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PERSPECTIVE

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# From local perception to global perspective

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**Recent sociological studies show that over short time periods the large day-to-day, month-to-month or year-to-year variations in weather at a specific location can influence and potentially bias our perception of climate change, a more long-term and global phenomenon. By weighting local temperature anomalies with the number of people that experience them and considering longer time periods, we illustrate that the share of the world population exposed to warmer-than-normal temperatures has steadily increased during the past few decades. Therefore, warming is experienced by an increasing number of individuals, counter to what might be simply inferred from global mean temperature anomalies. This behaviour is well-captured by current climate models, offering an opportunity to increase confidence in future projections of climate change irrespective of the personal local perception of weather.**

Recent extreme climate anomalies in densely populated regions, such as the cold 2011/12 and 2013/14 winters in the eastern United States, ongoing drought in California, heat waves in Europe (2003), Russia (2010) and Australia (2013), or floods in Pakistan (2010), Colorado (2013) and the United Kingdom (2014), have received broad media attention and fuelled the discussion on the attribution of such events to climate change[1]. From a purely physical point of view, the attribution of an individual extreme event solely to anthropogenic climate change is essentially impossible, as the synoptic, chaotic components will always dominate the genesis and evolution of an event. Attribution requires an increased number of events over time — hence enough data — so that a robust trend can be detected in the frequency of occurrence of extreme events. To tackle this issue, scientists have long used statistical and dynamical models to simulate such events multiple times, in order to increase the sample size or to conceptualize the genesis of these events and thus arrive at robust conclusions regarding the role of climate change in the story[2]. Along the same lines, scientists have also debated how a slightly changed background state (such as increased sea surface temperatures or increased moisture in the air) may influence the likelihood or magnitude of an individual extreme event occurring[3]. It is worth noting that the few robust trends that have already emerged from the short and noisy observational records are mostly temperature-related and agree well with our physical understanding of how such extremes will change in a warming climate[4].

Despite all the scientific evidence, local short-term variations in weather are more salient to an individual than a long-term trend and hence are critical for his or her perception of how weather and climate are interlinked[5–8]. By climate science standards, the studies in refs 5–8 focused on relatively short time periods and showed that seasonality and short-term trends in temperature can influence one's perception of whether it has actually become warmer or colder in a specific location[6]. They further emphasize how weather anomalies influence one's belief in the concept of climate change[5] or, vice versa, how pre-existing belief in climate change or political orientation affects the perception of a given weather anomaly[7].

## Observations

Using monthly temperature from observations[9] and climate model simulations, we illustrate how population-weighted climate data can help grasp the global scale of climate change, while retaining a close tie to the individual experience of short-term variations in temperature. The focus is on monthly temperature as it constitutes one of the longer and more reliable gridded climate records and is easily extracted from the climate model simulations on which the recent Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) based its future projections[10].

As an illustrative example of spatial heterogeneity, Fig. 1a shows temperature deviations during the past year (November 2013 to October 2014) from the 1951–1980 average for all land areas. While the eastern United States saw colder-than-average temperatures, most other land areas experienced an above-average year, in line with 2014 being the warmest (or second-warmest: http://www.skepticalscience.com/cowtan_way_2014_roundup.html) year on record globally. Figure 1b shows the same time period, but expressed as standard deviations ($\sigma$) from the same reference period. The standard deviation offers a more tangible expression of temperature anomalies as it takes into account the natural range of temperature at a given location on the planet. Exceeding a certain local $\sigma$ value therefore provides a good measure for how unusual a given temperature anomaly actually is for a person living there. Yet, people in the tropics might not notice small temperature changes, even if they are significant in light of the naturally small temperature variability there[11]. At high latitudes, on the other hand, people might have experienced large but statistically insignificant changes in temperature over the past decades. Further, the reference climate for an individual person would depend on that person's age, but this is not considered here. Therefore, other metrics than the one used here could be thought of to characterize human temperature exposure[12].

Expressed as $\sigma$ from the same reference period 1951–1980, most of the eastern United States experienced a year that would have been considered normal to slightly colder-than-normal back in 1951–1980 (Fig. 1b). Central Europe and parts of South America, central Africa and eastern Asia, on the other hand, experienced a $>4\sigma$ year — something to occur with a probability of about 0.006%, or once in over 15,000 years, in a hypothetically stable climate (with the characteristics of 1951–1980 and assuming normal distribution).

