

1 **Population-based emergence of unusual, unfamiliar and unknown climates**

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22 **Time of Emergence’ (ToE), which characterizes when significant signals of climate**
23 **change will emerge from existing variability, is a useful and increasingly common**
24 **metric.¹⁻³ However, a more useful metric for understanding future climate change in the**
25 **context of past experience may be the ratio of climate signal to noise (S/N) – a measure**
26 **of the amplitude of change expressed in terms of units of existing variability³. Here, we**
27 **present S/N projections in the context of emergent climates (termed ‘unusual’,**
28 **‘unfamiliar’ and ‘unknown’ by reference to an individual’s lifetime), highlighting**
29 **sensitivity to future emissions scenarios and geographical and human groupings. We**
30 **show how for large sections of the world’s population, and for several geopolitical**
31 **international groupings, mitigation can delay the onset of ‘unknown’ or ‘unfamiliar’**
32 **climates by decades, and perhaps even beyond 2100. Our results demonstrate that the**
33 **benefits of mitigation accumulate over several decades, a key metric for such benefits is**
34 **reducing S/N, or keeping climate as familiar as possible, and that a relationship exists**
35 **between cumulative emissions and patterns of emergent climate signals. Timely**
36 **mitigation will therefore provide the greatest benefits to those facing the earliest**
37 **impacts, many of whom are alive now.**

38

39 **Main Text**

40 We illustrate the effect of S/N on the degree of unfamiliarity that a new climate has using a
41 Gaussian distribution as an example (see methods). The curves in Figure 1a show the
42 relationship between climates passing different integer S/N values (denoted as SN1, SN2,
43 SN3 respectively) compared to a “base” period. Panel 1a shows that at SN1, temperatures are
44 unusual, but not unfamiliar – in the sense that they overlap with the base period
45 approximately 62% of the time, and that years warmer than the new mean would have been

46 experienced once every 6 years or so under the base climate – hence we denote SN1 as the
47 threshold for an “unusual” climate. At SN2 the overlap drops to 32%, implying that the
48 coldest three years out of every ten in the warmer climate are the same as the warmest three
49 years out of ten in the base period, but importantly the mean is warmer than 98% of base
50 period years – hence SN2 is denoted “unfamiliar” in that the new climate would occur as a 1-
51 in-44 year event under the older base climate. By SN3 the overlap between coldest projected
52 years and warmest base period years is only 13%, but the new mean climate is warmer than
53 99.9% of the base years; this mean climate state is “unknown” in the sense that it would be
54 experienced on average once every 740 years in the base climate, i.e. far beyond a human
55 lifetime.

56 Recent work^{4,5} considered the fraction of the global population crossing particular integer
57 S/N values in future. Panels 1b and 1c compare this global population-based metric with
58 fraction of global surface area passing SN1 (pink curve); SN2; (red curve) and SN3 (maroon)
59 for RCP4.5. Thick central curves mark the middle of the CMIP5 ensemble; bands represent
60 the 16-84% range of CMIP5 ensemble members. The vast majority of communities can
61 expect to experience “unfamiliar” climates by 2060, even if TCR is towards the low end of
62 CMIP5 estimates. If TCR is towards the high end of CMIP5 estimates, then the vast majority
63 of human communities will experience unknown climates, i.e. $S/N > 3$, by the 2040s.

64 Panel 1d highlights that the rate of emergence is faster for human populations than for surface
65 area in each RCP; in other words climates change faster where people live than where they do
66 not. Approximately 50% of the global population can expect to experience unfamiliar
67 climates (relative to 1986-2005) by approximately 2030 and unknown climates by mid-
68 century. Under the median RCP4.5 scenario, only 20% of people avoid living in unknown
69 climates by 2100; as we show later, these people live in the extra-tropics.

70 Increasing S/N values implies increasing damages from climate change: a point amplified if,
71 as many people argue⁶⁻⁹, climate change damages are convex functions of temperature
72 change. This effect is likely to be more pronounced if change is fast than if societies have
73 more time to adjust¹⁰. Where climate change impacts are sigmoidal¹¹ rather than convex,
74 impacts may asymptote to a fixed value beyond some S/N level. However, even if this is the
75 case, the geographical sequencing of emergence with time is still robust. Although important
76 institutional and geographical details may change the picture for certain regions and impacts,
77 in general our results suggest an urgent need to begin investing in adaptive capacity in those
78 regions which are expected to experience unknown climates earliest.

79 These regions are highlighted in Figure 2, which shows conventional maps and population-
80 weighted cartograms of late 21st-century (henceforth L21C) S/N values for the representative
81 concentration pathway RCP4.5. The cartograms distort geographical shapes by weighting the
82 size of grid boxes by the number of people who live in that grid box, and are a novel way of
83 differentiating human dimensions of climate emergence from geographical dimensions¹². For
84 example, while Figures 2a-c show that some areas of the tropics are likely to experience
85 unknown climates by L21C², Figures 2d-f emphasise that these regions are home to a
86 significant fraction of the world's population, such as Malaysia/Indonesia, Western India,
87 West Africa and Central America. Consistent with Figure 1d, Figure 2 shows that under the
88 RCP4.5 scenario, a greater fraction of population than area experiences “unknown” climates
89 by L21C, and that these people are predominantly in the tropics – a result that is more clearly
90 displayed in cartograms than conventional maps.

91 Under RCP4.5 the range in emergence values by the end of the century is mainly associated
92 with uncertainties in the climate response (defined using Transient Climate Response, or
93 TCR), with a smaller contribution from the amplitude of simulated variability, which affects

94 the estimated S/N values³. Some caution should be exercised in interpreting the very high
95 S/N values in the tropics – models sometimes underestimate aspects of variability (issues
96 discussed extensively in the Climate Model Evaluation Chapter of the most recent IPCC
97 assessment)¹³ and, coupled with the already small annual variability in tropical temperatures,
98 may inflate simulated tropical S/N values. However, it should be stressed that while the
99 details of extremely high tropical S/N values should be interpreted cautiously, it does not
100 affect our main conclusions, which are based on S/N values of 2-3, i.e. unfamiliar and
101 unknown climates.

102 Figure 3 shows S/N in the RCP8.5 and RCP2.6 scenarios, and the effect of mitigating
103 emissions from the former to latter scenario for the 16th and 84th percentile of the CMIP5
104 ensemble. Under RCP 2.6, S/N has a high chance of staying below 3 over most parts of the
105 world, in contrast to RCP 8.5, in which most areas are likely to exceed S/N=3 and experience
106 “unknown climates” by L21C (Figure 3). The bottom two rows show where mitigating can
107 make the greatest difference. Even in a low-TCR world, significant mitigation reduces L21C
108 S/N by 3 or more for large groups of people in the tropics. We suggest that a key measure of
109 successful mitigation should involve keeping climate as ‘familiar’ as possible. Additionally,
110 if mitigation benefits are measured in this manner, they are quantified reasonably well by the
111 difference plots of Figure 3. Interestingly, the qualitative patterns of the lower two rows of
112 Figure 3 emerge if we compare any pairwise set of RCPs, implying that a relationship exists
113 between S/N and cumulative emissions of carbon, and that this relationship is essentially a
114 matter of pattern scaling (on sufficiently large spatial scales), as is the case with other
115 temperature-based climate variables¹⁴. Even though we may not know the exact difference
116 between emissions trajectories in a world without climate policy, and a world with a strong
117 climate policy, we can be confident that the basic patterns summarized in Figure 3 describes
118 the benefits of mitigation in terms of S/N.

The evolution of S/N in time highlights the speed at which large groups of countries start to experience 'unknown' or 'unfamiliar' climates. Figure 4 considers such a selection of international groups with spatial scales large enough to be represented in GCMs, but with very diverse economic and social characteristics: "AOSIS"- the Association of Small Island States; "ASEAN" - the Association of South-East Asian Nations; "LDCs" - countries considered to be least developed (the "bottom billion"^{15,16}); "GEMs" - Global Emerging Markets¹⁷ (those G20 countries not in the OECD90 group¹⁷); "OECD90" (all member countries of the Organization for Economic Cooperation and Development as of 1990). The curves in Figure 4 show cumulative distributions of population experiencing successive values of S/N, grouped by the above international groups, and by RCP scenario.

The gains from mitigating from RCP 8.5 (red) to RCP 2.6 (blue) are shown on the right hand side column in orange. The blue curves in Figure 4 corresponding to RCP2.6 can also be considered a proxy for the minimum level of emergent temperature change to which people will have to adapt, unless mitigation strategies even more aggressive than those considered in RCP 2.6 are adopted. What is clear is that with levels of mitigation equivalent to RCP2.6, most people's climates in OECD90 and GEM can be prevented from ever becoming "unknown". Additionally, even though this is not the case for tropical groupings such as ASEAN and AOSIS, mitigation is arguably just as important here, if not even more, since the difference between S/N ~ 4 under RCP2.6 and S/N > 10 under RCP8.5 represents a very large amount of change-in-the-context-of-variability avoided.

Even if RCP8.5 is too pessimistic to warrant being considered the starting point for mitigation, the overall pattern of emergence avoided by mitigation (i.e. the benefits of mitigation) still resembles a scaled version of the right-hand column of Figure 4 irrespective of the exact details of the scenario used to portray worlds without climate mitigation. More

extensive results for regional economic groups, security-related groups, and climate negotiation blocs are presented in the Supplementary Information (Figure S5).

The larger values of S/N in groups such as AOSIS (Figure 4a) compared to OECD90 (Figure 4i) imply that the former grouping experiences earlier emergence of unusual or unfamiliar climates than the latter. Such relatively early change is likely to affect other places through economic, security or political spillover effects, especially where early climate impacts contribute to security and humanitarian issues in vulnerable countries or where trade in goods vulnerable to climate change is significant. Such groupings can be thought of as earliest common denominators of emergent change: patterns of emergent climate change within them affect those groups where ToEs are much later, depending on the strengths of the interactions between such groups.

Policymakers and scholars are sometimes under the mistaken impression that benefits of mitigation are remote: “[t]he time lag is at the very least longer than the lifetime of any adult. The upshot is that no one who is asked to curtail activities to reduce greenhouse gas concentrations will be likely to live long enough to enjoy the benefits of that curtailment”¹⁸; and “Mitigation will have global benefits but, owing to the lag times in the climate and biophysical systems, these will hardly be noticeable until around the middle of the 21st century” (IPCC AR4 TS 5.2). Our analysis demonstrates that vast numbers of potential beneficiaries of climate policy are actually alive today: assuming that climate emergence scales approximately with cumulative emissions, in a high carbon future (RCP 8.5), today’s young adults in the OECD90 group for example can expect to find only one year in two familiar from their childhoods by mid-century. For citizens of AOSIS or the LDCs, the picture is starker still. However, emergence everywhere is greatly reduced and delayed under a low carbon future, such as RCP2.6. Our analysis shows that near-term mitigation initiatives

can prevent many climates from becoming radically different from those experienced in the recent past, that such effects happen well within a human lifetime, and that this is especially true for those whose communities would otherwise change fastest. In other words, many of the long-term benefits of mitigation can be internalized by many people alive today.

