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Abstract

Extreme temperatures are one of the leading causes of death and disease in both developed and developing countries, and heat extremes are projected to rise in many regions. To reduce risk, heatwave plans and cold weather plans have been effectively implemented around the world. However, much of the world's population is not yet protected by such systems, including many data-scarce but also highly vulnerable regions. In this study, we assess at a global level where such systems have the potential to be effective at reducing risk from temperature extremes, characterizing (1) long-term average occurrence of heatwaves and coldwaves, (2) seasonality of these extremes, and (3) short-term predictability of these extreme events three to ten days in advance. Using both the NOAA and ECMWF weather forecast models, we develop global maps indicating a first approximation of the locations that are likely to benefit from the development of seasonal preparedness plans and/or short-term early warning systems for extreme temperature. The extratropics generally show both short-term skill as well as strong seasonality; in the tropics, most locations do also demonstrate one or both. In fact, almost 5 billion people live in regions that have seasonality and predictability of heatwaves and/or coldwaves. Climate adaptation investments in these regions can take advantage of seasonality and predictability to reduce risks to vulnerable populations.

Introduction

Extreme temperature is a leading contributor to morbidity and mortality for many of the world's most vulnerable people, including infants and the elderly (Bai *et al* 2014, Egondi *et al* 2015, Fouillet *et al* 2006, Gosling *et al* 2008, Hashizume *et al* 2009, Huynen *et al* 2001). Temperature extremes account for 75% of weather-related deaths in high-income countries (CRED *et al* 2015), as well as increases in morbidity (Astrom *et al* 2011, Li *et al* 2015). For example, the 2003 heatwave in France was estimated to cause 15 000 excess deaths, and in Bangladesh, mortality increases approximately 20% on heat-wave days (Fouillet *et al* 2006, Nissan *et al* 2017). In India, a coldwave in 2003 killed more than 900 people, and unusual cold temperatures were responsible for 370 excess deaths in Moscow in 2006 (De *et al* 2005, Revich and Shaposhnikov 2008).

However, temperature can be considered to be one of the most predictable meteorological surface variables (Haiden *et al* 2015), and extreme temperature early action systems have proven that they can save lives around the world (Ebi *et al* 2004, Tan *et al* 2007, Toloo *et al* 2013, Weisskopf *et al* 2002).

Heat Health Action Plans and Cold Weather Plans lay out roles and responsibilities for seasonal preparedness measures, short-term early action, and response and recovery measures (Public Health England 2015). For heatwaves, disaster managers provide drinking water, cooling shelters, and visits to isolated community members (Hajat *et al* 2010a, Knowlton *et al* 2014). For coldwaves, typical interventions include provision of blankets, shelter, and financial support for heating costs to vulnerable households (Daiski 2005, Fazel *et al* 2014, Hwang *et al* 2005, Wolf *et al* 2010).

Much of the world's population is not currently covered by such systems (Bittner *et al* 2013, Republique Francaise 2015). The implementation of extreme weather plans requires substantial capacity by local agencies, and many governments and civil society organizations have shown growing interest in these plans in recent years (Coughlan de Perez *et al* 2014, Fouillet *et al* 2008, IFRC 2009),

The goal of this study is to identify areas in the world that can benefit from extreme temperature early warning systems. To assess where such early action systems are likely to be impactful, we analyze the following three factors for all inhabited areas of the world: (1) long-term occurrence of heatwaves and coldwaves, (2) seasonality of heatwaves and coldwaves, and (3) short-term predictability of heatwaves and coldwaves, 3–10 days in advance.

First, to develop maps of the long-term occurrence of heatwaves and coldwaves, we need to define a heatwave and a coldwave. The definition of an impactful extreme event depends on local acclimatization, demographics, state of health, cultural norms, clothing, levels of physical activity, and access to temperature-controlled shelter (Hajat *et al* 2010b, Reid *et al* 2009). In a review of studies on heatwaves and morbidity, (Li *et al* 2015) found that effects range from 163.7% increase in cardiovascular disease in the elderly in Australia to 19% increase in preterm births in Italy. A review of global studies found that mortality rates increase by at least 5% on heatwave days in many cities, and are responsible for more deaths in the United States per year than all other natural disasters combined (Astrom *et al* 2011, Klinenberg 2015). Coldwaves have been associated with an average of 4% increase in risk in US cities; one study found a 13% increase in mortality in Shanghai (Ma *et al* 2013, Wang *et al* 2016). A meta review of studies of two-day cold spells show an overall agreement of an increase in mortality, especially among the elderly (Ryti *et al* 2016).