Using gridded population data[13], we count the people who are exposed to particularly warm or cold months, normalize

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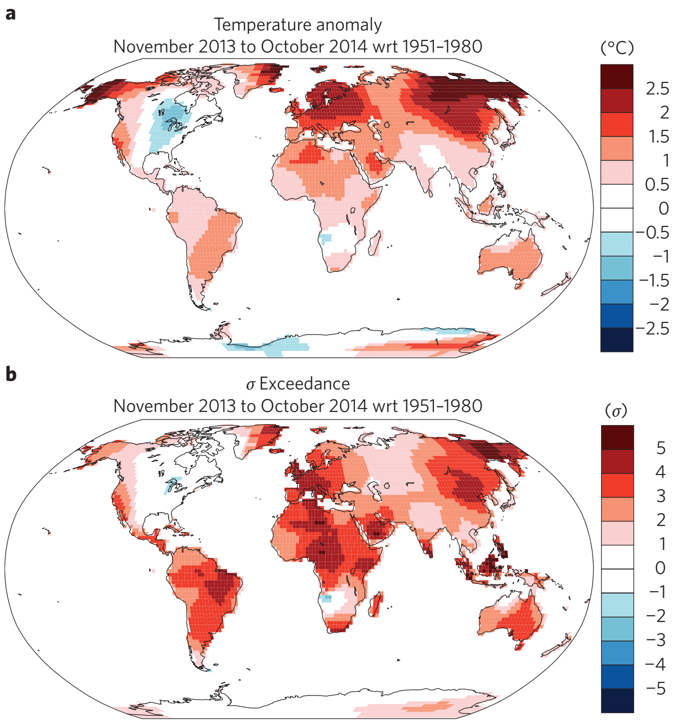

**Figure 1 | An example of spatial heterogeneity of temperature anomalies based on GISS surface temperature anomalies[9]. a**, Twelve-month mean temperature anomalies with reference to (wrt) the 1951–1980 period. **b**, As **a**, but expressed as standard deviations (σ).

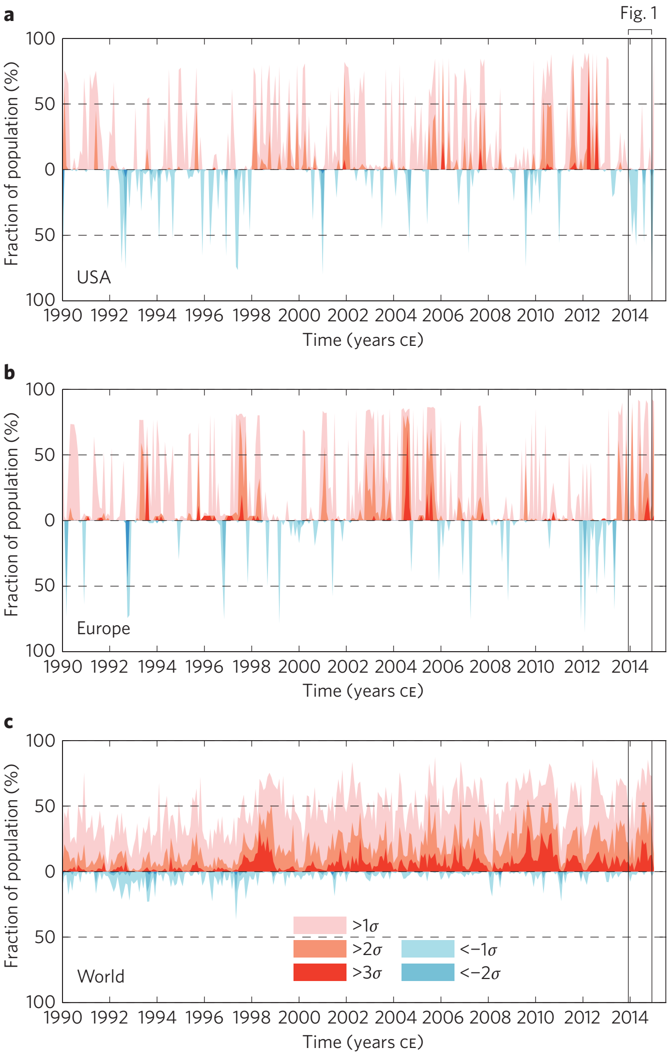

**Figure 2 | Time series of the fraction of population that experienced a 1σ, 2σ or 3σ exceedance with reference to 1951–1980. a**, For the United States; **b**, for Europe; **c**, for the entire world. The time period shown in Fig. 1 is marked in all panels.

them by the total population, and analyse this over time (Fig. 2). During 2014, the majority of the population of the United States experienced colder-than-average monthly temperatures, while the majority of Europeans saw warmer-than-normal months (Fig. 2a and b). During the past 15 years, however, both Americans and Europeans were exposed to mainly warmer-than-normal months and a fair number of months with >3σ, something that should only occur about one month in every 30 years. This indicates that the climate on these continents is clearly outside its 1951–1980 reference variability envelope.

