Projected timing of perceivable changes in climate extremes for terrestrial and marine ecosystems

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Abstract

Human and natural systems have adapted to and evolved within historical climatic conditions. Anthropogenic climate change has the potential to alter these conditions such that onset of unprecedented climatic extremes will outpace evolutionary and adaptive capabilities. To assess whether and when future climate extremes exceed their historical windows of variability within impact-relevant socio-economic, geopolitical, and ecological domains, we investigate the timing of perceivable changes (time of emergence; TOE) for 18 magnitude-, frequency- and severity-based extreme temperature (10) and precipitation (8) indices using both multi-model and single-model multi-realization ensembles. Under a high-emission scenario, we find that the signal of frequency- and severity-based temperature extremes is projected to rise above historical noise earliest in mid-latitudes, whereas magnitude-based temperature extremes emerge first in low and high latitudes. Precipitation extremes demonstrate different emergence patterns, with severity-based indices first emerging over mid-latitudes, and magnitude- and frequency-based indices emerging earliest in low and high latitudes. Applied to impact-relevant domains, TOE patterns suggest: (i) unprecedented consecutive dry day occurrence in >50% of 14 terrestrial biomes and 12 marine realms prior to 2100, (ii) earlier perceivable changes in climate extremes in countries with lower per capita GDP, and (iii) emergence of severe and frequent heat extremes well-before 2030 for the 590 most populous urban centers. Elucidating extreme-metric and domain-type TOE heterogeneities highlights the challenges adaptation planners face in confronting the consequences of elevated 21st century radiative forcing.

Keywords: climate change, climate extremes, time of emergence, terrestrial biomes, marine realms

Introduction

Considerable evidence suggests that the impact of climate change on human and natural systems is most acutely mediated during the occurrence of extreme events (Garcia, Cabeza, Rahbek, & Araújo, 2014; IPCC, 2013; Meehl et al., 2000; Parmesan, Root, & Willig, 2000). Possible changes in climatic extremes may exceed biological thresholds which are often neglected in ecological studies based on future climate scenarios, even though both gradual mean climatic trends and extreme climate have been implicated for various patterns of biological responses, such as local adaptation (e.g., morphological changes) or a poleward shift and an upward shift in elevation in the habitat range (Destouni, Jaramillo, & Prieto, 2013). Observational proof of this mediation is pervasive and diverse, e.g., decreased forest primary productivity in the presence of extreme heat and drought (Parmesan et al., 2000), higher rates of plant and human mortality under greater extreme heat and drought exposure (Oudin Åström, Forsberg, Ebi, & Rocklöv, 2013), infrastructure damage due to severe precipitation (Mailhot & Duchesne, 2010), increased wildfire risk due to drought-induced dieback (Jolly et al., 2015), and heightened food security challenges in water deficit years (Wheeler & Braun, 2013).

Future changes in climatic extremes are projected to exceed physiological, ecological, infrastructure, and technological thresholds developed during the historical experience window of human and natural systems (Burrows et al., 2014; Loarie et al., 2009; J. Sillmann, Kharin, Zhang, Zwiers, & Bronaugh, 2013; Zhang et al., 2011). As such, successful adaptation strategies will need to outpace the changing climate system. To quantify the requisite pace of adaptation to changing climate extremes, we employ the concept of TOE – if the signal (S) of climate change is of sufficient magnitude relative to climate variability (N), the climate change signal is said to be statistically significant, and the time of perceivable change in climate is referred to as TOE

(Hawkins & Sutton, 2012) or in ecological studies, “time of expulsion” (Power, 2014) (Fig. S1). TOE represents the pace of perceivable climate change, and thus it is a key indicator for predicting climate change impact to natural and human systems (Sherwood & Huber, 2010; Williams, Jackson, & Kutzbach, 2007). When the pace of changes in the climate system is beyond the adaptability limit of ecosystem, the ecosystem will encounter alterations to species compositions, productivity of plant communities and shifts in plant phenology (Jentsch & Beierkuhnlein, 2008; Reusch, Ehlers, Hammerli, & Worm, 2005), which will impact biodiversity and community resistance to invasion (Burrows et al., 2014; Loarie et al., 2009; Parmesan et al., 2000). If TOE is early, it gives little time for implementing effective adaptations and mitigation measures. However, knowledge about TOE of climate change will motivate people to take necessary actions to reduce greenhouse gas emissions, to defer or even to eliminate the projected TOE for climate change.

Several previous regional studies have examined changes in the magnitude of climate extremes relative to pre-industrial variability (Frame, Joshi, Hawkins, Harrington, & de Roiste, 2017; Harrington et al., 2016; King et al., 2015; Scherer & Diffenbaugh, 2014). However, we contend that the magnitude of change relative to historical variability is of greater relevance to human and natural systems because these systems developed, evolved, and adapted within historical climate variability (Diffenbaugh & Charland, 2016; Meehl et al., 2000; Parmesan et al., 2000; Sherwood & Huber, 2010; Williams et al., 2007). Despite general agreement amongst TOE methodologies that the signal of mean temperature is projected to emerge prior to 2100 across the world (Hawkins & Sutton, 2012; Williams et al., 2007), it is unclear when the TOE of extreme climate events will occur on both global and local scales.