Temperature-mortality curves are normally used to model the relationship between different magnitudes of temperature extremes and local impact. Even with access to health data, determining detailed temperature-mortality relationships is not straightforward, because of the time-varying nature of population vulnerability to heat and cold. Where such relationships have been assessed, simple indices of relative heat and cold tend to have equal association with local impacts as do more complicated heatwave and coldwave definitions (Barnett *et al* 2010, Dixon *et al* 2005, Nissan *et al* 2017). In fact, most heatwave and coldwave definitions that have been derived from local mortality relationships tend to show impact at the most extreme percentiles of the local temperature climatology (Astrom *et al* 2011, Gasparrini *et al* 2015).

We therefore define heat and cold as extreme temperatures relative to the local climate; when temperatures are persistently above/below this relative extreme, we assume that there will be an increase in morbidity or mortality in the most vulnerable local groups. These impacts will still be mediated by local context, including the availability of effective public health responses and early warning systems.

In the second factor, we investigate where seasonality can provide opportunities to take early action, by identifying areas that have a distinct annual cycle of temperature. Preparedness in advance of the high-risk months (e.g. summer) would be particularly important if short-term forecast skill is poor or if capacity is limited to maintain an early warning system.

For the third factor, we analyze short-term weather forecasts, which allow for early action immediately before and during an extreme event. Here, we use the word 'skill' to refer to the ability of the model to forecast heatwaves or coldwaves correctly, sometimes also called 'accuracy' or 'goodness' of the forecast. We are not aware of any existing global verifications for temperature forecasts that show skill for relative extremes. Several evaluations of extreme event forecasts have been done for specific locations, most commonly over data-rich areas, such as the US (Hamill *et al* 2013, Koster *et al* 2010). Areas with patchy observational data have rarely been researched, including much of Africa, as observations are needed both for initialization and evaluation.

Extreme events by definition have small sample sizes, so global forecasts tend to be evaluated for non-extremes or for extremes aggregated across space, to increase sample size (Barnston and Mason 2011, Gilleland *et al* 2010, Haiden *et al* 2015, Skok and Roberts 2016). However, forecasts are produced, and action is taken based on these forecasts, at scales much smaller than these aggregations. Variations in skill within the spatial aggregate would be very relevant for districts and other small locations, where skill differs from the aggregate. Overall, there is a considerable gap between current meteorological verification practice and societal need (Pappenberger *et al* 2008).

To understand local variability in forecast skill, we calculate the short-term skill of forecasts of extreme temperature for individual 1 degree gridboxes around the world. Large sample sizes are generated from two reforecast products of 20 and 31 years of daily data, respectively. We first verify each forecast model against its own analysis product, thereby generating a global map of gridbox-level results that is not affected by observational data availability. To verify the spatial patterns of predictability, we then carry out point evaluations in locations with available station data. This paper does not aim to establish the sources of predictability in all locations; it rather maps the predictability itself.

In this study, we identify where in the world temperature extremes happen, whether they can be anticipated as part of a seasonal cycle, and whether they can be predicted by weather forecasts. We use reforecast datasets from two major forecasting institutions: the US National Oceanic and Atmospheric Administration (NOAA) and the European Centre for Medium Range Weather Forecasts (ECMWF), and therefore our results are a first-order approximation of the global patterns forecast skill. Based on the results of the seasonality and short-term predictability analysis, we identify the optimum mix of preparedness measures for different regions of the globe.

Methods

Where do heatwaves and coldwaves occur?

Risk materializes due to a combination of hazard, vulnerability, and exposure. To see where these hazards occur, we define an extreme event threshold relative to the local climatology. A daily temperature value that is labeled as, say, the 95% percentile value implies that the temperature is higher than this value on 5% of the days in the climatological record. While the threshold represents an extreme event relative to what the general population is acclimatized to, vulnerability will vary between groups of people and will be affected by public health capacity.

Individual heatwaves are therefore defined as the maximum daily temperature (Tmax) exceeds the 95th percentile of all maximum daily temperatures derived from the local climatology AND the minimum daily temperature (Tmin) exceeds the 95th percentile of all minimum daily temperatures, for two consecutive days. Coldwaves are episodes during which the maximum daily temperature (Tmax) is less than the 5th percentile of all maximum daily temperatures AND the minimum daily temperature is less than the 5th percentile of all minimum daily temperatures for two consecutive days. The percentiles are relative to the climatology of each model in each location. We evaluated alternative percentiles and durations in the sensitivity analysis. Any two-day period that fulfills this definition is considered a single event, regardless of whether it overlaps with another two-day 'event'.

