of extreme hot occurrences and high changes in precipitation. In addition, we find the identified hotspot regions exhibit large relative change values in a number of different precipitation and temperature indicators.

Overall, this study identifies major climate change hotspots and their influencing factors under different levels of global warming, which provides a starting point for developing strategies to mitigate climate change. But climate risks are not dependent only on the severity of climate change; they also critically depend on a variety of socioeconomic, demographic, biophysical and other factors, and on regional ability to prepare for and manage changing risks. Future work should seek to identify multisectoral climate change hotspots with attention to such risk factors.

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Data Availability Statement

The CMIP6 data were downloaded from the WCRP Earth System Grid Federation (ESGF) website (https://esgf-node.llnl.gov/projects/cmip6/). GISTEMP data are freely available online (https://data.giss.nasa.gov/gistemp/).

References

Adler, R. F., & Gu, G. (2015). Spatial Patterns of Global Precipitation Change and Variability during 1901–2010. Journal of Climate, 28(11), 4431–4453. https://doi.org/10.1175/jcli-d-14-00201.1

Akhter, J., Das, L., Meher, J. K., & Deb, A. (2018). Uncertainties and time of emergence of multi-model precipitation projection over homogeneous rainfall zones of India. Climate Dynamics, 50(9), 3813–3831. https://doi.org/10.1007/s00382-017-3847-y
Barrow, E. M., & Sauchyn, D. J. (2019). Uncertainty in climate projections and time of emergence of climate signals in the western Canadian Prairies. *International Journal of Climatology, 39*(11), 4358–4371. https://doi.org/10.1002/joc.6079

Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., et al. (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters, 13*(5), 055012. https://doi.org/10.1088/1748-9326/aabf45

Chai, Y., Martins, G., Nobre, C., von Randow, C., Chen, T., & Dolman, H. (2021). Constraining Amazonian land surface temperature sensitivity to precipitation and the probability of forest dieback. *npj Climate and Atmospheric Science, 4*(1), 6. 10.1038/s41612-021-00162-1

Chen, Z., Zhou, T., Zhang, W., Li, P., & Zhao, S. (2020). Projected Changes in the Annual Range of Precipitation Under Stabilized 1.5°C and 2.0°C Warming Futures. *Earth's Future, 8*(9). https://doi.org/10.1029/2019ef001435

Contractor, S., Donat, M. G., & Alexander, L. V. (2020). Changes in Observed Daily Precipitation over Global Land Areas since 1950. *Journal of Climate, 34*(1), 3–19. https://doi.org/10.1175/JCLI-D-19-0965.1

de Elía, R., Biner, S., & Frigon, A. (2013). Interannual variability and expected regional climate change over North America. *Climate Dynamics, 41*(5), 1245–1267. https://doi.org/10.1007/s00382-013-1717-9

Diffenbaugh, N. S., & Giorgi, F. (2012). Climate change hotspots in the CMIP5 global
climate model ensemble. *Climatic Change, 114*(3-4), 813–822.

https://doi.org/10.1007/s10584-012-0570-x

Diffenbaugh, N. S., Giorgi, F., & Pal, J. S. (2008). Climate change hotspots in the United States. *Geophysical Research Letters, 35*(16). 10.1029/2008gl035075

Dosio, A., & Fischer, E. M. (2018). Will Half a Degree Make a Difference? Robust Projections of Indices of Mean and Extreme Climate in Europe Under 1.5°C, 2°C, and 3°C Global Warming. *Geophysical Research Letters, 45*(2), 935–944.

https://doi.org/10.1002/2017GL076222

Dosio, A., Zittis, G., Winger, K., Vogt, J. V., Vautard, R., Teichmann, C., et al. (2020). Future Global Meteorological Drought Hot Spots: A Study Based on CORDEX Data. *Journal of Climate, 33*(9), 3635–3661. https://doi.org/10.1175/jcli-d-19-0084.1