Methods

This study compares ensembles of models from the CMIP5 experiment run under representative concentration pathway (RCP) scenarios¹⁵. We estimate S/N for near-surface air temperature following previous published methods³ (and Kirtman et al. 2013, IPCC AR5 Chapter 11), using the CMIP5 simulations for the 25 models which ran each of RCP2.6, 4.5 & 8.5 scenarios, and presented relative to a baseline climate of 1986-2005.

The 'signal' is diagnosed by calculating the global mean surface air temperature (SAT) and fitting a 4th-order polynomial (GMST). SATs at each gridpoint are regressed against this smoothed GMST to derive a smoothed gridpoint signal which is proportional to the global mean. The 1986-2005 mean is then removed from the smoothed gridpoint data to produce the change in temperature (S). The N term is the standard deviation of annual mean temperatures in the pre-industrial control simulations at each grid point. The S/N is calculated for each model independently.³

To obtain the 16th and 84th percentile at each grid point, models are ordered from low to high, and we select the model which comes closest to representing a 16th and 84th percentile rank. So for the 25 models used (which had data across all 3 RCPs), we have selected the models which were ranked numbers 4 and 21 (with 1 being lowest S/N, 25 being highest).

Note that warming before 1986-2005 would add to the S/N values shown in this analysis.

Population and national boundary data are from the CIESIN dataset. We overlay the national boundary mask from CIESIN on the population dataset to obtain the number of residents in each 1/4° grid box (both the population data and the national boundary data have this resolution). Where there are multiple countries within a dataset we apportion the population evenly between them. This introduces small inaccuracies, but these are negligible at the international and normalized scales on which the paper focuses. We then aggregate the appropriate national population data onto the lower resolution grid of the climate model output. We do this for each of the CMIP5 models for which data are available under the three scenarios considered here. This gives us both a number of people (in each climate model grid box) and a S/N (for each climate model grid box and year) for each model, for each scenario.

Population changes over timescales relevant to this analysis, but there is uncertainty surrounding exactly how and where it will change the most. The presented analysis assumes 2015 population levels throughout, but we repeated the analysis for the 2000 distribution of population to consider how recent demographic change interacts with emergent climate change (see Figure S7). Essentially the results are very similar under both population distributions.

An important caveat is that natural variability places significant limits on our ability to give detailed estimates of exactly when climates cross integer S/N values, with both the simulation of natural variability and the models' ability to capture anthropogenic change playing a role in determining the time of emergence of climate signals¹⁷. In particular we note that global temperatures did not warm as fast as the mean of the CMIP5 models in the early 21st Century¹⁸, likely due to natural radiative forcings not included in the simulations, internal climate variability, a relatively low TCR, or a combination thereof. This slowdown implies that, on average, the very earliest projected emergence dates are likely to be slightly delayed.

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216 **Data Availability**

217 The data used in this study are being made available at <http://arcg.is/2m4RFOH>.

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223 **Author contributions**

224 MMJ and DJF conceived the project. DJF, EH and LJH performed the analysis, and MdR
225 produced the cartograms and maps. All authors wrote the paper.

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Figure 1: Emergence of climate change in idealized, geographical and population-weighted contexts. Panel (a) Schematic of the first four successive integer S/N values for a Gaussian distribution. Also shown in (a) are the fraction of the new distribution at successive integer S/N values which remains from the original distribution. Overlap between the base distribution and the distribution at successive standard deviation shifts of integer S/N values are shown as the grey segments – note that these are cumulative, i.e. in a shift from the base to the first S/N threshold the overlap includes all the grey segments. Panel (b) shows the cumulative fraction of the world's surface area passing S/N1-3 under RCP4.5; panel (c) shows the cumulative fraction of the world's population passing S/N1-3 under RCP4.5. Panel (d) shows the median rate at which cumulative fraction of global surface area passes SN1-3 compared with the median rate at which the cumulative fraction of the global population passes these thresholds.

Figure 2: Climate emergence under the RCP4.5 scenario. Panels (a-c) show modelled annual mean S/N for the 16th, 50th, and 84th percentiles of the CMIP5 models under the RCP4.5 scenario. Panels (d-f) display this information on a population-weighted cartogram, to show the effects of emergent climate change in the context of human settlement. The S/N data are displayed on a common scale, in units of local variability, N.

Figure 3: Climate emergence under high carbon (RCP8.5) and mitigation (RCP2.6) scenarios, and differences arising from mitigation. Panels (a-c) are maps of modelled annual mean S/N values for the end of the 21st Century (2071-2100) for the 16th, 50th and 84th percentiles of the RCP2.6 scenario. Panels (d-f): as for the top row but for the RCP8.5 scenario. Panels (g-i) show the benefits of mitigation, i.e. the S/N avoided by mitigation from RCP8.5 to RCP2.6. Panels (j-l): displays the same information as panels (g-i) as population-based cartograms to better illustrate the human dimension of avoiding high values of S/N. Not all modelling groups ran all scenarios, so in this analysis we have only considered those models which ran both RCP 8.5 and RCP 2.6 (a total of 25 models), so that we would be making a like for like comparison in terms of ensemble members (see Figure S3). The S/N data are displayed on a common scale, in units of local variability, N.

Figure 4: S/N values versus cumulative fraction of population in different international groups under RCP2.6 (blue), RCP8.5 (red) and the difference between these (orange – displayed in right hand column). Median values are shown as central solid lines; bands represent the 16th-84th percentile of models in the CMIP5 ensemble. The groups are (a-b) the Association of Small Island States (AOSIS); (c-d) the Association of South-East Asian Nations (ASEAN); (e-f) Least Developed countries (LDCs); (g-h) Global Emerging Markets (GEMs); and (i-j) Organisation for Economic Cooperation and Development, membership as of 1990 (OECD90). Additional groups are shown in the Supplementary information.

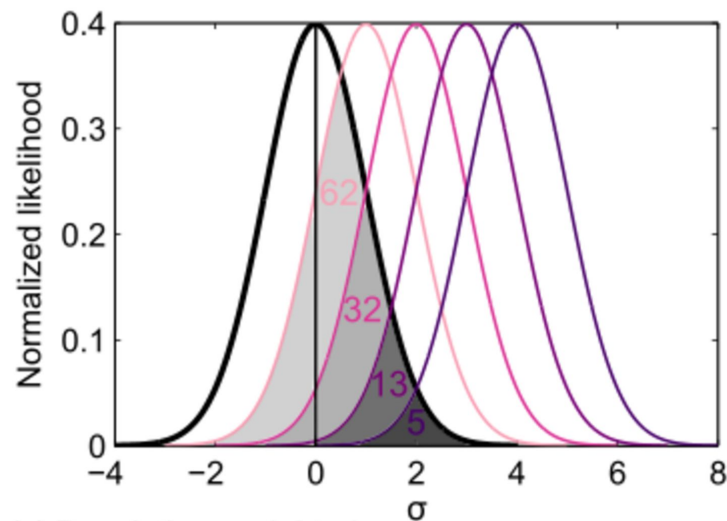
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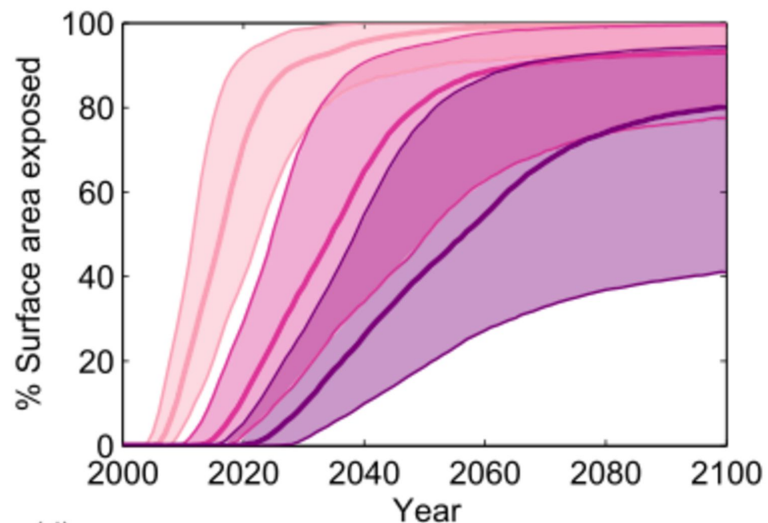
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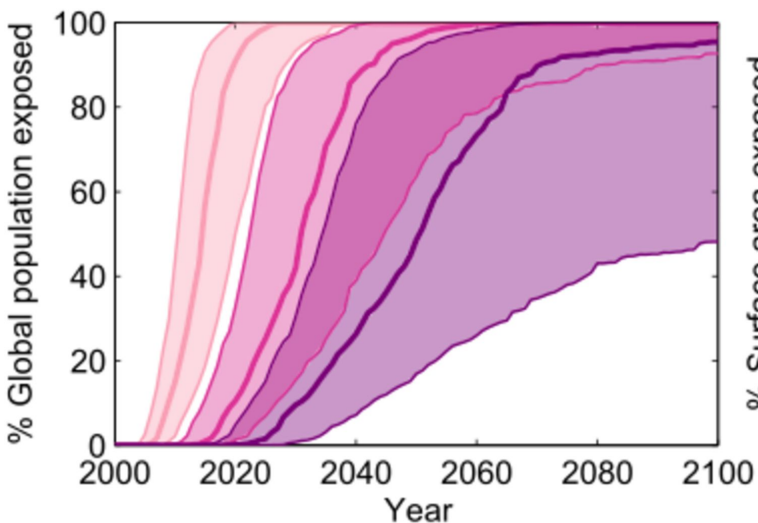
(a)