Both of the global models used here produce 'reforecasts', or hindcasts, using the current model version to forecast historical dates. These data can then be used to evaluate the skill of the current forecast model in operation. The NOAA 'GEFS Reforecast v2' product is produced at 3- and 6 hourly intervals from 1985–2015 (31 years), at 1 degree resolution. The ECMWF reforecasts are produced at the resolution of the current operational forecast (~18 km in this study) at 6 hourly timestep for only two days per week; they are run on Mondays and Thursdays for the past 20 years from the date the forecast is issued (ECMWF 2017). We then regrid these forecasts using a bilinear method to the 1 degree resolution. For both products, we calculate the daily minimum and daily maximum temperatures, making the assumption that the magnitude of the maxima/minima are well captured by data at this time resolution.

To estimate whether or not heatwave and coldwave hazards occur in a particular location, we calculate the frequency of heatwave and coldwave days in Day 0 (first lead time) of the NOAA reforecast, which is later used for the verification. Because the ECMWF reforecasts are only available for two days per week, we use the ECMWF analysis product, which is available daily and is used to initialize the forecast. Heat and cold 'waves' of consecutive extreme hot/cold days rarely occur in some places, therefore this study focuses on areas that have an average of more than five heatwaves/coldwaves in a 31 year period.

Lastly, we combine hazard frequency with UN-adjusted population density estimates for 2015, from the Center for International Earth Science Information Network (CIESEN Center for International Earth Science Information Network 2016), to identify locations that have human exposure to these hazards.

Where do heatwaves/coldwaves follow a distinct seasonal pattern?

In this section, any 90 day period is defined as a 'season', to avoid the use of calendar months. We want to identify how many heatwaves happened, on average across the years, in each season. Starting with January 1, we identify how many years had a heatwave/coldwave during the 90 days starting on January 1. We then repeat for the 90 days starting on January 2, etc, until we have done this for 366 possible seasons. We map locations with a distinct annual cycle, in which at least one of those possible 90 day seasons had a heatwave/coldwave, as defined above, in more than half of the years of analysis. The data used is the Day 0 (first lead time) of the NOAA reforecasts and the analysis product of the ECMWF forecasts.

Where is there skill in short-term forecasts of heatwaves/coldwaves?

Here, we analyze how well the two global models can predict heatwaves and coldwaves at lead times of 3 days and 10 days, to provide a global perspective. National forecasts and limited area models might perform better than these results, due to local data assimilation or topographic resolution. They might also perform more poorly, in cases where there are data and technology gaps. Therefore, our results provide a first indication, and can also serve as a point of departure and comparison for local model results.

Because station data for temperature are limited in many places of the world, we carry out two verifications, one verification comparing each model against its own analysis, and the other verifying each model against station data from sample locations around the world. For the first, we analyze the NOAA and ECMWF forecasts by verifying heatwaves and coldwaves at lead times 3 and 10 days against the first lead time of the forecast (NOAA), and ERA-Interim Land reanalysis (ECMWF), as mentioned above. Some biases may exist; for example, the ECMWF hindcast system is derived from a more recent model version with a higher resolution than the reanalysis against which it is compared.

For the second verification, we selected 57 freely-available stations from the Global Historical Climatology Network Daily Database, version 2, to provide a sample from different regions and climates. Many large cities were selected; cities are often areas that suffer the largest impact of heatwaves due to the concentration of vulnerability and exposure, as well as the urban heat island effect. Urban preparedness actions can also reach many people relatively quickly. All stations selected have at least five heatwaves or coldwaves during the 1985–2015 period. To compare station data with forecasted temperatures, we extract lead times 3 and 10 days of the gridded forecast products using nearest neighbor interpolation to the coordinates of the station. Because the heatwave and coldwave definitions use percentiles relative to the climatology of the data itself, we do not carry out a correction for the urban heat island effect, which is likely not picked up in the reanalysis but would occur in the station data, or any elevation differences between the station and model.

Both forecasts have 11 ensemble members, and we calculate the probability of the extreme event as the number of ensembles that forecast the event divided by the number of members. This is based on several assumptions, including that the ensembles represent equally likely future scenarios and that there are enough ensembles to represent the full range of possible futures. However, with such a small number of ensembles, it is not possible for them to represent the full range of possible futures. For example, if all 11 ensemble members show a heatwave in 10 days, this would be recorded as a 100% chance of a heatwave. To avoid an overconfident forecast, in which all ensembles forecast the event or non-event, we have added a single '*naïve* ensemble member' as a benchmark that always forecasts the event at 0.5, instead of 0 or 1 in the normal ensemble members, as in (Broecker 2012). With the addition of this member, the probability of the event will never be 0% or 100%. In our example, if all ensembles forecasted a heatwave in 10 days, the forecast would be 11.5/12, or a 96% chance of a heatwave.