Dottori, F., Szewczyk, W., Ciscar, J.-C., Zhao, F., Alfieri, L., Hirabayashi, Y., et al. (2018). Increased human and economic losses from river flooding with anthropogenic warming. *Nature Climate Change, 8*(9), 781–786.

https://doi.org/10.1038/s41558-018-0257-z

Dunn, R. J. H., Alexander, L. V., Donat, M. G., Zhang, X., Bador, M., Herold, N., et al. (2020). Development of an Updated Global Land In Situ - Based Data Set of Temperature and Precipitation Extremes: HadEX3. *Journal of Geophysical Research: Atmospheres, 125*(16). https://doi.org/10.1029/2019jd032263

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor,
K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development, 9*(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Fan, X., Duan, Q., Shen, C., Wu, Y., & Xing, C. (2020). Global surface air temperatures in CMIP6: historical performance and future changes. *Environmental Research Letters, 15*(10), 104056. https://doi.org/10.1088/1748-9326/abb051

Feng, S., Hu, Q., Huang, W., Ho, C.-H., Li, R., & Tang, Z. (2014). Projected climate regime shift under future global warming from multi-model, multi-scenario CMIP5 simulations. *Global and Planetary Change, 112*, 41–52. https://doi.org/10.1016/j.gloplacha.2013.11.002

Fujimori, S., Hasegawa, T., Krey, V., Riahi, K., Bertram, C., Bodirsky, B. L., et al. (2019). A multi-model assessment of food security implications of climate change mitigation. *Nature Sustainability, 2*(5), 386–396. https://doi.org/10.1038/s41893-019-0286-2

Gao, Y., Jia, J.J., Lu, Y., Yang, T.T., Shi, K., Zhou, F., et al. (2021). Determining dominating control mechanisms of inland water carbon cycling processes and associated gross primary productivity on regional and global scales. *Earth-Science Reviews, 213*, 103497. https://doi.org/10.1016/j.earscirev.2020.103497

Gao, Y., Jia, J.J., Lu, Y., Sun, X.M., Wen, X.F., He, N.P., et al. (2020). Progress in watershed geography in the Yangtze River basin and the affiliated ecological security perspective in the past 20 years, China. *Journal of Geographical Sciences,*
Giorgi, F. (2006). Climate change hot-spots. *Geophysical Research Letters, 33*(8). https://doi.org/10.1029/2006gl025734

Giorgi, F., & Bi, X. (2009). Time of emergence (TOE) of GHG-forced precipitation change hot-spots. *Geophysical Research Letters, 36*(6). https://doi.org/10.1029/2009gl037593

Giorgi, F., Raffaele, F., & Coppola, E. (2019). The response of precipitation characteristics to global warming from climate projections. *Earth System Dynamics, 10*(1), 73–89. https://doi.org/10.5194/esd-10-73-2019

Gu, H., Yu, Z., Wang, J., Ju, Q., Yang, C., & Fan, C. (2014). Climate Change Hotspots Identification in China through the CMIP5 Global Climate Model Ensemble. *Advances in Meteorology, 2014*, 1–10. https://doi.org/10.1155/2014/963196

Hansen, J., Ruedy, R., Sato, M., & Lo, K. (2010). Global Surface Temperature Change. *Reviews of Geophysics, 48*(4). https://doi.org/10.1029/2010rg000345

Hawkins, E., & Sutton, R. (2011). The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics, 37*(1), 407–418. https://doi.org/10.1007/s00382-010-0810-6

Hawkins, E., & Sutton, R. (2012). Time of emergence of climate signals. *Geophysical Research Letters, 39*(1). https://doi.org/10.1029/2011GL050087

Hu, M., Lin, H., Wang, J., Xu, C., Tatem, A. J., Meng, B., et al. (2020). The risk of COVID-19 transmission in train passengers: an epidemiological and modelling
IPCC (2013), Climate Change 2013: The Physical Science Basis Report, Cambridge University Press, Cambridge, UK, and New York, NY, USA.