Considering the entire world population, for which short-term trends and regional patterns as discussed in Fig. 1 tend to cancel out, a picture of a persistently warmer-than-normal decade emerges (Fig. 2c). Interestingly, based on a survey in 2007/2008 it was found that, when aggregated to a representative sample size, the majority of the world population did indeed notice local warming during the five years prior to the survey (ref. 6). In fact, despite a slowdown in land surface temperature in the recent decade (Fig. 3a), the fraction of the world population that saw 1σ, 2σ or 3σ temperature exceedances has increased unabated since 1980 (Fig. 3b). This population fraction has also increased more strongly than the fraction of the total global surface area as well as the land-only surface area. This indicates that the human population is located predominantly in areas with early emergence from the reference envelope. It is worth noting that this does not simply follow from the fact that the land warms faster than the ocean, as owing to the specific heat capacities of land and ocean the land has generally a higher σ than the ocean and would therefore require higher absolute temperature anomalies to exceed its thresholds[14]. The result of these competing effects is a slower increase of the fractional exceedance of σ thresholds over land as compared with over ocean (Supplementary Fig. S1). As most people live on continents, this would work in favour of fewer people being exposed to threshold exceedances. However, the fact that the population fraction still increases faster than either the land or ocean fractions emphasizes the particularity of the human population distribution.

Based on the smoothed data from 2000 to 2014, individuals exposed to 1σ, 2σ and 3σ increased by 36%, 77% and 94%, respectively (Fig. 3b). This underlines that from the point of personal human perception, the so-called global warming hiatus did not take place. Rather, it stresses the need to disentangle the media's convolution of global mean temperature and the actual impacts of climate change on humans and natural systems[15].

## Climate models and future projections

To test the ability of climate models to capture the observed changes, we apply the same analysis to simulated temperature from the CMIP5 (Fifth Coupled Model Intercomparison Project) simulations (Fig. 4). The observed increase in 1σ and 3σ exceedances over the past decades is well encompassed by the multi-model range, suggesting that the models are skilful in this metric.

We then combine CMIP5 projections with population projections to estimate exposure until the end of the current century. Under the business-as-usual scenario (RCP 8.5), the exceedance of the 3σ threshold is projected to affect >50% of the world's population by 2050 and >90% by 2100. The exceedance of the 5σ threshold,