We investigate the TOE of annual extreme climate variables represented by 18 indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Zhang et al., 2011)

(Table S1). The 18 ETCCDI indices describe a myriad of extreme climate conditions including the magnitude, frequency and severity of temperature and precipitation events relevant to human and ecological systems. For example, the magnitude of temperature extremes is based on the hot/cold tolerance of plants (Parmesan et al., 2000). Even if the magnitude of temperature and precipitation extremes remain the same, changes in the frequency of hot and cold extremes could lie outside of the physiological tolerance of a particular species. Life dieback, mortality and reproductive failure in large areas on a continental scale are usually linked with severe drought and heatwaves (Allen et al., 2010; Penuelas et al., 2013) that can be described by severity indices (Jentsch, Kreyling, Boettcher-Treschkow, & Beierkuhnlein, 2009). Heavy precipitation reduced the flowering length by several days (Butt et al., 2015; Jentsch et al., 2009). Therefore, in this paper, we reported the impacts of projected changes in climate extremes to terrestrial and marine ecosystems in the broad range of extreme indices derived from the Coupled Model Inter-comparison Project Phase 5 (CMIP5) multi-model ensemble and the Community Earth System Model – Large Ensemble Community Project (CESM-LENS) single-model multi-realization ensemble which capture the model structure uncertainty and internal natural variability, respectively.

Materials and methods

Model simulations and extreme climate indices

We estimate the TOE of extreme climate indices for both high- and mid-emission scenario Representative Concentration Pathways 8.5 and 4.5 (RCP8.5 and RCP4.5) simulations in the CMIP5 multi-model (30 members) ensemble, and high-emission scenario (RCP8.5) simulations in CESM-LENS single-model multi-realization (39 members) ensemble (hereafter referred to as multi-model and single-model, respectively). The analysis was done with extreme climate indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Zhang et al.,

2011) using daily maximum/minimum temperature and precipitation data simulated by the multi-model and single-model ensembles, for both the baseline historical and climate scenario projection periods. The global extreme temperature and precipitation data simulated by GCMs of CMIP5 have been widely assessed and found to be robust for extreme climate change impacts by various studies (Donat, Alexander, Herold, & Dittus, 2016; Donat, Lowry, Alexander, O’Gorman, & Maher, 2016; Easterling et al., 2000; Fischer, Beyerle, & Knutti, 2013; Fischer & Knutti, 2014; King et al., 2015; Pfahl, O’Gorman, & Fischer, 2017; Sillmann, Donat, Fyfe, & Zwiers, 2014; Sillmann, Kharin, Zhang, et al., 2013). 18 annual indices (Table S1; including 10 extreme temperature and 8 extreme precipitation indices) were computed from data simulated by multi-GCMs for historical experiments over the baseline (1971-2005) and the future period (2006-2100) projections under RCP 8.5 climate scenario in both CMIP5 and CESM-LENS ensembles, and under RCP4.5 climate scenario in the CMIP5 ensemble (Table S2). Only one realization (“r1i1p1”) of each GCM from CMIP5 was selected for this study. The magnitude, frequency and severity of extreme temperature and precipitation were estimated regarding three types of indices, e.g., absolute, percentile and threshold indices (see the type of indices in Table S1). We used GCMs’ simulations for the baseline period as the historical data to minimize the effect of bias of GCMs on TOEs estimated from the results of CMIP5 and CESM-LENS.

Since there may be some uncertainties associated with the intra-model simulations, we used 39 model simulations from the CESM-LENS (Kay et al., 2015) to calculate projected ETCCDI indices of annual scale and we estimated the TOE for these 39 model simulations. Using the 1979-2005 ERA-Interim reanalysis (Dee et al., 2011) daily data as the “observed” data and the empirical quantile mapping bias correction method, we corrected possible biases in model simulations of CESM-LENS ensembles used to estimate projected extreme climate indices. ERA-Interim 1979-

2005 and GCM 1979-2005 data were used to obtain parameters for quantile mapping using the “fitQmapQUANT” function and then CESM-LENS 1979-2100 data were bias-corrected using the “doQmap” function implemented in the R package “qmap” (Gudmundsson, Bremnes, Haugen, & Engen-Skaugen, 2012). To assess the effects of model simulation bias that are possibly large in projected extreme climate indices (especially threshold-based ones) (Cannon, Sobie, & Murdock, 2015; Scherer & Diffenbaugh, 2014; J. Sillmann, Kharin, Zhang, et al., 2013), we compared ensemble median TOEs derived from raw model simulations versus bias-corrected model simulations for all indices that were used in this study. Given the spatial distributions of TOEs for all indices derived from raw (Figs. S2 and S4) and bias-corrected (Figs. S13-S14) datasets are consistent with each other, we, therefore, used TOEs derived from raw model simulations instead of bias-corrected ones for further analysis of impacts of extreme climate change.