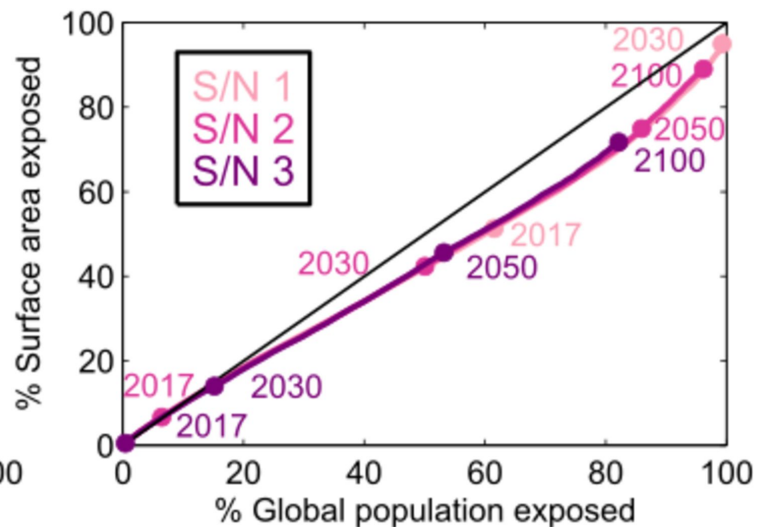
(b) Area-weighted



(c) Population-weighted



(d)