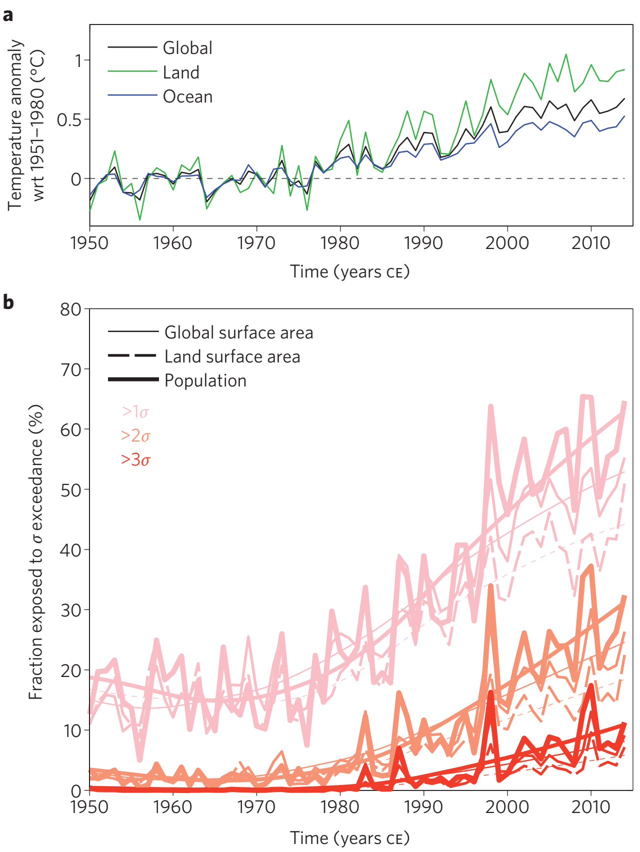

**Figure 3 | Annual mean temperature anomaly and temperature exceedances. a**, Annual mean temperature anomaly with reference to 1951–1980 for the entire globe, land only and ocean only. **b**, Fraction of the global surface area, of the land surface area and of the world population that experienced $1\sigma$, $2\sigma$ or $3\sigma$ temperature exceedances. The time series are calculated with monthly mean temperature anomalies, but, for optical reasons, only annual means of these time series are shown here. The smoothed lines are 30-year filtered time series.

something that has never affected more than about 3% of the world population even in recent years, is projected to increase rapidly in coming decades and affect >25% of the population by 2050 and >70% by 2100.

Under the mitigation scenario (RCP 2.6), the fraction of the world population experiencing $3\sigma$ stabilizes at about 38% and for $5\sigma$ at about 10%. In other words, the warming until about 2030–2040, which is independent of the scenario and to which humanity is therefore committed, will increase the likelihood for $>3\sigma$ and $>5\sigma$ months several-fold. However, with mitigation, the fraction of the world population experiencing extreme heat of $>5\sigma$ can be kept at a minimum[16].

Studies have shown that because of their small interannual temperature variability, tropical regions are among the first to emerge from their reference climate under global warming[11]. At the same time, future population growth is projected to be largest in the tropics, irrespective of the population scenario considered (Supplementary Fig. S2). This would increase the fraction of the world population exposed to significant temperature departures. Yet, compared with scenarios with smaller population growth or even population held constant at year-2000 values, the transient projections do not result in significantly more people being affected by threshold exceedances (Supplementary Fig. S3). It should be noted, however, that for individual climate models the population affected by $5\sigma$ exceedances can increase by more than 10% in the transient population scenarios as compared with constant population, leaving some climate model-related uncertainty with this result (not shown).

## Discussion

The results here imply that the debate on whether reduced decadal trends of global mean temperatures are undermining people's belief in climate change (or climate models) is essentially decoupled from the actual temperature perception based on population-weighted climate data over the past decades. It indicates that by focusing communication solely on global mean temperature changes over the past 15 years, objective information on the real temperature exposure of humans can be effectively obscured. Instead, the ability of climate models to capture recent trends in temperature threshold