There are many ways to calculate the 'skill' of a forecast. Here, we calculated the Area Under the Receiver Operating Characteristic Curve (AUC) to assess the skill for each location at each lead time, which assesses both the false alarms and the correct forecasts (Mason and Graham 2002). Results range from 0.5 (not skillful) to 1 (essentially perfect). We determine 95% confidence intervals using 2000 stratified bootstrap replicates to generate resampled AUCs (Robin *et al* 2011).

We carried out a sensitivity analysis on the forecast verification, to estimate the impact of the parameters used in this study. First, we perturbed the definition of a heatwave and coldwave, changing the temperature percentiles and duration. Second, we used deterministic skill scores (Symmetric Extremal Dependence Index and False Alarm Ratio) to verify the ensemble mean forecast. Lastly, we repeated the NOAA analysis using the same time period as was used for the shorter ECMWF analysis. In all of these cases, the global maps of skill were very similar to those shown here, leading to the same conclusions about which locations tend to have more predictability than others.

Results

Where do heatwaves and coldwaves occur?

Heatwaves and coldwaves occur in different regions. Almost the entire world experiences heatwaves (blue areas in figure 1(*a*)), with the exception of isolated locations in the tropics, including Indonesia, Central Africa, and Western South America. In contrast, large areas of the world do not experience sustained extreme cold, according to both models. This includes northern South America, Central Africa, parts of East and West Africa, the south east of India, and much of the Maritime Continent.

There are fewer extreme heat and cold events in areas with tropical climates (intensity of blue in figure 1). The northern latitudes and the Eastern coast of India tend to have the largest number of heatwaves. For coldwaves, the higher latitudes tend to have the greatest number.

There are no significant differences between the NOAA and ECMWF climatology, therefore we plot here only the NOAA results (figure 1). There are some minor discrepancies in the Pacific Islands, with NOAA modeling more events than ECMWF.

Where is there seasonality of heatwaves/coldwaves?

Focusing on areas where heatwaves and coldwaves occur and there is human exposure, we identify regions that have a distinct seasonality that could be used for seasonal preparedness. In both the NOAA and ECMWF datasets, almost all of the northern extratropics has such a distinct seasonality (dark green areas, figure 2). Parts of East and Southern Africa, Southern South America, and the Pacific Islands also show a distinct seasonality; however, the climatology of the two models displays differing estimates of the size of these Southern Hemisphere regions.

For coldwaves, there is a clear latitudinal divide. Regions that are poleward of 15 degrees latitude have distinct seasons of coldwaves, with exceptions including the interior of Central America, parts of Mozambique, and southern Australia.