Jian, B., Li, J., Zhao, Y., He, Y., Wang, J., & Huang, J. (2020). Evaluation of the CMIP6 planetary albedo climatology using satellite observations. *Climate Dynamics*, 54(11-12), 5145–5161. https://doi.org/10.1007/s00382-020-05277-4

Joetzjer, E., Douville, H., Delire, C., & Ciais, P. (2013). Present-day and future Amazonian precipitation in global climate models: CMIP5 versus CMIP3. *Climate Dynamics*, 41(11), 2921-2936. 10.1007/s00382-012-1644-1

Krishnan, A., & Bhaskaran, P. K. (2020). Skill assessment of global climate model wind speed from CMIP5 and CMIP6 and evaluation of projections for the Bay of Bengal. *Climate Dynamics*, 55(9), 2667–2687. https://doi.org/10.1007/s00382-020-05406-z

Kumar, R., & Mishra, V. (2020). Increase in Population Exposure Due to Dry and Wet Extremes in India Under a Warming Climate. *Earth's Future*, 8(12). https://doi.org/10.1029/2020ef001731

Li, C., Zwiers, F., Zhang, X., Li, G., Sun, Y., & Wehner, M. (2020). Changes in annual extremes of daily temperature and precipitation in CMIP6 models. *Journal of Climate*, 1–61. https://doi.org/10.1175/JCLI-D-19-1013.1

Liang, L., & Gong, P. (2017). Climate change and human infectious diseases: A synthesis of research findings from global and spatio-temporal perspectives.
https://doi.org/10.1016/j.envint.2017.03.011

Lu, Y., Gao, Y., Jia, J.J., Xia, S.X., Wen, X.F., Yu, X.B., et al. (2021). Revealing carbon balance characteristics in a water conveyance-type lake and differences in carbon sources through its connective hydrological channels. *Journal of Hydrology*, 592, 125820. https://doi.org/10.1016/j.jhydrol.2020.125820

Luo, W., Jasiewicz, J., Stepinski, T., Wang, J., Xu, C., & Cang, X. (2016). Spatial association between dissection density and environmental factors over the entire conterminous United States. *Geophysical Research Letters*, 43(2), 692–700. https://doi.org/10.1002/2015GL066941

Nguyen, T.-H., Min, S.-K., Paik, S., & Lee, D. (2018). Time of emergence in regional precipitation changes: an updated assessment using the CMIP5 multi-model ensemble. *Climate Dynamics*, 51(9-10), 3179–3193. https://doi.org/10.1007/s00382-018-4073-y

O’Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., et al. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, 9(9), 3461–3482. https://doi.org/10.5194/gmd-9-3461-2016

Piontek, F., Muller, C., Pugh, T. A., Clark, D. B., Deryng, D., Elliott, J., et al. (2014). Multisectoral climate impact hotspots in a warming world. *Proceedings of the National Academy of Sciences*, 111(9), 3233–3238.
Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., et al. (2014). Hydrological droughts in the 21st century, hotspots and uncertainties from a global multimodel ensemble experiment. *Proceedings of the National Academy of Sciences, 111*(9), 3262. https://doi.org/10.1073/pnas.1222471110

Raftery, A. E., Zimmer, A., Frierson, D. M. W., Startz, R., & Liu, P. (2017). Less than 2 °C warming by 2100 unlikely. *Nature Climate Change, 7*(9), 637–641. https://doi.org/10.1038/nclimate3352

Ridder, N. N., Pitman, A. J., Westra, S., Ukkola, A., Hong, X. D., Bador, M., et al. (2020). Global hotspots for the occurrence of compound events. *Nature Communications, 11*(1), 5956. https://doi.org/10.1038/s41467-020-19639-3

Rivera, J. A., & Arnould, G. (2020). Evaluation of the ability of CMIP6 models to simulate precipitation over Southwestern South America: Climatic features and long-term trends (1901–2014). *Atmospheric Research, 241*, 104953. https://doi.org/10.1016/j.atmosres.2020.104953