Metric for time of emergence

For each grid of each ensemble member (Fig. S1), we estimate the year when the trend S exceeds n times the noise N , i.e., $S/N > n$. S is estimated using a normal distribution for frequency and severity indices, and a generalized extreme value distribution for magnitude indices. N is the standard deviation of the baseline time series with S removed. The S/N noise-exceedance threshold n (Table S1) is based on previous studies of mean temperature and precipitation (Hawkins & Sutton, 2012; Maraun, 2013). The ensemble median TOE is calculated for each ETCCDI index.

We estimated the 1971-2100 trend signal (S) from individual time series of selected ETCCDI indices for each grid cell of a GCM fitted with a non-stationary normal distribution for frequency and severity indices, and a non-stationary generalized extreme value (GEV) distribution for magnitude indices, respectively. Thus for year t_i , $i = 1, \dots, K=130$, a climate index y_i is described as $y_i \sim Normal(\mu_i, \sigma)$ with $\mu_i = a + St_i$ for the non-stationary normal distribution, or

157 $y_i \sim GEV(\mu_i, \sigma_i, \xi)$ with $\mu_i = a_\mu + S_\mu t_i$, $\sigma_i = a_\sigma + S_\sigma t_i$ and $S = S_\mu - S_\sigma/\xi + S_\sigma/\xi \Gamma(1-\xi)$ for
 158 the non-stationary GEV distribution (Coles, 2001; Maraun, 2013), respectively. Probability
 159 distribution parameters, $\mu_i, a, a_\mu, a_\sigma, S, S_\mu, S_\sigma, \sigma, \sigma_i$ and ξ , were derived from a least-squares
 160 regression for normally distributed indices and the maximum likelihood method implemented in
 161 the R package “extRemes” (Gilleland & Katz, 2011) for GEV distributed indices, respectively.
 162 The noise (N) is the interannual variability computed as the detrended standard deviation of a time
 163 series y during 1971-2005, $N^2 = (1/K - 1) \sum_{i=1}^K (y_i - \mu_i)^2$. The TOE, emergence of a signal from
 164 a fraction, n , of the internal variability relative to the reference year of 2000, is
 165 $ToE(n) = 2000 + n \cdot |N/S|$ (Fig. S1). Because spatial averaging could reduce the variability of
 166 climate indices in grid cells (Kendon, Rowell, Jones, & Buonomo, 2008), TOEs tend to be earlier
 167 in larger than smaller spatial scales (Maraun, 2013). Therefore, for each extreme climate index
 168 selected, instead of normalizing S and N estimated from multi-GCMs before estimating TOEs, we
 169 first estimated TOE for each grid cell of each GCM data. After that, we regridded TOEs derived
 170 from each GCM to a standard $1^\circ \times 1^\circ$ grid to estimate the ensemble median TOE. The uncertainty
 171 of the TOE is based on the 16th and 84th percentile of TOEs from GCMs. For each extreme
 172 precipitation index, when more than 80% of simulations show the same sign of trends (increase,
 173 +, or decrease, -) in CMIP5 and CESM-LENS ensembles, respectively, we say trends are consistent.
 174 TOEs for grids where time series are not projected with consistently positive or negative trends in
 175 simulations were regarded as missing values. For grids where the time series of indices showing
 176 the magnitude of extreme precipitation cannot be appropriately described by the non-stationary
 177 GEV distribution, TOEs were also regarded as missing values.

178 *Time of emergence for human and ecosystems*

We estimate the TOE of extreme conditions globally, by country, and across impact-relevant domains such as terrestrial biomes, marine eco-regions, and major urban population centers. TOEs for 14 major terrestrial biomes and 12 marine realms of the world are based on the World Wildlife Fund (WWF) terrestrial ecoregions (Olson et al., 2001) and marine ecoregions (Spalding et al., 2007), respectively. By overlaying maps of terrestrial and marine ecoregions with maps of median TOE values of each extreme climate index, we extracted TOEs for each ecoregion. Then we estimated the cumulative fraction of grids showing TOE for each terrestrial biome and each marine realm. To assess possible impact of extreme climate change on human societies, the same procedure as those of ecosystems was conducted using maps for global populations (2010) and urban populations (2010) of the largest 590 cities in the world obtained from the archive of Demographia World Urban Areas, and maps of GDP per person for all countries of the world in 2010 obtained from the World Bank (Fig. S10). Urban residents are substantially more susceptible to impacts of extreme climate such as extreme heat waves (Smoyer, Rainham, & Hewko, 2000), droughts and floods (Ciavarella, Stott, & Lowe, 2017; McMichael, Woodruff, & Hales, 2006), than rural residents, so we related TOE of climate extremes to both global population and major urban residents to see possible differences in impacts of extreme climate change on urban and rural residents.