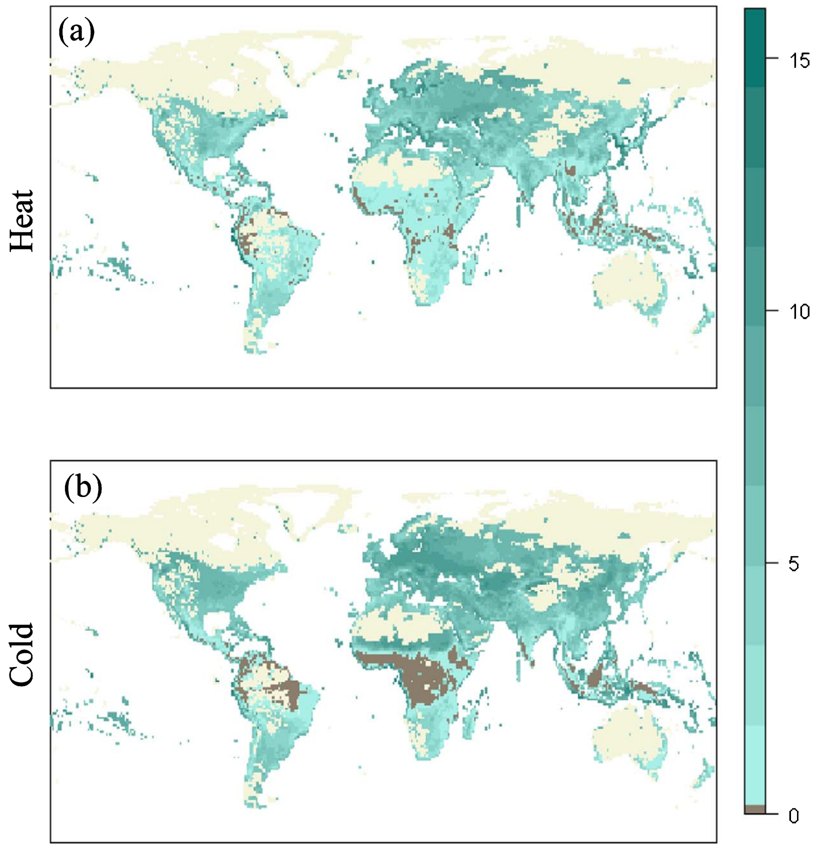

Figure 1. Climatological occurrence and human exposure of (*a*) heatwaves and (*b*) coldwaves for the NOAA model. Results are similar to ECMWF model output. Cream areas have a population density of less than 1 person per km^2, and do not show heatwave/coldwave information. Brown areas indicate locations with fewer than five heatwaves/coldwaves in a 31 year period, and therefore excluded from this analysis. Blue areas are the regions where heatwaves or coldwave do occur, and the shade of blue indicates the average number of heatwave-days or coldwave-days per year.

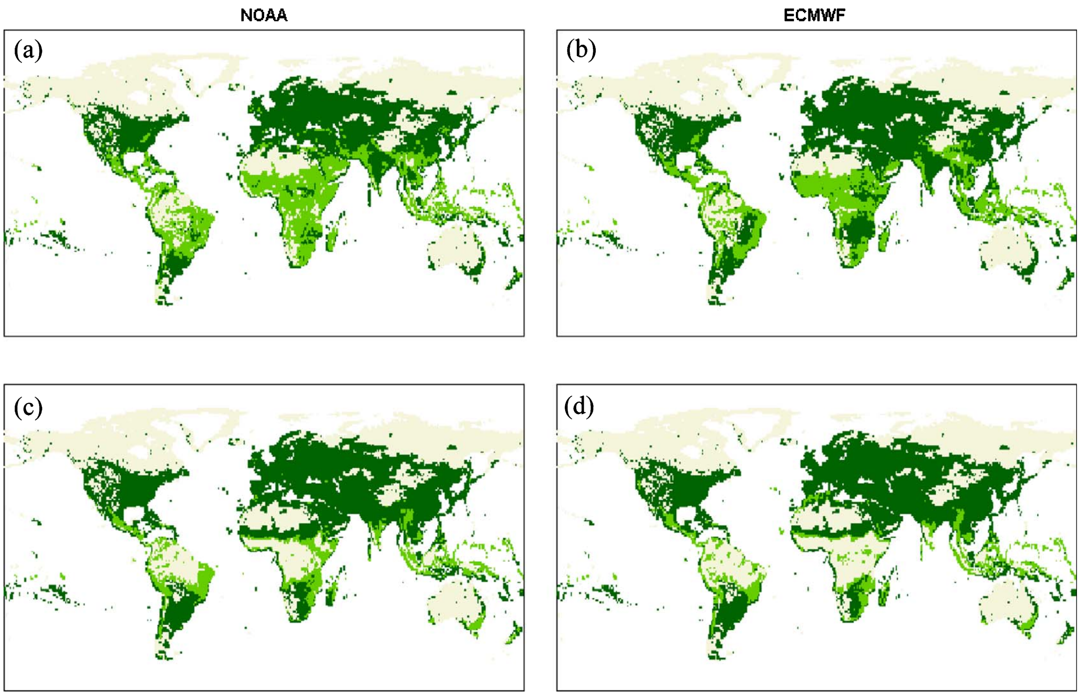

Figure 2. Seasonality of heatwaves (top row) and coldwaves (bottom row) in areas with exposure for the NOAA (left column) and ECMWF (right column) models. Dark green indicates regions that have a distinct seasonality that could be used for seasonal preparedness. In these regions, there is at least one 90 day season in which there was a heatwave/coldwave in half of the years analyzed. Light green areas do not have this seasonality. Cream colored areas have low human exposure to heatwaves or coldwaves, a combination of having fewer than 1 person/km^2 or few extreme events (combination of cream and brown in figure 1).

Where is there skill in short-term forecasts of heatwaves/coldwaves?

To summarize the results of the short-term predictability, we define several categories of forecast characteristics (lead time, skill level), suggestive for the type of preparatory action that could be considered. These 'categories' should be adjusted based on the lead-time and skill levels needed for specific local actions, and they are used here only as a general guide to the global results (full results available in supplementary information available at stacks.iop.org/ERL/13/054017/mmedia).

For heatwave forecasts at long lead times of 10 days or more, both models show the highest skill in much of Eastern Europe, the Middle East, Eastern India, most of Russia, and Central US/Canada (figures 3(*a*) and (*b*)). In these areas, we expect that there should be time for 'advance action' to be taken to prepare for an extreme event (dark red color in figures 3(*a*) and (*b*)). The ECMWF forecasts see a greater portion of land area covered by this category than NOAA: 44% and 34% of populated areas, respectively. In particular, ECMWF shows higher skill than the NOAA forecasts at longer lead times for much of the US, China, and Southern Europe.