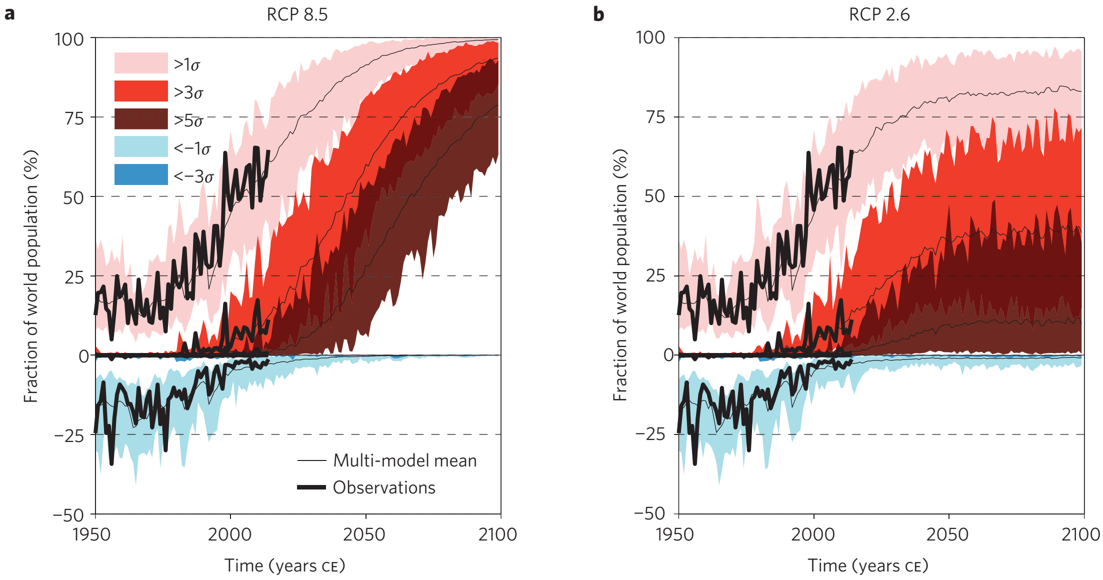

**Figure 4 | Fraction of the world population that experiences a specific temperature σ exceedance as simulated by the CMIP5 models. a**, For the RCP 8.5 scenario; **b**, for the RCP 2.6 scenario. The shading gives the range of the CMIP5 models, thin black lines give the multi-model mean; observations are in thick black lines. The high scenario population projections are used here (see Supplementary Fig. S2). The time series are calculated with monthly mean temperature anomalies; however, for clarity, only annual means of these time series are shown here.

exceedances should enable the public and commentators to refer to model projections with more confidence in this quantity, which in addition provides a view on climate change that is more tailored to the human perception than global mean temperature.

Beyond individual perception of climate change, these results have a wider importance because humans primarily use ecosystems services close to their place of residence. Projections of how such services might evolve under climate change need to take into consideration how many people depend on them at a specific location.

## Methods

Methods and any associated references are available in the online version of the paper.

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## Author contributions

F.L. and T.F.S. designed the study and wrote the article. F.L. analysed the data.

## Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence should be addressed to F.L.

## Competing financial interests

The authors declare no competing financial interests.

## Methods

For temperature observations we use the 2° × 2° Goddard Institute for Space Studies Surface Temperature Analysis (GISTEMP) as monthly anomalies to the reference period 1951–1980, a period of relatively little trend in global mean temperature and hence a good time frame for estimating natural variability[9]. Before estimating the standard deviation ($\sigma$) from this period, we linearly detrend temperature at each location over these 30 years. The CMIP5 models used for each scenario combination (historical + RCP 8.5 and historical + RCP 2.6) are listed in Supplementary Table S1. All simulations were bilinearly regridded to 2° × 2° and treated in the same way as the observations to estimate $\sigma$. Using an alternative dataset from the Hadley Centre and the Climate Research Unit (HadCRUT4[17]) did not alter the conclusions.

The population data stem from the History Database of the Global Environment (HYDE 3.2; ref. 13 and K. Klein Goldewijk and A. Beusen, manuscript in preparation), which incorporates census data from the UN World Population Prospects (http://www.un.org/en/development/desa/population/theme/trends/index.shtml) for 1950–2010 and bases on the Shared Socioeconomic Pathways (SSP)[18] for 2010–2100. Its future projections are compatible with both the RCP 8.5 and RCP 2.6 scenarios in terms of socio-economic trajectory. The data have been regridded to 2° × 2°, conserving global population.

In case of $\sigma$ exceedance for a given grid cell, the full population in that grid cell is counted towards the population experiencing the particular $\sigma$ exceedance. Similar to ref. 2, we thereby aggregate both climate and population data to a spatial scale that may lead to an underestimation of the coupling between temperature anomaly and perception.

The multi-model range in Fig. 4b illustrates that for the metric presented here there are larger uncertainties associated with the mitigation scenario (RCP 2.6) than with the business-as-usual scenario (RCP 8.5), something that does not follow simply from the global or regional mean temperature, which show a comparable spread for RCP 2.6 and RCP 8.5 in the latest IPCC assessment[19]. Instead, it seems to be difficult for models to agree on whether temperatures exceed a given threshold, at the locations where the majority of the world population lives, in the presence of a weak climate change signal (RCP 2.6), while they agree better for a scenario with a strong climate change signal (RCP 8.5). Seemingly a signal-to-noise issue, the reasons for this scenario-dependence of model agreement are not easily diagnosed from the existing literature[16] and may merit further investigation that is beyond the work presented here.