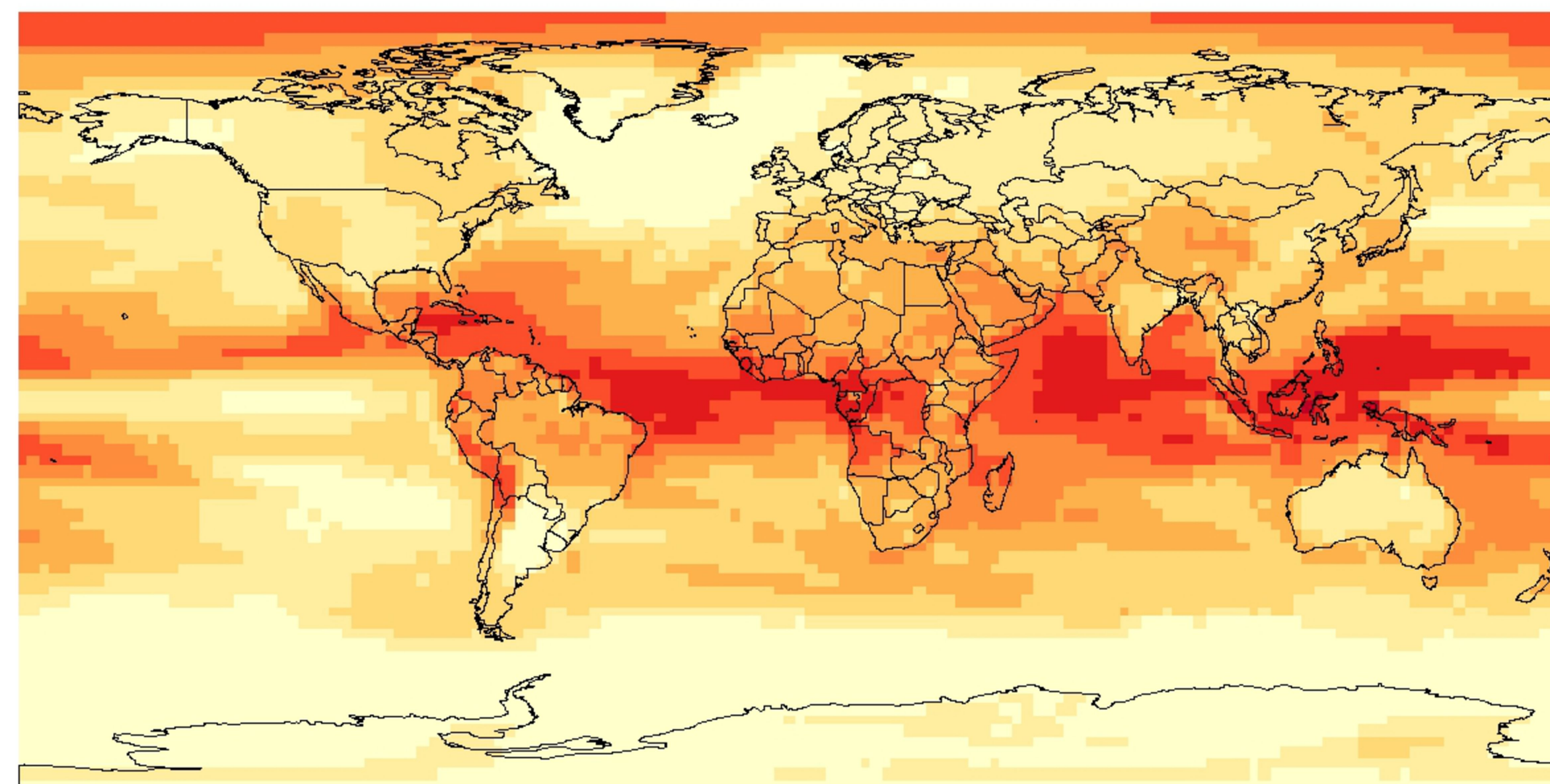


16th percentile CMIP5 ensemble

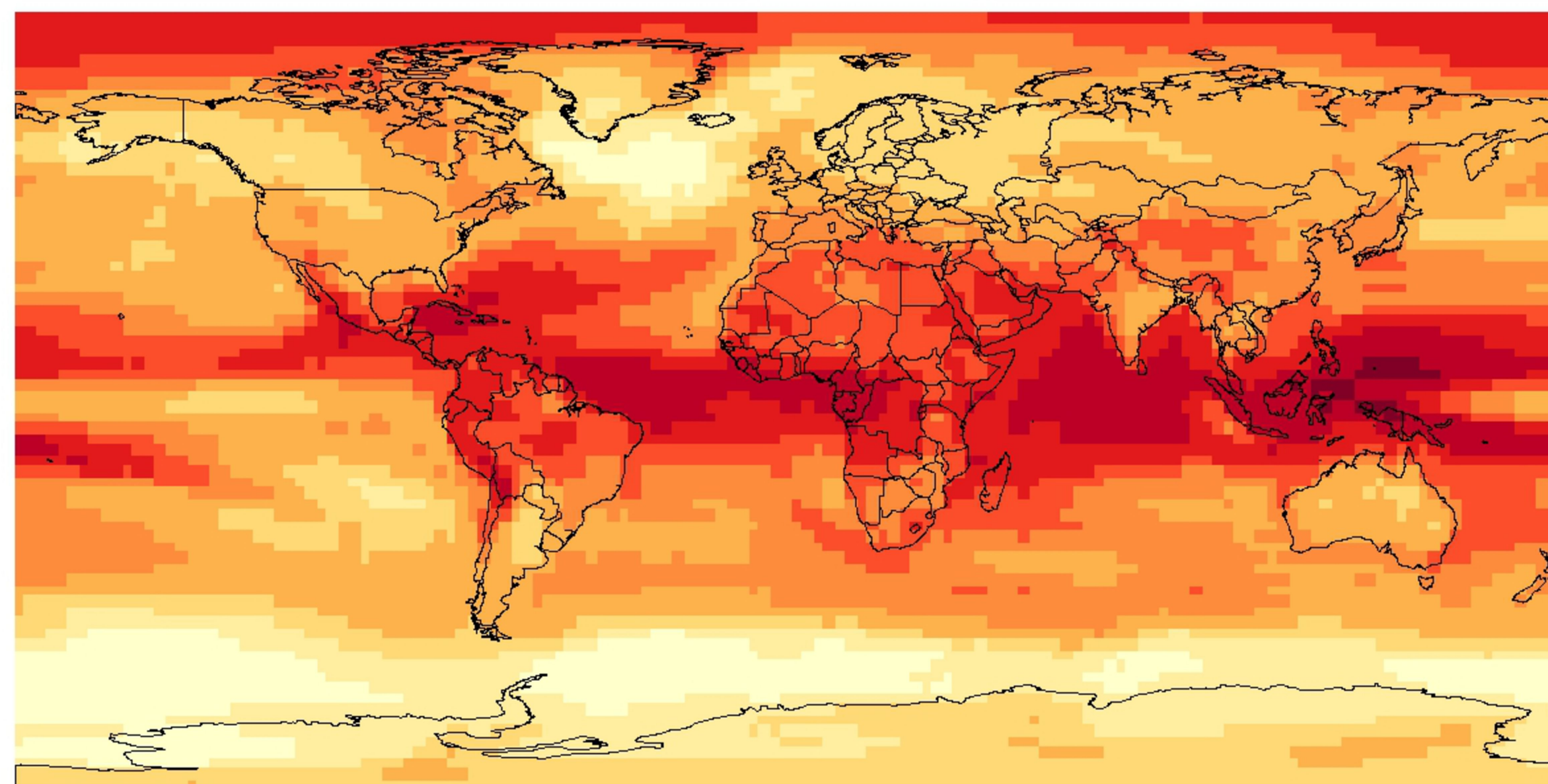
50th percentile CMIP5 ensemble

84th percentile CMIP5 ensemble

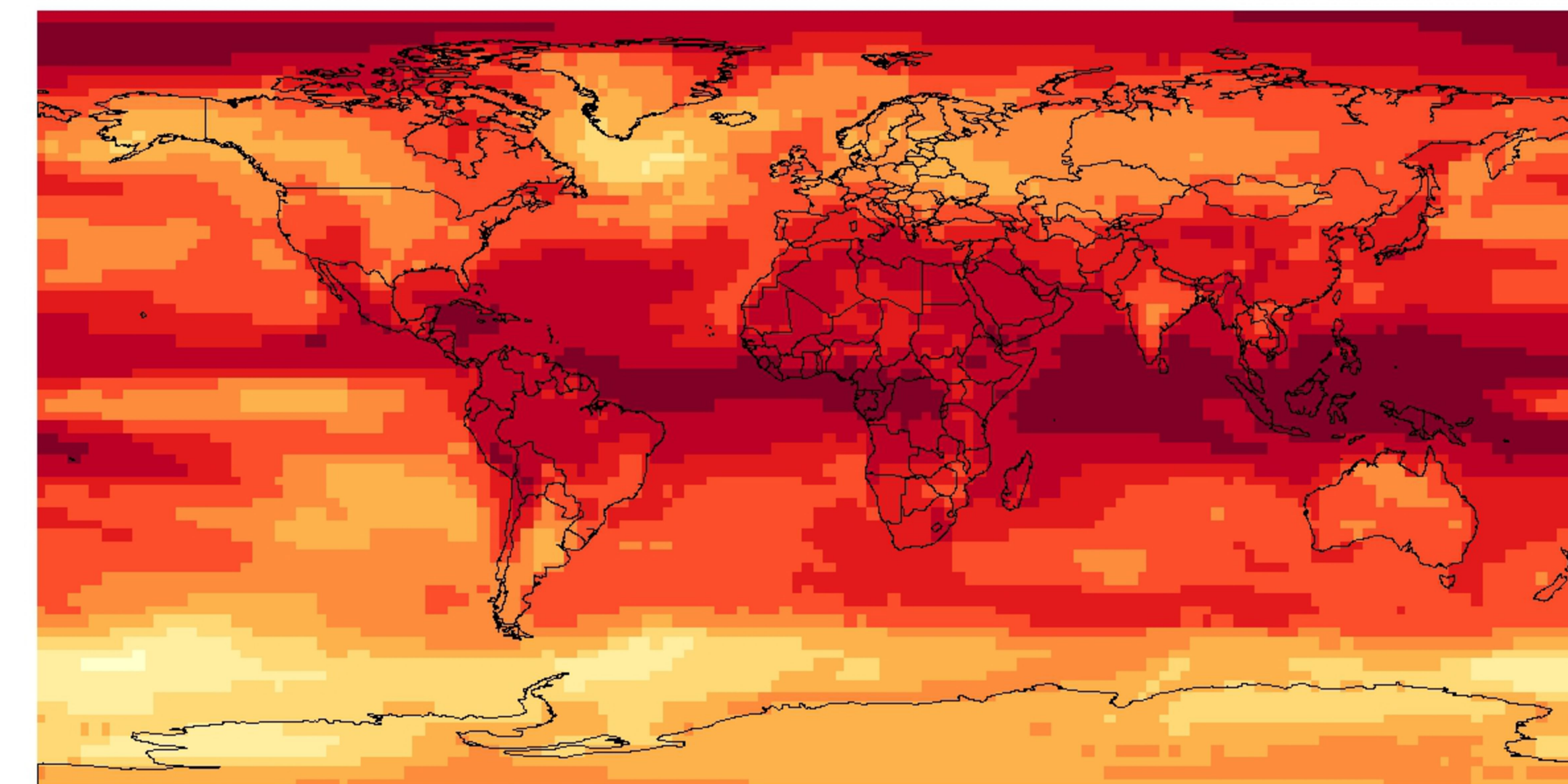
Conventional
map



a

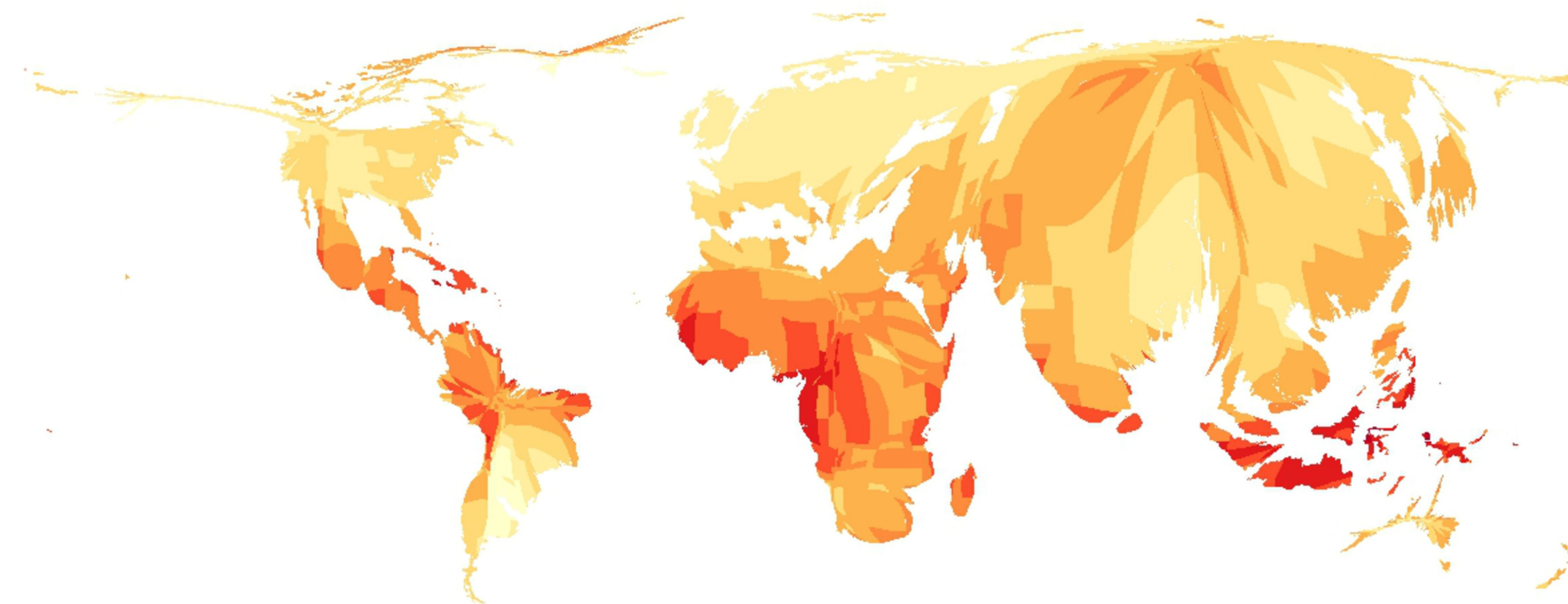


b

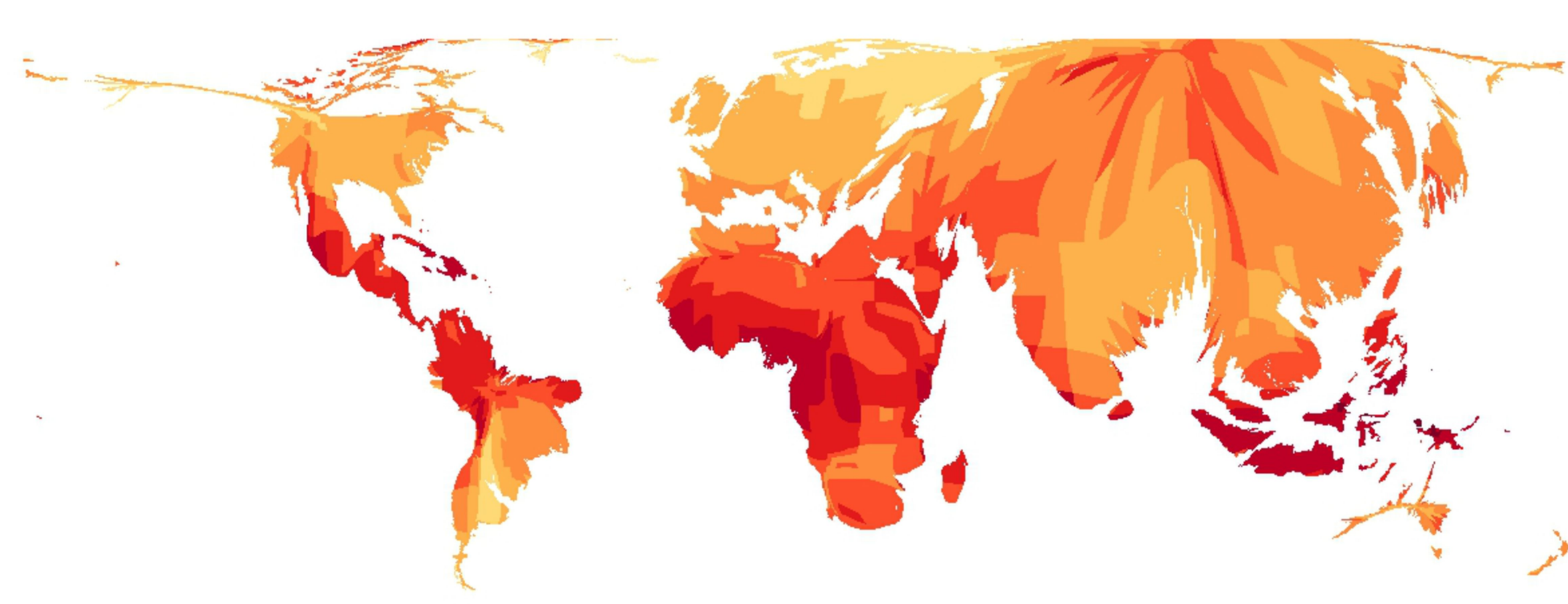


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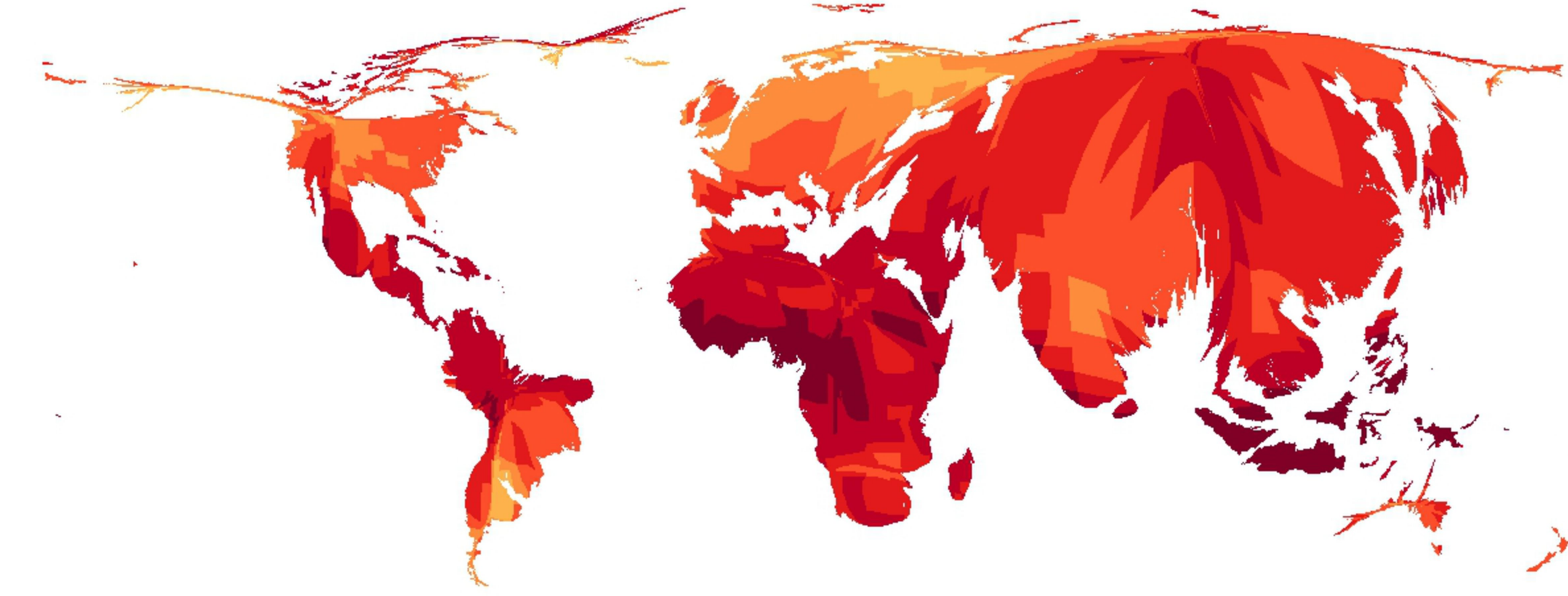
Population
weighted
cartogram