These patterns are confirmed in the station data verification (figure 3(*c*)), in which the skill obtained by verifying the model against its analysis product is strongly correlated with the skill calculated by verifying the model against station data. While the model analysis verification overestimates skill relative to the station verification, both sets of results generally agree about which cities have better skill than others.

Skill across the tropics is varied, ranging from little skill at any lead time in Central Africa and the Maritime Continent to high skill at long lead times in much of Brazil and parts of East Africa. While the two models show differing results for many locations, there is an indication that at least one of the models could have skill in parts of East Africa, Southern Africa, and South America. Neither model is able to skillfully predict heatwaves in the Caribbean, much of Central Africa, and much of the Maritime Continent. In summary, predictability for heatwaves at 3–10 days is generally high in the extratropics, but varies from location-to-location in the tropics.

When it comes to coldwaves (figure 4), the NOAA and ECMWF models show broadly similar patterns of skill. In both models, 'advance action', or good skill at the 10 day lead time, is possible in much of the US, Canada, North and Eastern Europe, China, Russia, and Southeast Asia. Good skill at the 3 day lead time, or 'rapid action', is possible in Southern Africa, Southern South America, Central America, and Australia. While the NOAA model shows areas of patchy skill in the Maritime Continent, this is not reflected in the ECMWF model.

One of the largest gradients of skill occurs in India, where both models have good skill in forecasting coldwaves in Western India, transitioning into little to no skill in and near Bangladesh.

Discussion

Where should we be investing in extreme temperature early action plans, and what should they look like?

A large percentage of the world's inhabited surface area could benefit from heatwave and coldwave plans that incorporate both seasonal preparedness actions as well as action based on shorter-term early warnings (see black areas of figure 5). The sum of population living in areas with both seasonality and short-term predictability is 5 billion people for heatwaves, and 4.9 billion for coldwaves. This combination of seasonality and short-term predictability is ideal, as seasonal preparedness can lay the groundwork for supplies and training needed to ensure short-term action is as extensive and rapid as needed.

In the extratropics, seasonality and predictability are almost uniformly available. In these regions, atmospheric blocking causes persistent heat and cold events, as does feedback from dry soils and snow, both of which increase predictability of extreme events, even offering the potential to extend lead-times into sub-seasonal timeframes that would be valuable for enhanced preparedness (Fischer *et al* 2007, Nissan *et al* 2017, Purich *et al* 2014).

In the Caribbean, many locations of the Maritime Continent, and many Pacific Islands, there is little predictability in the short-term for heatwaves. This lack of predictability is likely due to the fact that many islands are too small to be accurately represented by the resolution of these global models, and heatwaves can be extremely localized. There is low variability in temperature in maritime areas, such that changes in large-scale circulation do not bring remarkably different temperatures to the region. Higher resolution models might be able to better resolve the microclimates and small temperature variations in these areas. Further research is needed to determine the health impacts of relative extremes in these regions, where absolute variability is not as large as in the extratropics.

However, many island locations do show good short-term predictability for coldwaves. Station data from Cuba demonstrate this contrast; coldwave predictability is much greater than heatwave predictability, likely because the coldwaves are caused by larger features such as extratropical troughs that have ventured equatorward. In regions that have this contrast, cold weather early warning systems would be an impactful investment.

The opposite is true on the small west coast strip of South America, where some of the highest skill in predicting heatwaves overlaps with the lowest skill in predicting coldwaves, reflected both in the model