Sanford, T., Frumhoff, P. C., Luers, A., & Gulledge, J. (2014). The climate policy narrative for a dangerously warming world. *Nature Climate Change, 4*(3), 164–166. https://doi.org/10.1038/nclimate2148

Schellnhuber, H. J., Rahmstorf, S., & Winkelmann, R. (2016). Why the right climate target was agreed in Paris. *Nature Climate Change, 6*(7), 649–653. https://doi.org/10.1038/nclimate3013
Srivastava, A., Grotjahn, R., & Ullrich, P. A. (2020). Evaluation of historical CMIP6 model simulations of extreme precipitation over contiguous US regions. *Weather and Climate Extremes, 29*, 100268. https://doi.org/10.1016/j.wace.2020.100268

Sun, Q., Miao, C., Hanel, M., Borthwick, A. G. L., Duan, Q., Ji, D., & Li, H. (2019). Global heat stress on health, wildfires, and agricultural crops under different levels of climate warming. *Environment International, 128*, 125–136. https://doi.org/10.1016/j.envint.2019.04.025

Surendran Nair, S., King, A. W., Gulledge, J., Preston, B. L., McManamay, R. A., & Clark, C. D. (2020). Economic losses from extreme weather in the U.S. Gulf Coast region: spatially differential contributions of climate hazard and socioeconomic exposure and vulnerability. *Environmental Research Letters, 15*(7), 074038. https://doi.org/10.1088/1748-9326/ab7b9a

Tai, A. P. K., Martin, M. V., & Heald, C. L. (2014). Threat to future global food security from climate change and ozone air pollution. *Nature Climate Change, 4*(9), 817–821. https://doi.org/10.1038/nclimate2317

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society, 93*(4), 485–498. https://doi.org/10.1175/bams-d-11-00094.1

Tebaldi, C., Debeire, K., Eyring, V., Fischer, E., Fyfe, J., Friedlingstein, P., et al. (2020). Climate model projections from the Scenario Model Intercomparison Project (ScenarioMIP) of CMIP6. *Earth System Dynamics Discussion, 2020*, 1–50.
Tokarska, K. B., Stolpe, M. B., Sippel, S., Fischer, E. M., Smith, C. J., Lehner, F., & Knutti, R. (2020). Past warming trend constrains future warming in CMIP6 models. *Science Advances, 6*(12), eaaz9549. https://doi.org/10.1126/sciadv.aaz9549

Torres, R. R., & Marengo, J. A. (2013). Climate change hotspots over South America: from CMIP3 to CMIP5 multi-model datasets. *Theoretical and Applied Climatology, 117*(3-4), 579–587. https://doi.org/10.1007/s00704-013-1030-x

Turco, M., Palazzi, E., von Hardenberg, J., & Provenzale, A. (2015). Observed climate change hotspots. *Geophysical Research Letters, 42*(9), 3521–3528. https://doi.org/10.1002/2015gl063891

UNFCCC (2015), Adoption of the Paris Agreement Rep., Report No FCCC/CP/2015/L9/Rev12015.

Vignesh, P. P., Jiang, J. H., Kishore, P., Su, H., Smay, T., Brighton, N., & Velicogna, I. (2020). Assessment of CMIP6 Cloud Fraction and Comparison with Satellite Observations. *Earth and Space Science, 7*(2). https://doi.org/10.1029/2019ea000975

Wahl, T., Jain, S., Bender, J., Meyers, S. D., & Luther, M. E. (2015). Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nature Climate Change, 5*(12), 1093–1097. https://doi.org/10.1038/nclimate2736

Waits, A., Emelyanova, A., Oksanen, A., Abass, K., & Rautio, A. (2018). Human infectious diseases and the changing climate in the Arctic. *Environment*
Wang, J. F., Li, X. H., Christakos, G., Liao, Y. L., Zhang, T., Gu, X., & Zheng, X. Y. (2010). Geographical Detectors - Based Health Risk Assessment and its Application in the Neural Tube Defects Study of the Heshun Region, China. *International Journal of Geographical Information Science, 24*(1), 107–127. https://doi.org/10.1080/13658810802443457