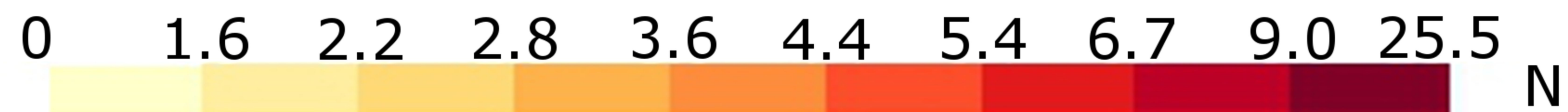
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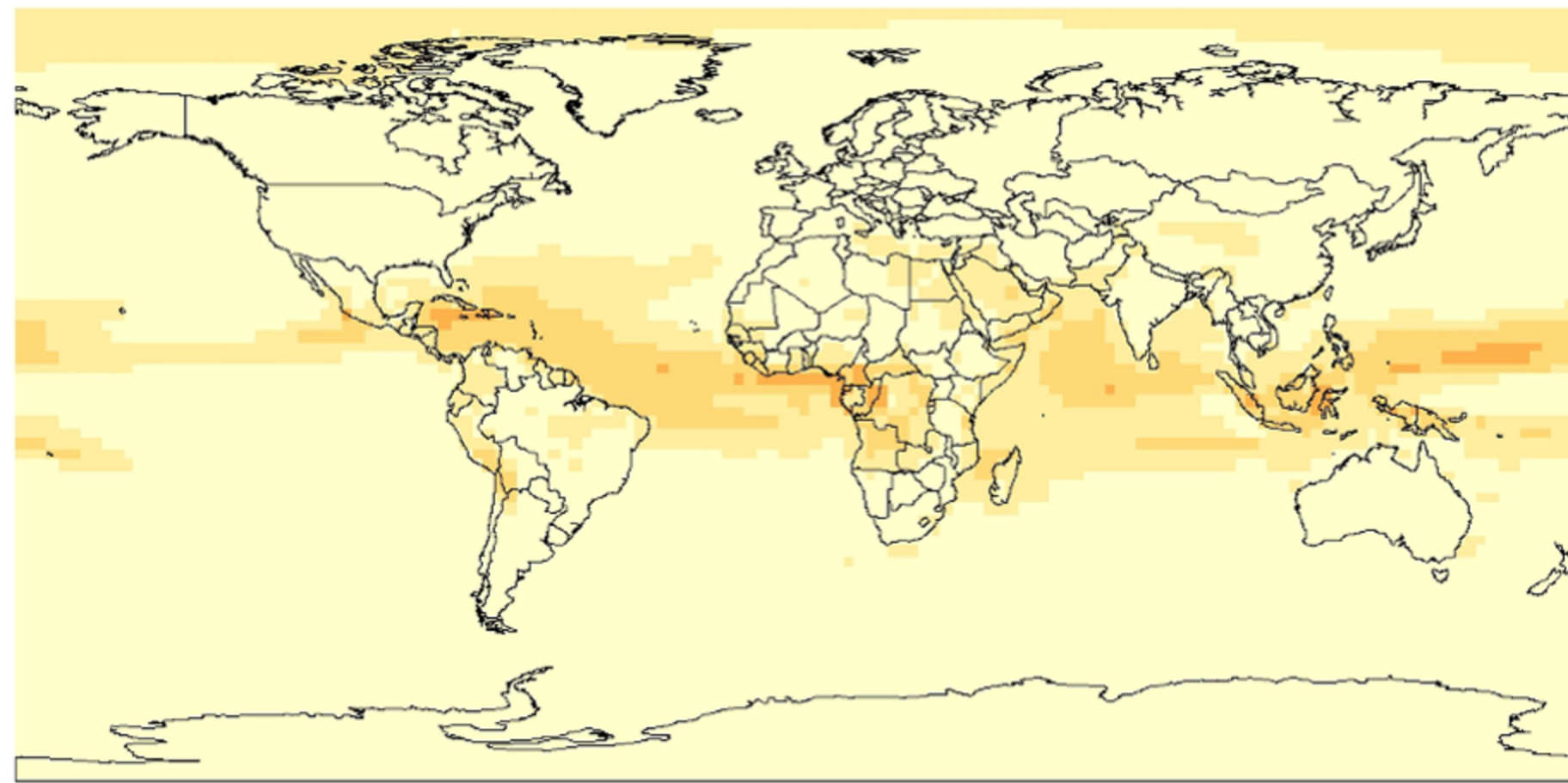