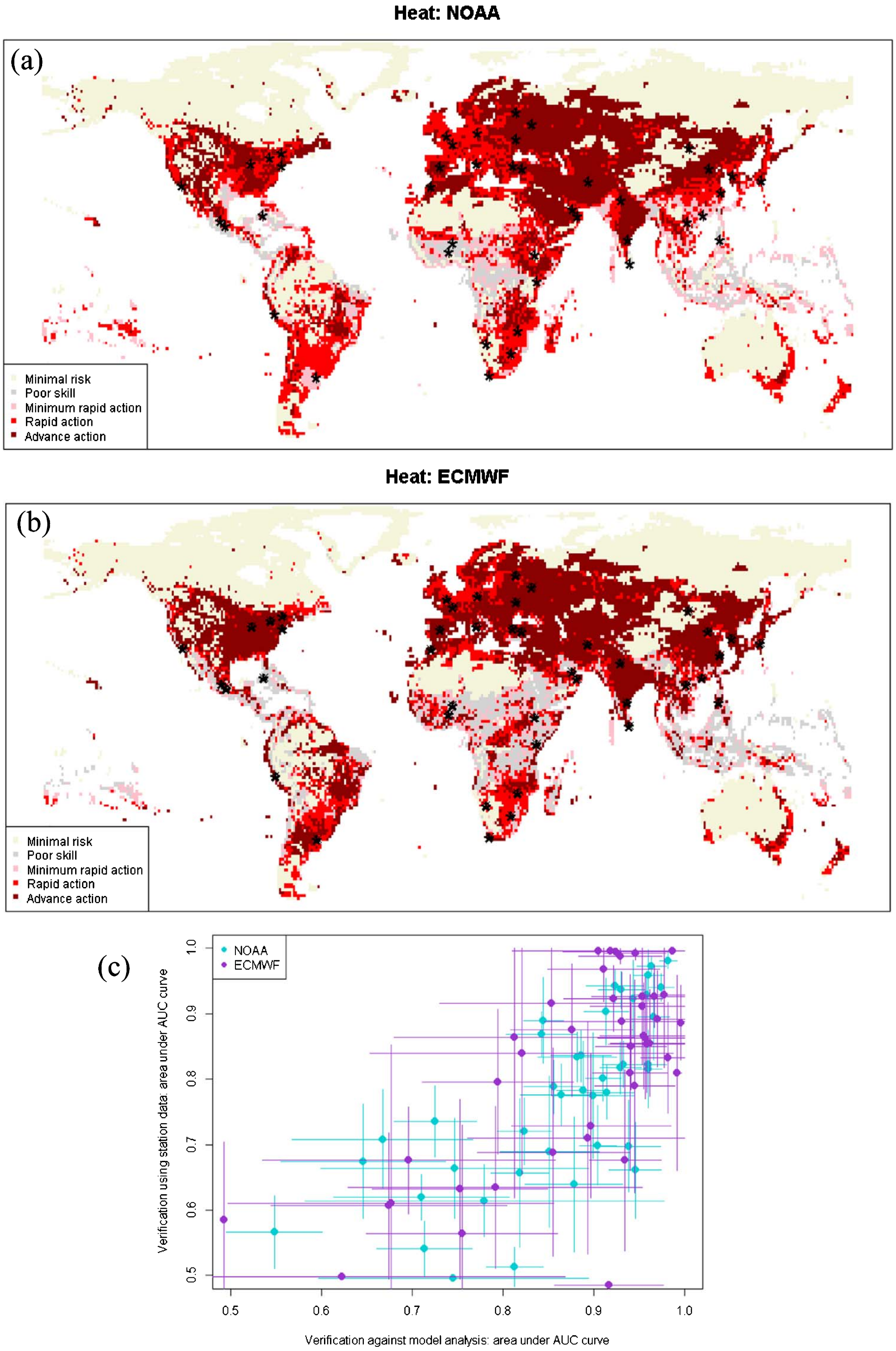

Figure 3. Skill in predicting extreme heat events in the (*a*) NOAA and (*b*) ECMWF models, classified by how the model could be used to take action. In the top two plots, skill is calculated per gridbox by verifying each model against its own analysis. Dark red indicates areas with good skill at the 10 day lead time, classified as 'advance action' (AUC of ROC > 0.8). Red indicates remaining areas with good skill at the 3 day lead time, classified as 'rapid action' (AUC of ROC > 0.8). Pink indicates remaining areas with limited skill at the 3 day lead time, classified as 'minimum rapid action' ($0.7 <$ ROC < 0.8). Grey areas have little skill (AUC of ROC < 0.3), and cream-colored areas have no human exposure. The bottom plot (*c*) shows a comparison of verification results of the model against its analysis (*x*-axis) with verification of the model against station data (*y*-axis). The area under the ROC Curve is plotted for all cities marked with a black star on the global maps, for NOAA (blue) and ECMWF (purple). Error bars indicate 95% confidence intervals.

analysis and in station data from Lima, Peru. The predictability for heatwaves is likely derived when the region occasionally receives anomalously warm water off the coast in El Nino events, which has health implications on the local population (Checkley *et al* 2000).