Results

Comparison of time of emergence between CMIP5 and CESM-LENS ensembles

Globally and regionally, we find similar TOE spatial patterns in the multi-model and single-model ensembles (Fig. 1-2 and Figs. S2-S5). The median of TOEs derived from 39 CESM-LENS ensembles is generally similar to the median of TOEs derived from multi-model simulations, even though the difference in TOEs for precipitation extremes between CMIP5 and CESM-LENS

ensembles is larger than that for temperature extremes. The uncertainty and range of TOEs of the CESM-LENS ensemble is substantially less than that of the CMIP5 ensemble (Figs. S3 and S5). Compared to the single-model, key differences in the multi-model ensemble include: a stronger signal in the magnitude of temperature extremes and the frequency and severity of cold extremes while a weaker signal in the frequency and severity of hot extremes (Figs. S6a and S6d-f); a lesser variance in the frequency and severity of temperature extremes (Fig. S7b-c and S7g-j); a slightly stronger (weaker) signal in the frequency (magnitude and severity) of precipitation extremes (Fig. S8); and a greater variance in the frequency and magnitude of precipitation extremes (Fig. S9). The multi-model ensemble median magnitude of temperature extremes (Figs. S3a and S3d-f), the magnitude of precipitation extremes (Figs. S5a and S5d), the frequency of precipitation extremes (Figs. S5b, S5e and S5g-h), and the severity of precipitation extremes (Figs. S5c and S5f) emerge ~2, 3-7, 3-6 and 5-9 decades earlier than those of the single-model ensemble, respectively, while the frequency of cold extremes emerges ~3 decades later (Figs. S4h-i). The uncertainty of TOE within the single-model multi-realization ensemble demonstrates that the CESM-simulated internal natural variability is substantially lower than the structural uncertainty captured in the multi-model ensemble (Figs. S3 and S5), especially for extreme temperature indices. Due to a greater variability of TOE captured in the CMIP5 ensemble, in the main text we focus our results on the multi-model ensemble, however global and impact-domain relevant single-model ensemble results can be found in the supplemental materials.

Geographical pattern of time of emergence

Estimated decades of TOE vary considerably between extreme climate indices (Fig. 1). TOE of all magnitude indices of temperature extremes is projected over the majority of Earth's surface prior to 2100 (Fig. 1a and 1d-f), with a global median of 2060 decade. TOE of heat frequency

extremes is projected to occur prior to 2050, with a global median of 2020 decade. Global median TOE for the severity of hot extremes is projected prior to 2030 decades. Spatially, TOE for extreme temperature magnitudes will occur 2-3 decades earlier in low-latitudes than in mid-latitudes (Fig. 1a and 1d-f) due to lower variability in low-latitudes (Figs. S7a and S7d-f), similar to TOE for the mean daily temperature (Anderson, 2011; Hawkins & Sutton, 2012). TOE for the magnitude of cold extremes tends to occur earlier in northern high-latitudes due to larger magnitude trends than in mid-latitudes (Figs. S6d, S6f, S7d and S7f). However, TOEs for the frequency of hot and cold extremes are projected to occur earlier in mid-latitudes due to lower variability than in low- and high-latitudes (Figs. S2b-c).

Even though the median global TOE for precipitation extremes is estimated to occur after 2100, the magnitude, frequency and severity of extreme precipitation are projected to show perceivable changes in many regions prior to 2050 (Figs. 2 and Fig. S4). Since the variability (signal) of extreme precipitation is significantly lower (higher) in high- and low-latitudes than in mid-latitudes, TOEs for the magnitude and frequency of extreme precipitation are projected to occur earlier in high- and low-latitudes than in mid-latitudes, while TOEs for the severity of extreme precipitation are projected to occur earlier in mid-latitudes than in high- and low-latitudes (Fig. 2 and Fig. S4).

Terrestrial and marine ecosystem exposure to change in climate extremes

Since the wide range of spatial variability in TOE could result in great differences in climate change impacts between various ecosystem and human societies, so we further interpret results on impact-relevant and granular regions which will be more useful for strategic planning in climate adaptation. TOEs of severe and frequent hot extremes are projected to occur prior to 2050 for all terrestrial biomes and marine realms (Fig. 3). Unprecedented consecutive dry days are projected

to occur in >50% of all terrestrial biomes and marine realms prior to 2100 (Fig. 4). TOEs for the frequency of hot extremes in all terrestrial biomes and marine realms are projected to be five decades earlier than those for the magnitude of hot extremes. The perceivable changes in severe hot extremes are projected to occur the earliest, with one decade earlier than the frequency of hot extremes (Figs. 3-4).