16th

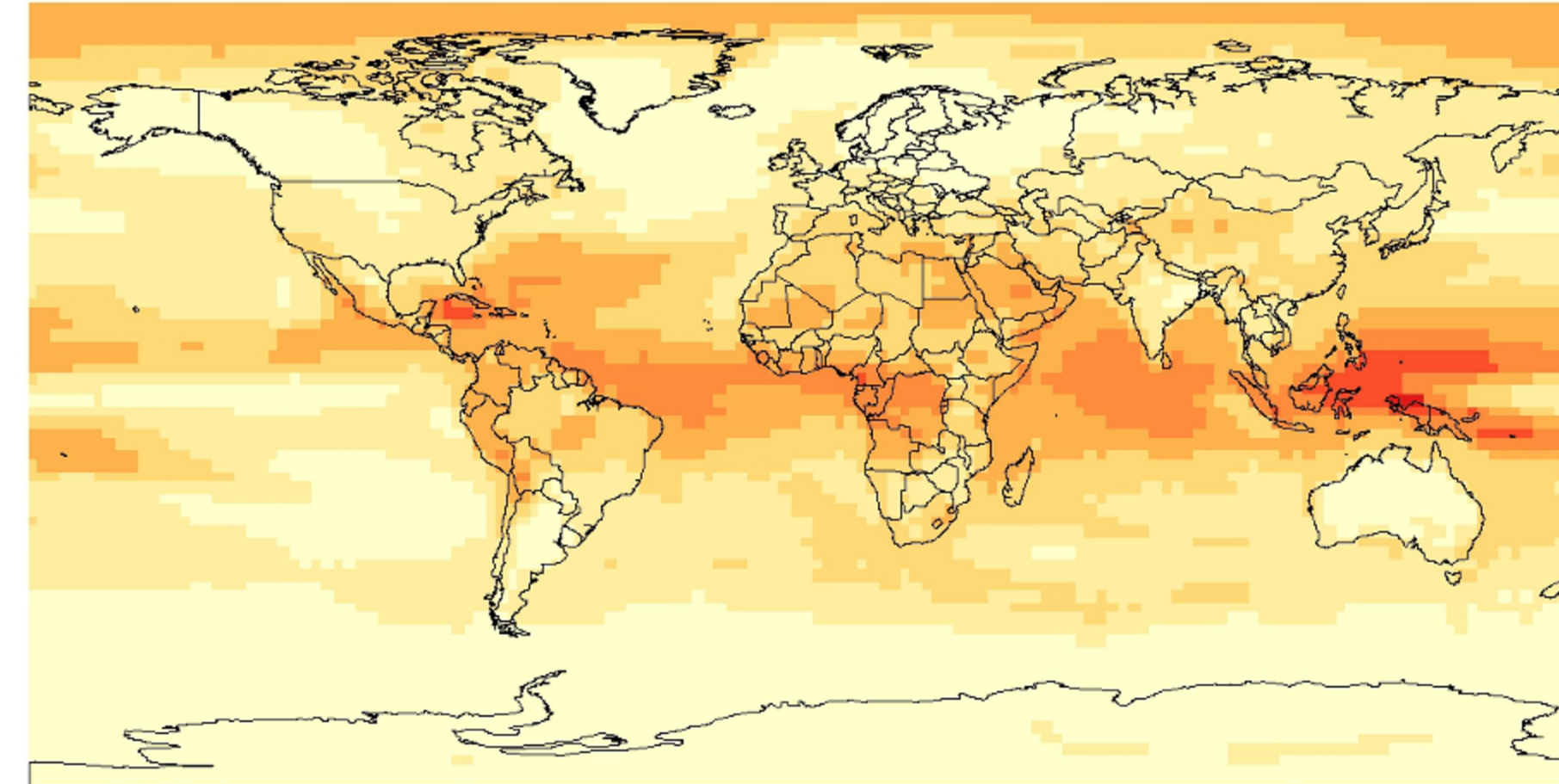
50th

84th

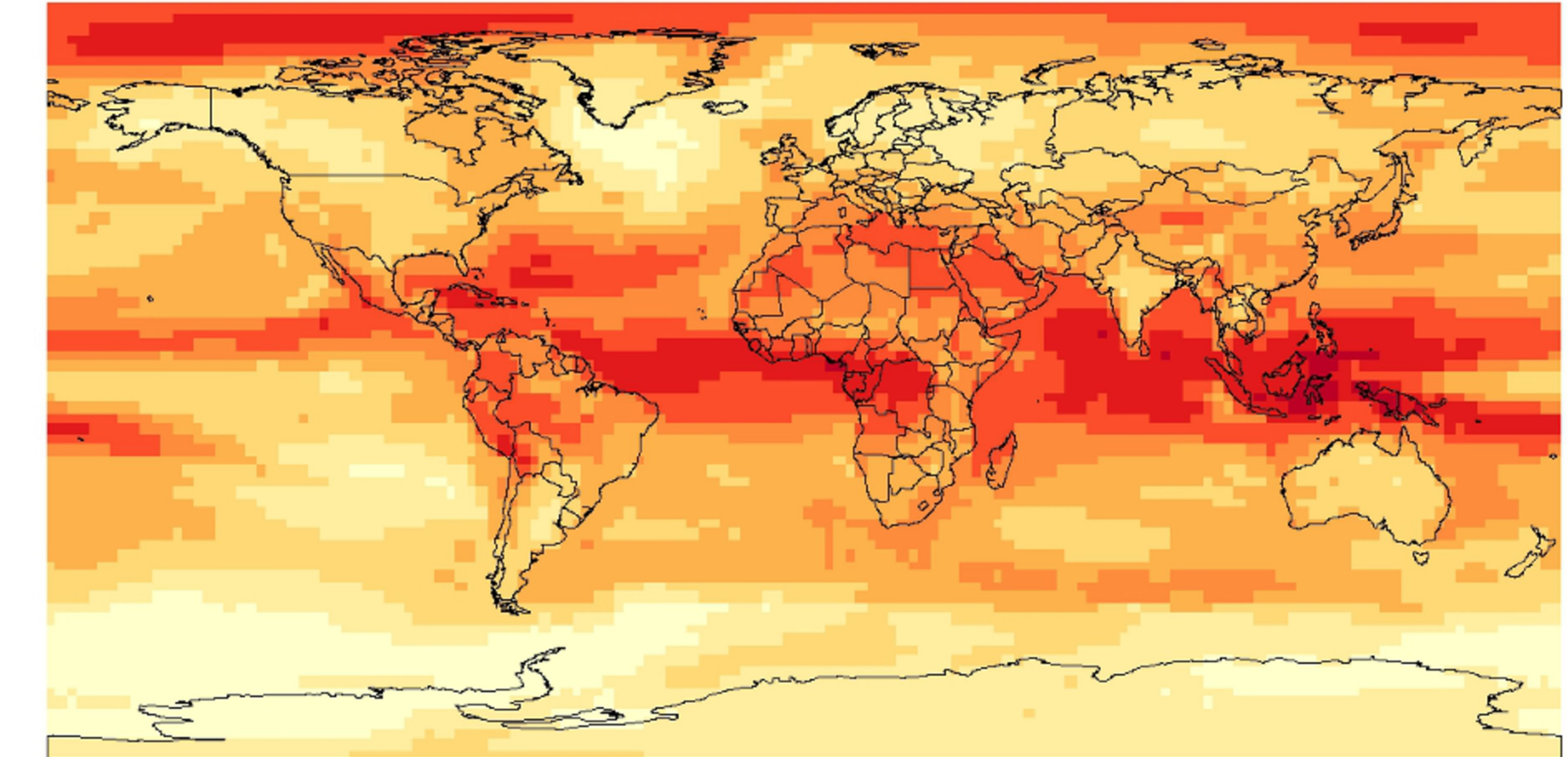
RCP 2.6



a

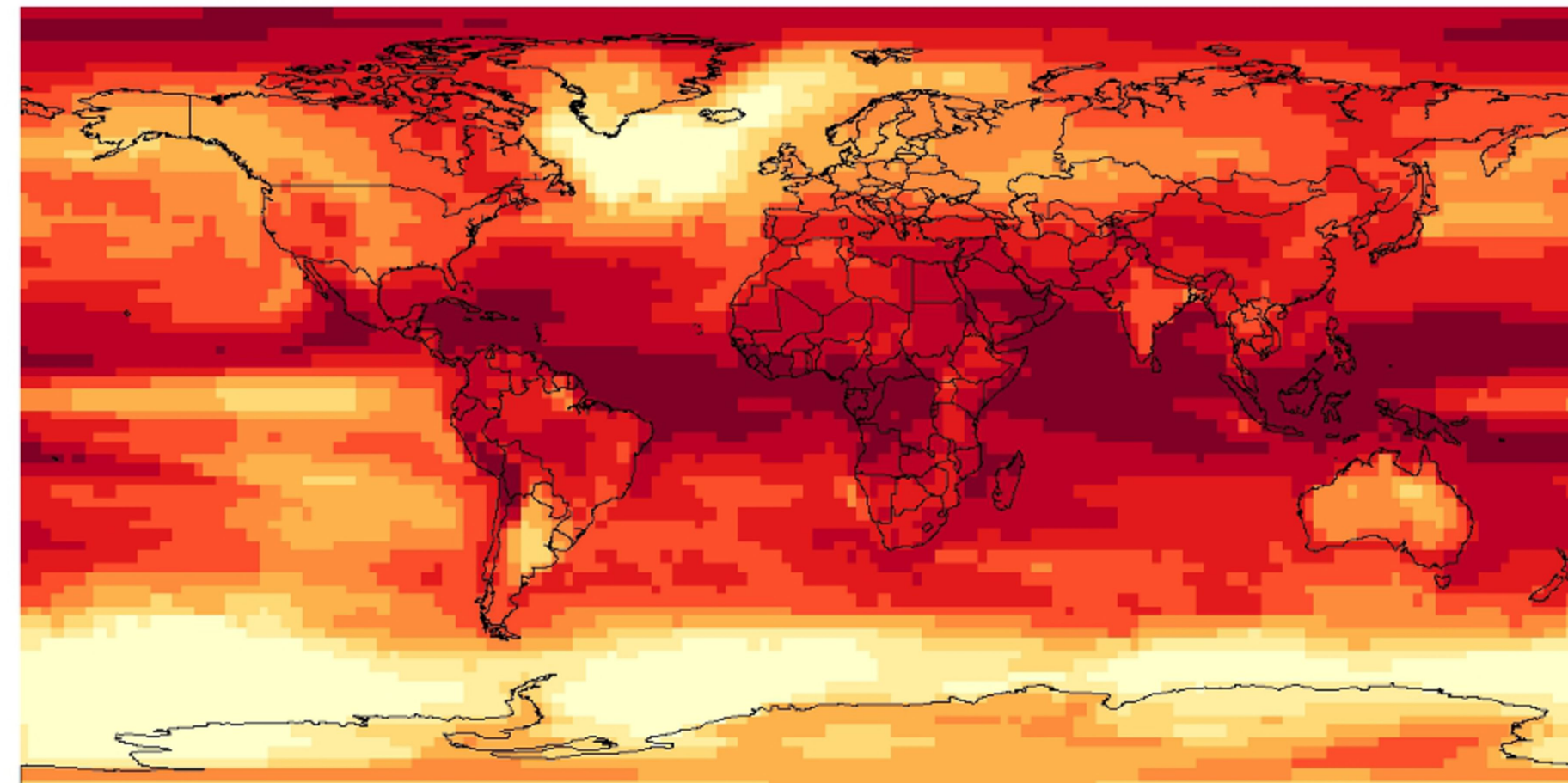


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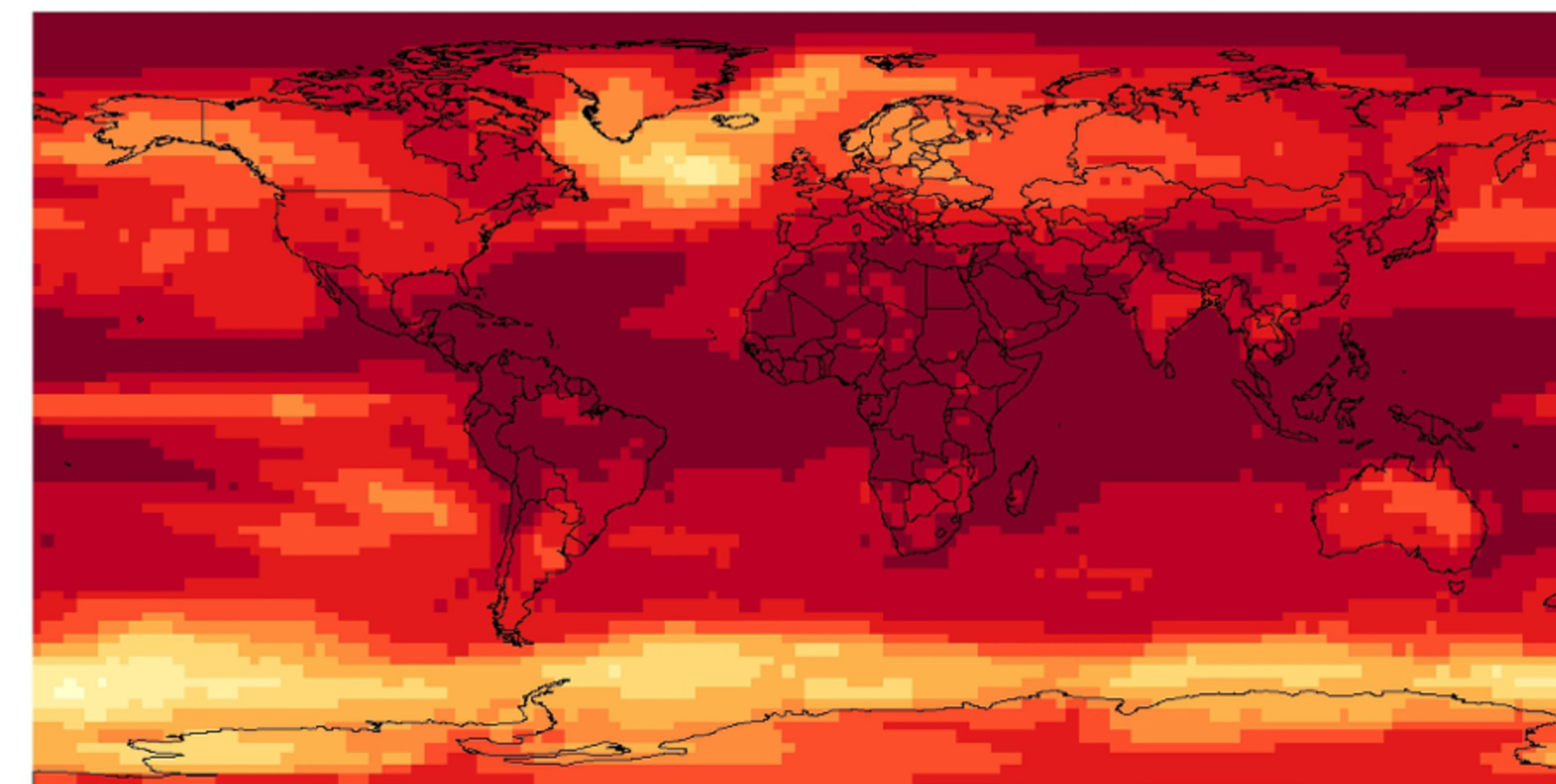