Wang, J. F., Zhang, T. L., & Fu, B. J. (2016). A measure of spatial stratified heterogeneity. *Ecological Indicators, 67*, 250–256. https://doi.org/10.1016/j.ecolind.2016.02.052

Watts, N., Amann, M., Arnell, N., Ayeb-Karlsson, S., Beagley, J., Belesova, K., et al. (2020). The 2020 report of The Lancet Countdown on health and climate change: responding to converging crises. *The Lancet*. https://doi.org/10.1016/s0140-6736(20)32290-x

Xu, L., Wang, A., Wang, D., & Wang, H. (2019). Hot Spots of Climate Extremes in the Future. *Journal of Geophysical Research: Atmospheres, 124*(6), 3035–3049. https://doi.org/10.1029/2018jd029980

Yin, Q., Wang, J., Ren, Z., Li, J., & Guo, Y. (2019). Mapping the increased minimum mortality temperatures in the context of global climate change. *Nature Communications, 10*(1), 4640. https://doi.org/10.1038/s41467-019-12663-y

Zhao, W., Hu, Z., Guo, Q., Wu, G., Chen, R., & Li, S. (2020). Contributions of Climatic Factors to Interannual Variability of the Vegetation Index in Northern China
Grasslands. *Journal of Climate*, 33(1), 175–183. https://doi.org/10.1175/JCLI-D-18-0587.

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**Figure Captions**

Figure 1. The relative aggregate climate change of the CMIP6 ensemble mean calculated using the standard Euclidean distance (SED) between the baseline period (1995–2014) and future periods. The columns show the spatial distribution of SED for each SSP scenario. The rows show the SEDs at each specific warming level and at the end of the 21st century. Note that global temperature change did not reach +3 °C relative to preindustrial levels by the end of the 21st century under the SSP1-2.6 scenario, and it did not reach +4 °C under the SSP2-4.5 scenario.

Figure 2. Inter-model uncertainty for SED measured by standard deviation (STD). The columns show the spatial distribution of STD for each SSP scenario. The rows show the STDs at each specific warming level and at the end of the 21st century.

Figure 3. Time of emergence (TOE) of detectable annual surface air temperature warming based on signal-to-noise ratios (SNR) > 1. TOE over the global land under the SSP5-8.5 scenario is indicated in the map. The surrounding seven panels illustrate changes in the SNR over time for the seven hotspot regions for the four emission scenarios: SSP1-2.6 (green line), SSP2-4.5 (blue line), SSP3-7.0 (red line) and SSP5-8.5 (purple line). Dashed lines in the seven panels indicate threshold values for SNR. The seven hotspot regions are Western Arctic (WARC), Central and western Africa (CWAF), Eastern Arctic (EARC), Central America (CAM), Amazon Basin (AMZ), Tibetan Plateau (TP) and Indonesia (IDN).
Figure 4. Same as Figure 3, but for emergence of an annual precipitation response to climate change. The blank areas in the map of time of emergence (TOE) indicate areas where the climate change signal does not exceed the noise before the end of the 21st century in the SSP5-8.5 scenario.

Figure 5. The impacts (q values) of the seven climatic factors on the spatial distribution of SED under scenarios SSP1-2.6 (green line), SSP2-4.5 (blue line), SSP3-7.0 (red line) and SSP5-8.5 (purple line) for four specific warming levels (a: 1.5 °C, b: 2 °C, c: 3 °C and d: 4 °C) and the end of the 21st century (e). All q values pass the test of significance at the 0.05 level (p < 0.05).

Figure 6. The normalized absolute values of changes in seven climate indicators (unitless) between the base period (1995–2014) and the years when specific warming levels are reached under the SSP5-8.5 scenario. Note that the changes of the seven variables for the four seasons were integrated into annual changes.
(a) 1.5 °C

(b) 2 °C

(c) 3 °C

(d) 4 °C

(e) 2080 – 2099

- SSP1-2.6
- SSP2-4.5
- SSP3-7.0
- SSP5-8.5
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