Tropical and subtropical forests are projected to experience earlier TOEs for the magnitude and frequency of extreme temperature (2010-2050) than other biomes (2020-2070) (Fig. 3). For most biomes, higher fractions of grids are projected to experience earlier TOEs for the severity than the frequency and magnitude of extreme precipitation. For 95% of grids in biomes of Tropical and subtropical coniferous forests and Mediterranean forest, TOEs of the severity of droughts are projected to occur prior to 2100, with median TOEs of 2050 and 2045, respectively. However, high-latitude biomes such as Boreal Forest, Taiga and Tundra are projected to experience earlier perceivable changes in the frequency than the magnitude and severity of extreme precipitation (Fig. 4). Tundra biome has the highest percentage of grids (>80%) that are projected to experience TOEs prior to 2100 in the magnitude, frequency and severity of extreme precipitation than other biomes (Fig. 3).

TOEs for extreme temperature magnitude in the Tropical Atlantic, Indo-Pacific, and Tropical eastern Pacific (2025-2050) are projected to occur much earlier than other marine realms (beginning in the 2030s) (Fig. 4). TOEs for the magnitude of temperature extremes in marine realms of low- and mid-latitudes in the Northern Hemisphere (Realms 3-8 in Fig. 3; 2020-2070) are projected to occur earlier than those in the Southern Hemisphere (Realms 9-12 of Fig. 4; later than 2030). Similar to high-latitude terrestrial biomes, high-latitude marine realms such as the Arctic, Temperate Northern Pacific and Atlantic are also projected to experience more widespread

perceivable changes in precipitation extremes (Fig. 4). Only about half the grids of low- and mid-latitude marine realms in the Northern Hemisphere, such as tropic Atlantic, Indo-Pacific, are projected to experience TOEs for precipitation extremes, irrespective of whether it is for the magnitude, frequency or severity. However, TOEs for precipitation extremes over marine realms in the Southern Hemisphere are projected to occur late in the century and beyond (2075 and after that).

Human exposure to change in climate extremes

Human health will also be impacted by extreme climate events including heatwaves, droughts and heavy precipitation of long duration (Haines, Kovats, Campbell-Lendrum, & Corvalan, 2006; McMichael et al., 2006). About 53% of urban residents currently living in major cities (Fig. S10) across the world could experience perceivable changes in the magnitude of hot extremes before 2050, while 20% and 23% of urban residents could experience perceivable changes in the magnitude and frequency of extreme precipitation before 2050, respectively (Fig. 5b). The fraction of the urban population projected to be exposed to the severity of droughts (38%) before 2050 is considerably higher than those projected to the severity of heavy precipitation (6%). All urban residents will encounter perceivable changes in the frequency and severity of hot extremes prior to 2030. Changes in the frequency and severity of hot extremes will be more alarming for major urban residents than non-major urban residents, as a higher fraction of major urban residence will be exposed to these perceivable changes, compared to all the global population (Figs. 5a-d). However, a higher fraction of non-major urban residents (~82% well before 2050) will experience earlier TOEs for the magnitude of hot extremes and the frequency and magnitude of extreme precipitation than that of major urban residents (Figs. 5a-d).

Based on generally positive relationships between median TOEs for grids over a country and

GDP per capita of that country considered (Figs. 5e), perceivable extreme climate change tends to occur earlier in developing countries with a low GDP per capita. This implies a challenge to take actions for mitigating and adapting climate change, as developed countries will likely benefit less from mitigating climate change. However, because wealthy countries tend to suffer much more loss of properties from extreme events which likely occur more frequently and in greater severity because of climate change impact, they should be motivated to reduce GHG emissions.

Discussion

Uncertainty of projected TOE for climate extremes

A large uncertainty in TOE arises from the inter-model differences in simulating both signal and noise. This uncertainty is at least 30 years and as much 60 years in some regions for mean climate (Hawkins et al., 2014; Hawkins & Sutton, 2012). Particularly for the precipitation-based indices, there can be a wide disagreement about the sign of change between the models in some regions (Sillmann, Kharin, Zwiers, Zhang, & Bronaugh, 2013). The uncertainty of TOEs for both temperature and precipitation extremes are dependent on climate indices. Based on S/N thresholds we adopted to estimate TOE, except the uncertainty range of TOE for the magnitude of temperature extremes (< 30 years), those for other extreme climate indices could be more than 200 years over certain latitudes (Figs. S3 and S5).