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SUPPLEMENTARY INFORMATION

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**Perspective**

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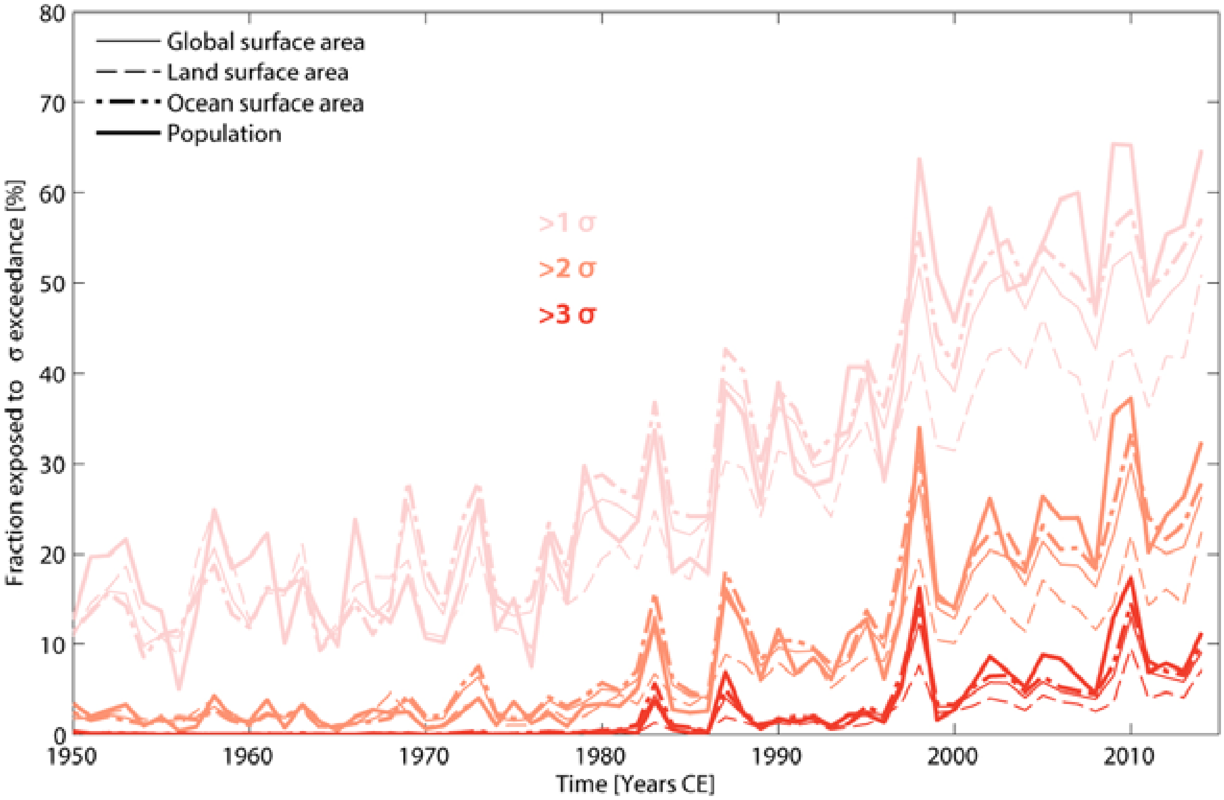

*Figure S 1: Fraction of the global surface area, the land surface area, the ocean surface area, and the world population that experienced 1−, 2−, or 3−σ temperature exceedances. The time series are calculated with monthly mean temperature anomalies, however, annual means of these time series are plotted here for optical reasons. Besides the time series for the ocean, this figure is as Fig. 3 of the main text.*