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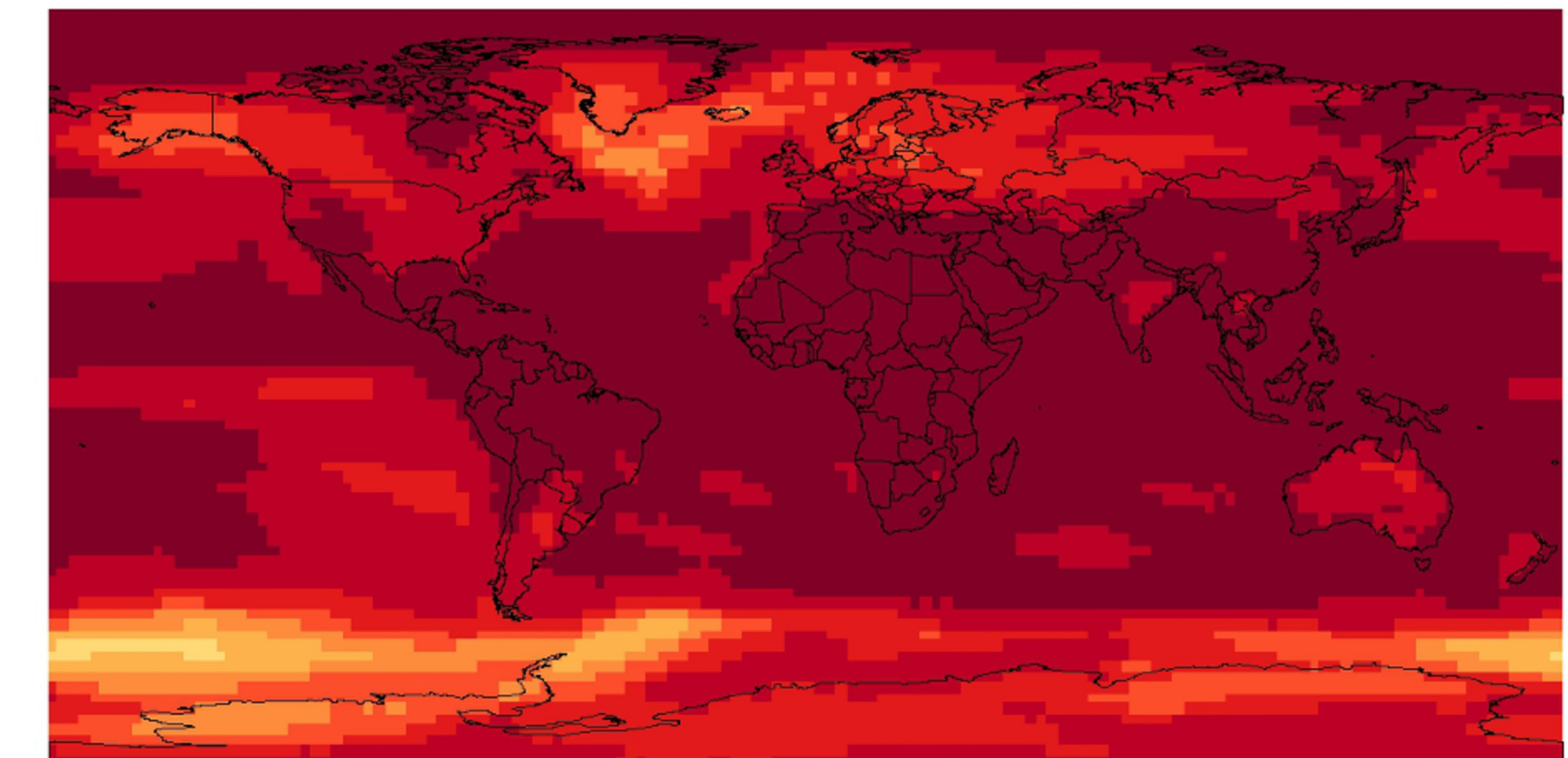
RCP 8.5



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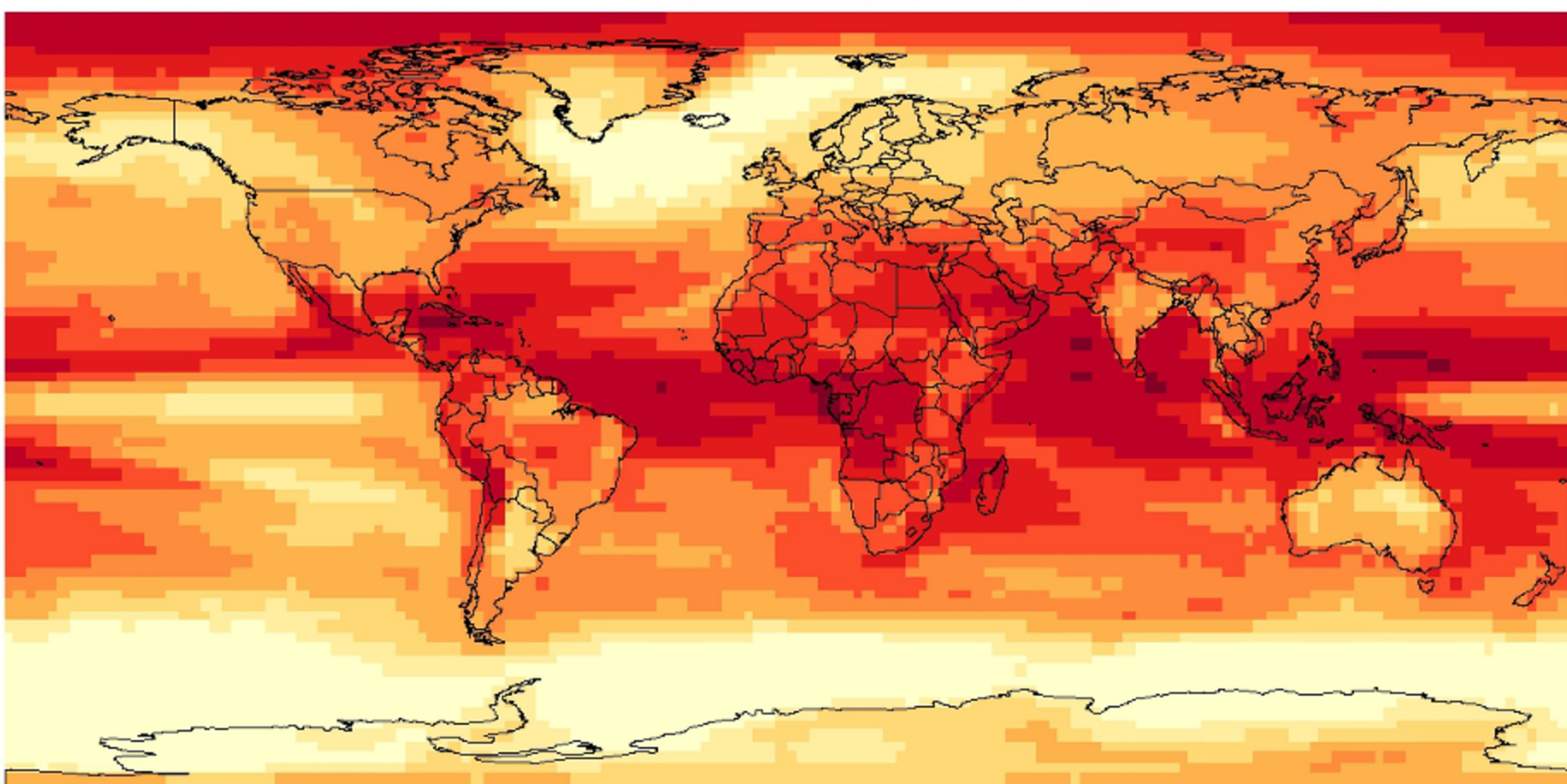


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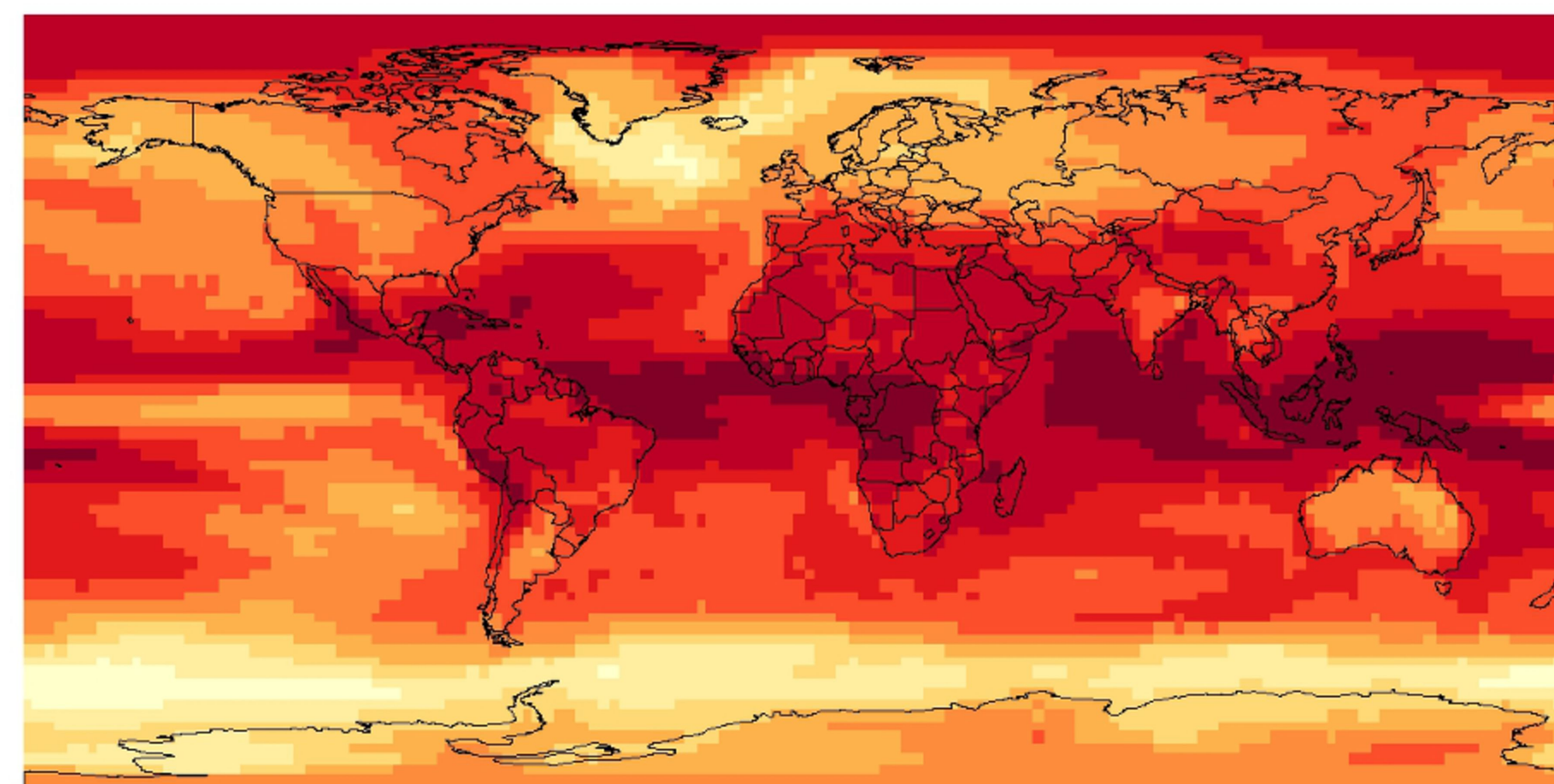