To make the TOE between different extreme climate indices more comparable, we also derived projected values of S/N ratio in 2100 (S/N_{2100}), using the climate change signal showing in the year of 2100 relative to the start of the 21st century and assuming the trends estimated will be permanently after 2100. S/N_{2100} can quantify the varying levels of extreme climate emergence. Under RCP8.5, S/N_{2100} for extreme temperature and precipitation indices will be up to ~ 35 and 3.5, while ~ 25 and 1.8 for RCP4.5, respectively (Fig. S15). If we use the same value of S/N threshold

for all extreme climate indices to estimate TOE, then the wide range of S/N_{2100} means a small uncertainty of TOE, and vice versa. Because there is large variability in precipitation extremes and TOE estimate is considerably sensitive to the variability, the uncertainty of TOE for precipitation extremes with S/N_{2100} ranging 0-1.8 is larger than those for temperature extremes with S/N_{2100} ranging 0-20 (Fig. S15).

Even though both the CMIP5 multi-model ensemble (Diffenbaugh & Charland, 2016) and the CESM-LENS single-model multi-simulation ensemble (Diffenbaugh et al., 2017) are respectively used in extreme climate change impact assessment, their differences in climate simulations were not examined. We comprehensively compared the uncertainty between them in terms of the climate change signal, variance and TOE. Compared to the CMIP5 ensemble, the CESM-LENS ensemble shows low climate change signal but high variance in the frequency and severity of cold extremes (Figs. S6g-j and S7g-j). However, the CESM-LENS ensemble also shows high signal in the magnitude of precipitation extremes over tropic regions where the Inter-Tropical Convergence Zone locates, and low variances for extreme precipitation indices except the severity of droughts. Spatial difference and uncertainties between and within the CMIP5 and CESM-LENS ensembles are large for precipitation extremes over the mid-latitude oceans. Moreover, our findings show considerably higher uncertainties of TOE in the CMIP5 ensemble than the CESM-LENS ensemble. This implies that even though most uncertainties of the magnitude of temperature and precipitation extremes resulting from internal climate variability could not be reduced by a perfect model (Fischer et al., 2013), the uncertainties of the variances of temperature and precipitation extremes resulted from model deficiencies, which points to opportunities to improve model deficiencies in simulating variances of climate extremes, other than the signal of climate extremes that is already highlighted.

Implications of terrestrial and marine climate extremes

Limited by long-term observed climate and ecological data, the interaction and feedback between climate and ecological systems are not well-understood. How the ecosystem has been modulated by climate extremes remains not clear (Ummenhofer & Meehl, 2017). Although individual species are affected by climate extremes differently (e.g., different species are more susceptible to different aspects of climate extremes), our analysis highlights some ecosystem hot-spots that are projected to experience intensive changes in climate extremes in terms their magnitude, frequency and severity. Vulnerable terrestrial ecosystems are tropical and subtropical forests for the magnitude of hot extremes, Tropical and subtropical coniferous forests and Mediterranean forest for the severity of precipitation extremes, Boreal Forest, Taiga and Tundra for the frequency of precipitation extremes, Tundra for all aspects of precipitation. For oceans, Tropical Atlantic, Indo-Pacific, and Tropical eastern Pacific would be vulnerable to hot extremes, and high-latitude marine realms to precipitation extremes.

Frequent and severe hot extremes and droughts are associated with lower ecosystem respiration and primary productivity of terrestrial ecosystems (Ciais et al., 2005). Hot and dry weather is also one driver of forest wildfire which could have severe ecological impacts such as carbon sequestration (Reichstein et al., 2013) and wildlife habitat availability (Stephens et al., 2018). Marine heatwaves and cold spells could also affect ecosystem structure severely such as mass bleaching, low primary productivity and wide mortality of sea animals. Compared to terrestrial climate extremes, marine climate extremes were less studied, especially those associated with organisms and ecosystems such as marine heat waves (Frolicher & Laufkotter, 2018). Our analysis shows a high vulnerability of both terrestrial and marine ecosystems to climate extremes.

Severe and frequent hot extremes for all terrestrial biomes and marine realms are projected

to exceed their adapted variability in 2050 by up to 17.5 times (half of S/N_{2100} shown in Fig. S15). ETCCDI indices more represent the “moderate” climate extremes, our TOEs for ETCCDI indices is meaningful for temperature and precipitation extremes that may cause recurring influence in terrestrial and marine ecosystems, but not for determining design values which is more extreme and probability-related. Because we lack detailed knowledge on the adaptation ability of ecosystem to the changing climate extremes (Palmer et al., 2017; Smith, 2011), there is a lack of truly S/N threshold for each extreme climate index beyond which the ecological responses of a specific ecosystem would be outside the bounds of normal variability of that ecosystem. However, our analysis gives a broad range of ecosystem exposure to projected climate extremes. Further research is needed to determine ecological responses and evolutionary consequences of climate extremes.