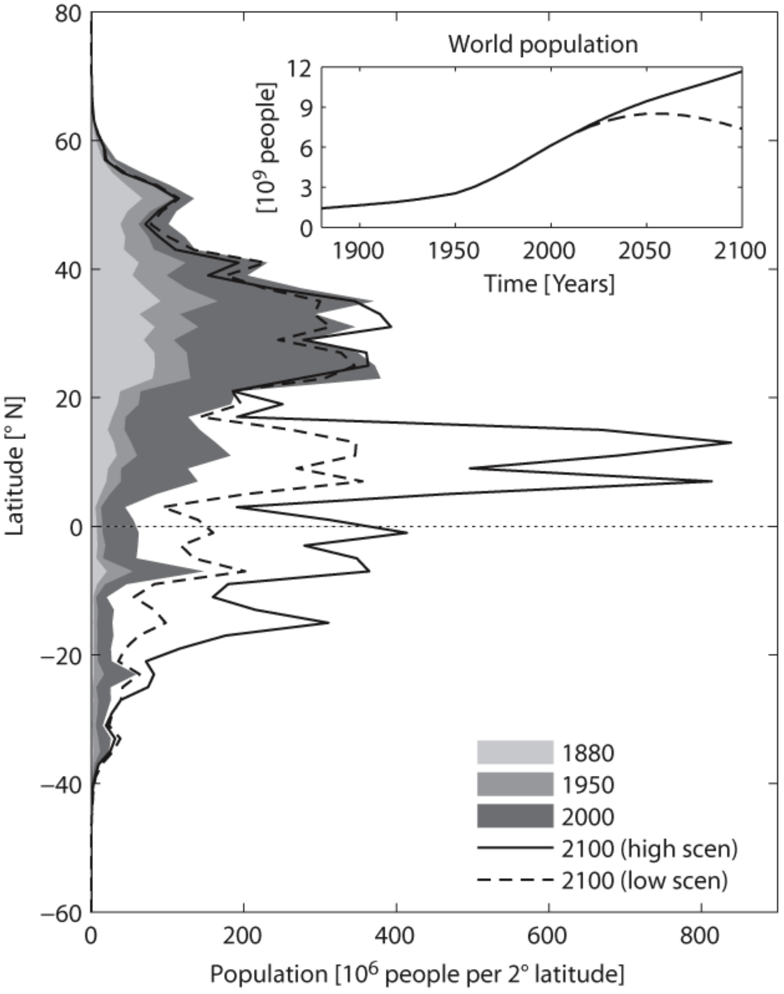

*Figure S 2: Zonally integrated population for different years. The inset shows the entire world population. The high and low scenarios are selected to represent the maximum and minimum world population at year 2100, about 12 billion and 7 billion, respectively.*