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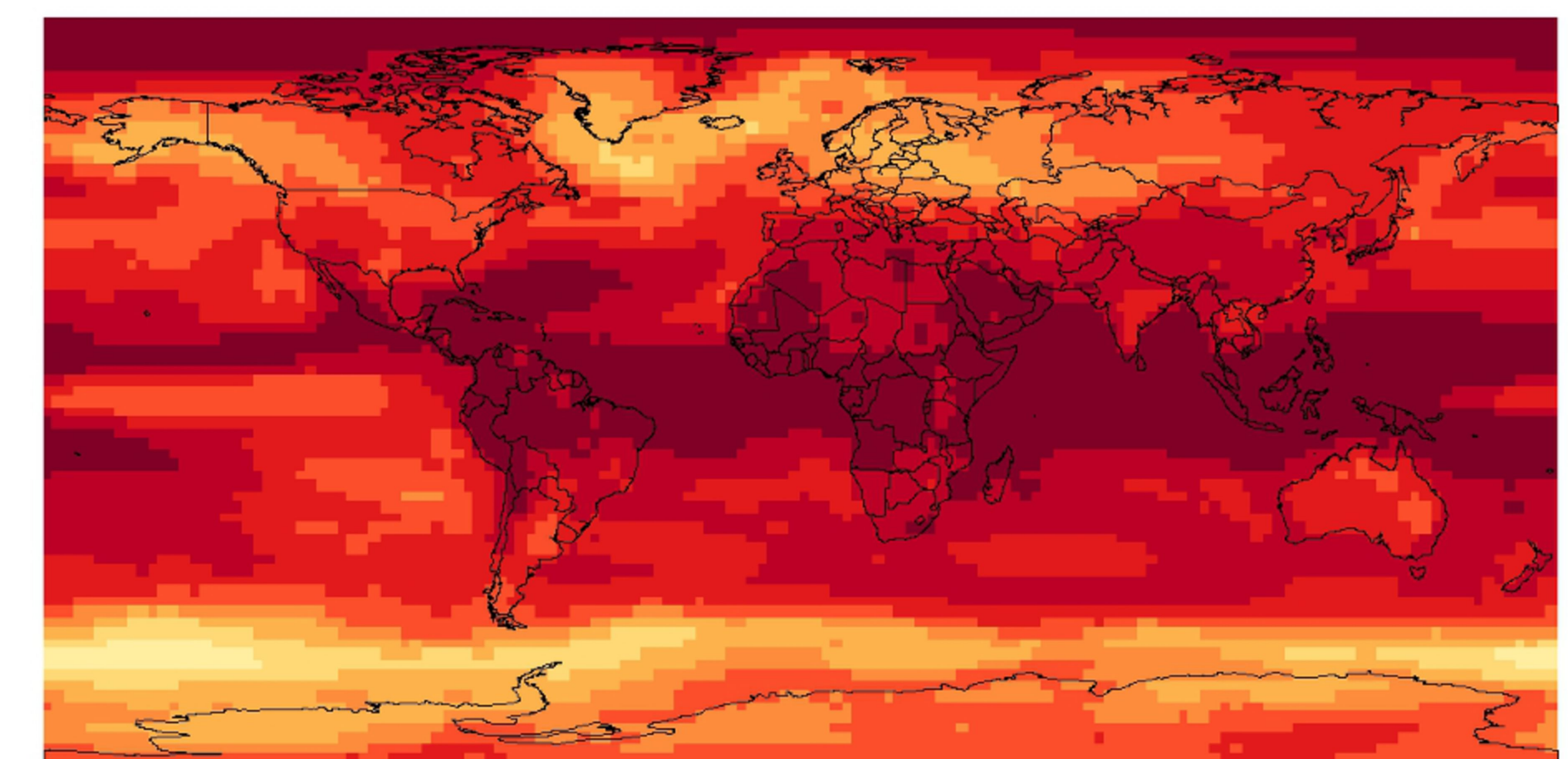
Avoided S/N



g



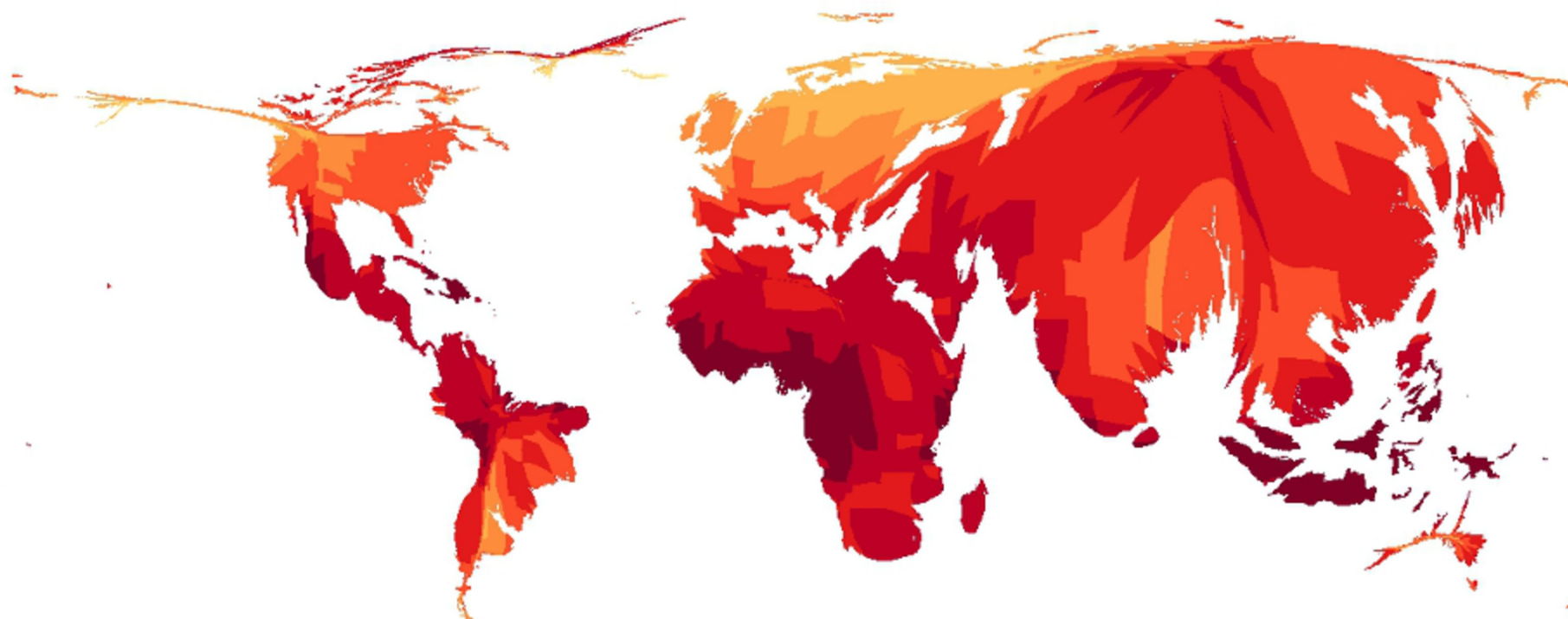
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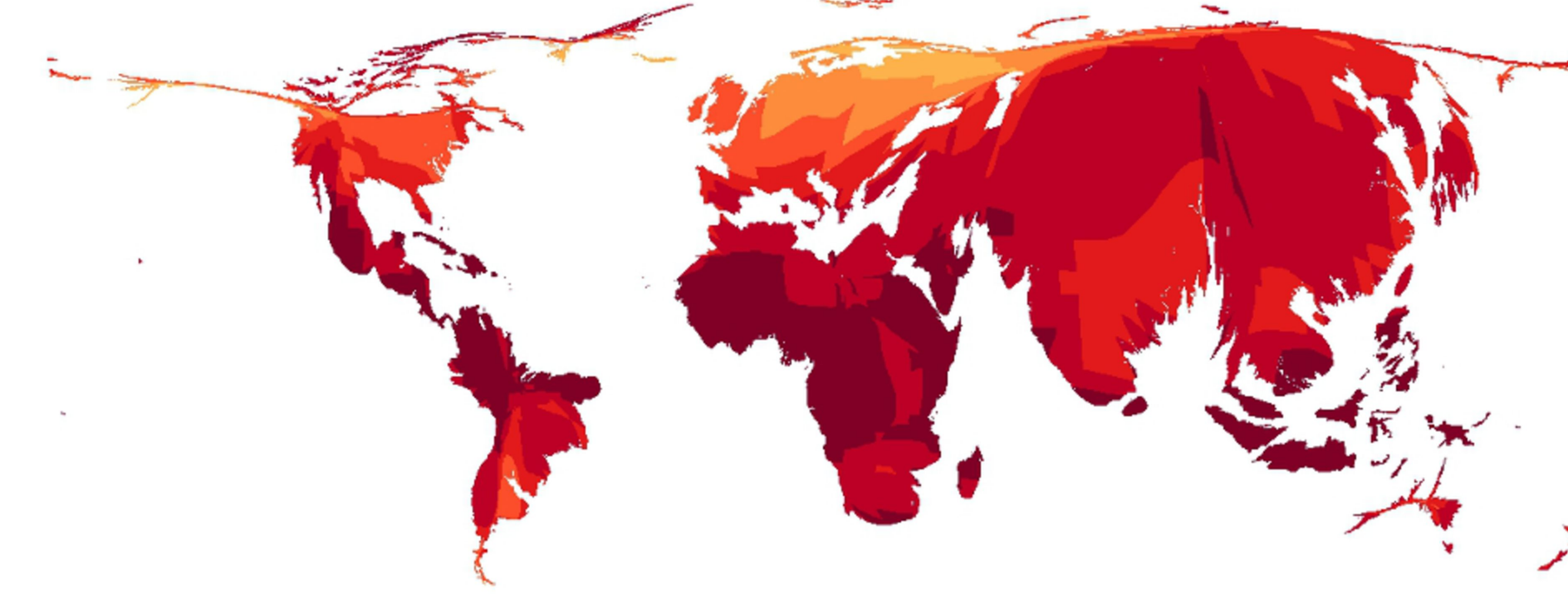
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Avoided S/N
population
weighted
cartograms

k



l



m

0 1.6 2.2 2.8 3.6 4.4 5.4 6.7 9.0 25.5

N

Cumulative population fraction exposed