Effects of climate mitigation on time of emergence

In addition to climate change detection and attribution implications, our analysis on TOE projections of climate extremes at impact-relevant scales and on a geophysical granular level can potentially alert societal governance agencies to those most in need of adaptation and resilience building, as well as to identify natural systems on the precipice of unprecedented environmental stress and potential ecological crisis. TOEs of extreme climate indices projected for RCP4.5 are generally about two decades later than those projected for RCP8.5 (Figs. S11-S12). At the end of 21st century, the magnitude of extreme temperature and the magnitude, frequency and severity of extreme precipitation will remain within the historical range in most terrestrial lands under RCP4.5 (see $S/N_{2100} < 1$ in Figs. S11 and S15). The benefits of mitigation are also shown by the reduced S/N_{2100} from scenario RCP8.5 to RCP 4.5 as S/N_{2100} of RCP8.5 is up to 15 times of that of RCP4.5 for extreme temperature indices and 20 times for extreme precipitation indices. Therefore, our

results demonstrate that globally human and ecosystem will benefit from a lower carbon future (e.g., RCP 4.5) by a greatly reduced and delayed emergence of perceivable changes in climate extremes, not only the magnitude (Ciavarella et al., 2017) but also the frequency and severity. Hotspots of extreme climate changes found in terrestrial and marine ecosystems spread across the world. It is necessary to consider not only the magnitude but also the frequency and severity of extreme climate change as important dimensions to expanding protected areas or making conservation strategies.

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Conflict of interest

The authors declare that they have no conflict of interest.

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Figure Captions

Fig. 1. Multi-model ensemble median TOEs for temperature extremes under the high-emission scenario. **a**, txx, annual maximum daily maximum temperature; **b**, tx90p, percentage of days when daily maximum temperature is larger than the 90th percentile of daily maximum temperature; **c**, wsdi, annual count when at least six consecutive days' maximum temperature is larger than the 90th percentile of daily maximum temperature; **d**, txn, annual minimum value of daily maximum temperature; **e**, tnx, annual maximum value of daily minimum temperature; **f**, tnn, annual minimum value of daily minimum temperature; **g**, tn90p, percentage of time when daily minimum temperature is larger than 90th percentile; **h**, tx10p, percentage of time when daily maximum temperature is less than 10th percentile, **i**, percentage of time when daily minimum temperature is less than 10th percentile; **j**, csdi, annual count when at least six consecutive days of minimum temperature is less than 10th percentile. Magnitude indices are txx, txn, tnx and tnn; frequency indices are tx90p, tn90p, tx10p and tn10p; and severity indices are wsdi and csdi. Note that txx, tnx, tx90p, tn90p and wsdi (txn, tnn, tx10p, tn10p and csdi) are hot (cold) extreme indices. The thresholds of *S/N* for the TOE estimate are shown in table S1. Blank grids show TOE will not occur prior to 2100.

Fig. 2. Multi-model ensemble median TOEs for precipitation extremes under the high-emission scenario. **a**, rx1day, annual maximum 1-day precipitation,; **b**, r20mm, annual count when daily precipitation is larger than 20 mm; **c**, cdd, annual maximum number of consecutive days when daily precipitation is lower than 1 mm; **d**, rx5day, maximum consecutive 5-day precipitation; **e**, r10mm, annual count when precipitation is larger than 10 mm; **f**, maximum number of consecutive days when precipitation is larger than 1 mm; **g**, r95p, annual total precipitation from days when precipitation is larger than 95th percentile; and **h**, r99p, annual total precipitation from days when precipitation is larger than 99th percentile. Magnitude indices are rx1day and rx5day; frequency indices are r10mm, r20mm (absolute threshold-based), r95p and r99p (percentile threshold-based); and severity indices are cwd (wet) and cdd (drought). The thresholds of *S/N* for the TOE estimate are shown in table S1. Stippling in maps indicates consistently positive or negative trends for precipitation extremes in the multi-model ensemble. Consistent trends means more than 80% of models show the same sign (positive or negative) of trends. Blank grids show TOE will not occur prior to 2100.

Fig. 3. Terrestrial biomes exposure to perceivable changes in climate extremes under the high-emission scenario. TOE values versus the cumulative fraction of grids of each terrestrial biome for 6 representative extreme climate indices under RCP8.5. TOE values are estimated from the median TOE of the multi-model ensemble with particular *S/N* thresholds. Definitions and the thresholds for extreme climate indices are given in Fig. 1's legends and table S1. The background color of each panel title strip on the top corresponds to the color in the map that represents that terrestrial biome. The bold line shows the median value for each extreme climate index and the band shows the 16-84th percentile range of values in the multi-model ensemble. Since the multi-model ensemble shows inconsistently negative and/or positive trends in extreme precipitation

indices for some terrestrial biomes, the uncertainties of TOE values for extreme precipitation indices is much higher than those for extreme temperature indices and therefore not presented.