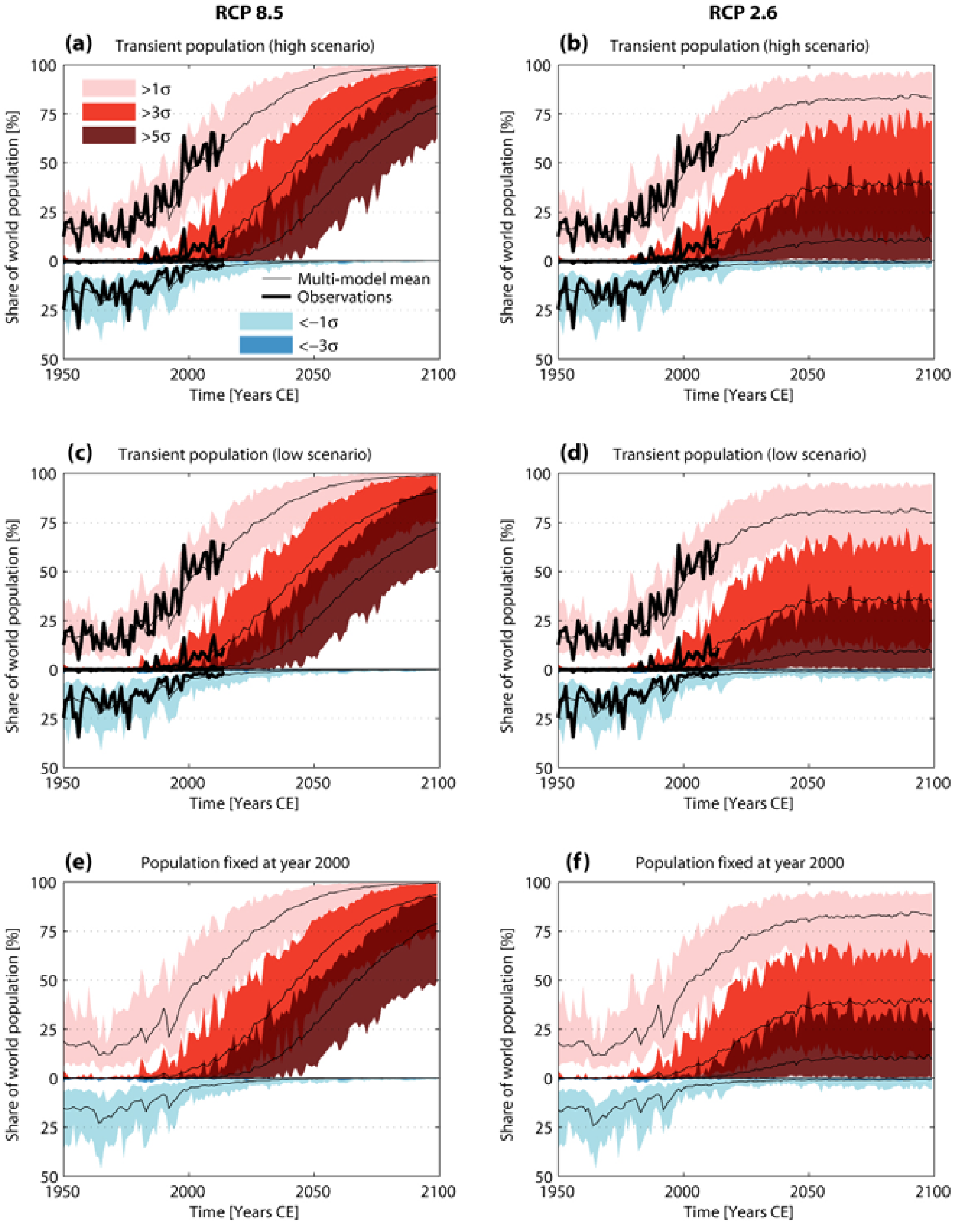

*Figure S 3: Comparing the effect of different population scenarios. (a) and (b) are the same as in Fig. 4. (c) and (d) are as (a) and (b), but with the low population scenario. (e) and (f) are with population fixed at year 2000.*

*Table S1: Simulations used from the CMIP5 archive.*

| **Model** | **historical** | **rcp85** | **rcp26** |
|---|---|---|---|
| ACCESS1-0 | r1i1p1 | r1i1p1 | |
| ACCESS1-3 | r1i1p1 | r1i1p1 | |
| bcc-csm1-1-m | r1i1p1 | r1i1p1 | r1i1p1 |
| bcc-csm1-1 | r1i1p1 | r1i1p1 | r1i1p1 |
| BNU-ESM | r1i1p1 | r1i1p1 | r1i1p1 |
| CanESM2 | r1i1p1 | r1i1p1 | r1i1p1 |
| CCSM4 | r1i1p1 | r1i1p1 | r1i1p1 |
| CESM1-BGC | r1i1p1 | r1i1p1 | |
| CESM1-CAM5 | r1i1p1 | r1i1p1 | r1i1p1 |
| CMCC-CESM | r1i1p1 | r1i1p1 | |
| CMCC-CMS | r1i1p1 | r1i1p1 | |
| CMCC-CM | r1i1p1 | r1i1p1 | |
| CNRM-CM5 | r1i1p1 | r1i1p1 | r1i1p1 |
| CSIRO-Mk3-6-0 | r1i1p1 | r1i1p1 | r1i1p1 |
| EC-EARTH | r8i1p1 | r8i1p1 | r8i1p1 |
| FGOALS-g2 | r1i1p1 | r1i1p1 | r1i1p1 |
| GFDL-CM3 | r1i1p1 | r1i1p1 | r1i1p1 |
| GFDL-ESM2G | r1i1p1 | r1i1p1 | r1i1p1 |
| GFDL-ESM2M | r1i1p1 | | r1i1p1 |
| GISS-E2-H-CC | r1i1p1 | r1i1p1 | r1i1p1 |
| GISS-E2-H | r1i1p1 | r1i1p1 | r1i1p1 |
| GISS-E2-R-CC | r1i1p1 | r1i1p1 | |
| GISS-E2-R | r1i1p1 | r1i1p1 | r1i1p1 |
| HadGEM2-AO | r1i1p1 | r1i1p1 | r1i1p1 |
| HadGEM2-CC | r1i1p1 | r1i1p1 | |
| HadGEM2-ES | r1i1p1 | r1i1p1 | r1i1p1 |
| inmcm4 | r1i1p1 | r1i1p1 | |
| IPSL-CM5A-LR | r1i1p1 | r1i1p1 | r1i1p1 |
| IPSL-CM5A-MR | r1i1p1 | r1i1p1 | r1i1p1 |
| IPSL-CM5B-LR | r1i1p1 | r1i1p1 | |
| MIROC5 | r1i1p1 | r1i1p1 | r1i1p1 |
| MIROC-ESM-CHEM | r1i1p1 | r1i1p1 | r1i1p1 |
| MIROC-ESM | r1i1p1 | r1i1p1 | r1i1p1 |
| MPI-ESM-LR | r1i1p1 | r1i1p1 | r1i1p1 |
| MPI-ESM-MR | r1i1p1 | r1i1p1 | r1i1p1 |
| MRI-CGCM3 | r1i1p1 | r1i1p1 | r1i1p1 |
| NorESM1-ME | r1i1p1 | r1i1p1 | r1i1p1 |
| NorESM1-M | r1i1p1 | r1i1p1 | r1i1p1 |