Fig. 4. Marine realms exposure to perceivable changes in climate extremes under the high-emission scenario. TOE values versus the cumulative fraction of grids of each marine realm for 6 representative extreme climate indices under RCP8.5. TOE values are estimated from the median TOE of the multi-model ensemble with particular *S/N* thresholds. Definitions and the thresholds for extreme climate indices are given in Fig. 1's legends and table S1. The background color of each panel title strip on the top corresponds to the color in the map that represents that marine realm. The bold line shows the median value for each extreme climate index and the band shows the 16-84th percentile range of values in the multi-model ensemble. Since the multi-model ensemble shows inconsistently negative and/or positive trends in extreme precipitation indices for some marine realms, the uncertainties of TOE values for extreme precipitation indices is much higher than those for extreme temperature indices and therefore not presented.

Fig. 5. Exposure of human societies to perceivable changes in climate extremes. TOE values versus the cumulative global population (**a** and **c**) and urban residents in 590 large cities (**b** and **d**) exposed to perceivable changes in temperature extremes (**a** and **b**; *txx*, *tx90p* and *wsgi*) and precipitation extremes (**c** and **d**; *rx1day*, *r20mm* and *cdd*) under RCP 8.5. The bold lines (**a-d**) show the median values for each index, and the bands for temperature extremes (**a** and **b**) and precipitation extremes (**c** and **d**) show the 16-84th percentile range of values in the multi-model ensemble. The scatterplots between the GDP per capita for 231 countries and the median TOEs in years (**e**). The median TOE for a country is the 50th percentile of the median TOE for all grids that a country encompasses. TOE values are derived from the multi-model CMIP5 ensemble. Least-squares regression lines and confidence intervals (grey bands) are shown in the scatterplot. Definitions of indices are given in Fig. 1's legends and table S1.

Figures

Fig. 1. Multi-model ensemble median TOEs for temperature extremes under the high-emission scenario. **a**, txx, annual maximum daily maximum temperature; **b**, tx90p, percentage of days when daily maximum temperature is larger than the 90th percentile of daily maximum temperature; **c**, wsd, annual count when at least six consecutive days' maximum temperature is larger than the 90th percentile of daily maximum temperature; **d**, txn, annual minimum value of daily maximum temperature; **e**, tnx, annual maximum value of daily minimum temperature; **f**, tnn, annual minimum value of daily minimum temperature; **g**, tn90p, percentage of time when daily minimum temperature is larger than 90th percentile; **h**, tx10p, percentage of time when daily maximum temperature is less than 10th percentile; **i**, percentage of time when daily minimum temperature is less than 10th percentile; **j**, csdi, annual count when at least six consecutive days of minimum temperature is less than 10th percentile. Magnitude indices are txx, txn, tnx and tnn; frequency indices are tx90p, tn90p, tx10p and tn10p; and severity indices are wsd and csdi. Note that txx, tnx, tx90p, tn90p and wsd (txn, tnn, tx10p, tn10p and csdi) are hot (cold) extreme indices. The thresholds of S/N for the TOE estimate are shown in table S1. Blank grids show TOE will not occur prior to 2100.

Fig. 2. Multi-model ensemble median TOEs for precipitation extremes under the high-emission scenario. **a**, rx1day, annual maximum 1-day precipitation,; **b**, r20mm, annual count when daily precipitation is larger than 20 mm; **c**, cdd, annual maximum number of consecutive days when daily precipitation is lower than 1 mm; **d**, rx5day, maximum consecutive 5-day precipitation; **e**, r10mm, annual count when precipitation is larger than 10 mm; **f**, maximum number of consecutive days when precipitation is larger than 1 mm; **g**, r95p, annual total precipitation from days when precipitation is larger than 95th percentile; and **h**, r99p, annual total precipitation from days when precipitation is larger than 99th percentile. Magnitude indices are rx1day and rx5day; frequency indices are r10mm, r20mm (absolute threshold-based), r95p and r99p (percentile threshold-based); and severity indices are cwd (wet) and cdd (drought). The thresholds of S/N for the TOE estimate are shown in table S1. Stippling in maps indicates consistently positive or negative trends for precipitation extremes in the multi-model ensemble. Consistent trends means more than 80% of models show the same sign (positive or negative) of trends. Blank grids show TOE will not occur prior to 2100.

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Fig. 4. Marine realms exposure to perceivable changes in climate extremes under the high-emission scenario. TOE values versus the cumulative fraction of grids of each marine realm for 6 representative extreme climate indices under RCP8.5. TOE values are estimated from the median TOE of the multi-model ensemble with particular S/N thresholds. Definitions and the thresholds for extreme climate indices are given in Fig. 1's legends and table S1. The background color of each panel title strip on the top corresponds to the color in the map that represents that marine realm. The bold line shows the median value for each extreme climate index and the band shows the 16-84th percentile range of values in the multi-model ensemble. Since the multi-model ensemble shows inconsistently negative and/or positive trends in extreme precipitation indices for some marine realms, the uncertainties of TOE values for extreme precipitation indices is much higher than those for extreme temperature indices and therefore not presented.

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