In many regions in the east of South America, there is no strong seasonality for either heatwaves or coldwaves, but there is good short-term predictability for these events. In these cases, early warning systems would need to be ready throughout the entire year

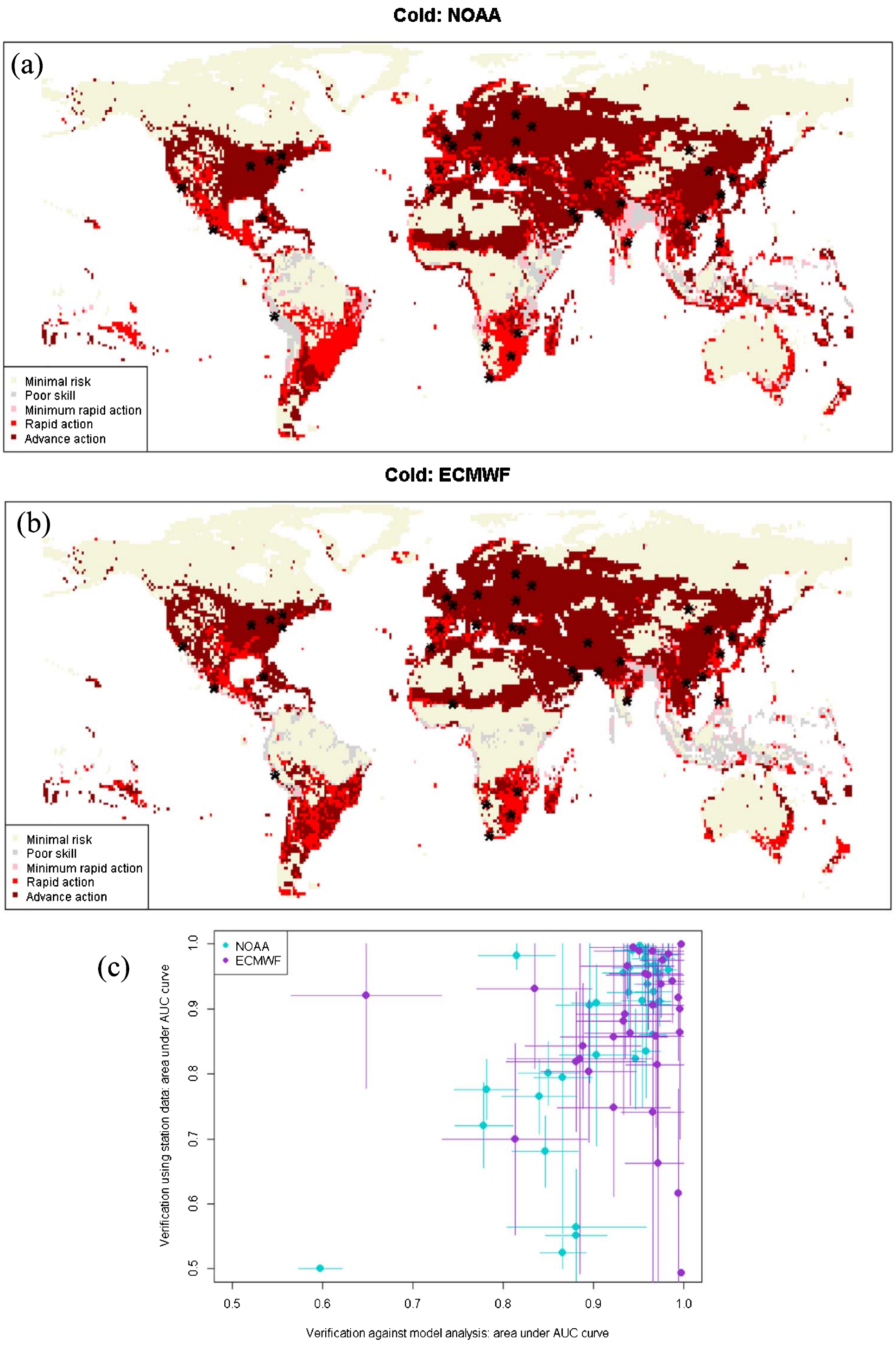

Figure 4. As in figure 3, for coldwaves.

to activate short-term preparedness actions at short notice, especially to support those who might not be adequately preparing for such events.

Across most of the low latitudes in Africa, the climatology of heat extremes is remarkably different between the NOAA and ECMWF models (Donat *et al* 2014). Each model identifies specific locations across the continent where there is seasonality (figure 3) or skillful heatwave prediction (figure 4). Therefore, model validation and selection will be critical for heat early action in those regions, and multi-model results might be more skillful than single models. There are limits to using global data for local action, and local observations should be used in locations seeking to verify these results.

The Sahel stands out as an area that is likely to have excellent predictability for coldwaves, as well as a distinct seasonal cycle that could be used for preparedness. Such short-term forecasts could be used to take preparedness actions for climate- and weather-sensitive health effects e.g. influenza or respiratory illnesses in the region (Jusot *et al* 2012).

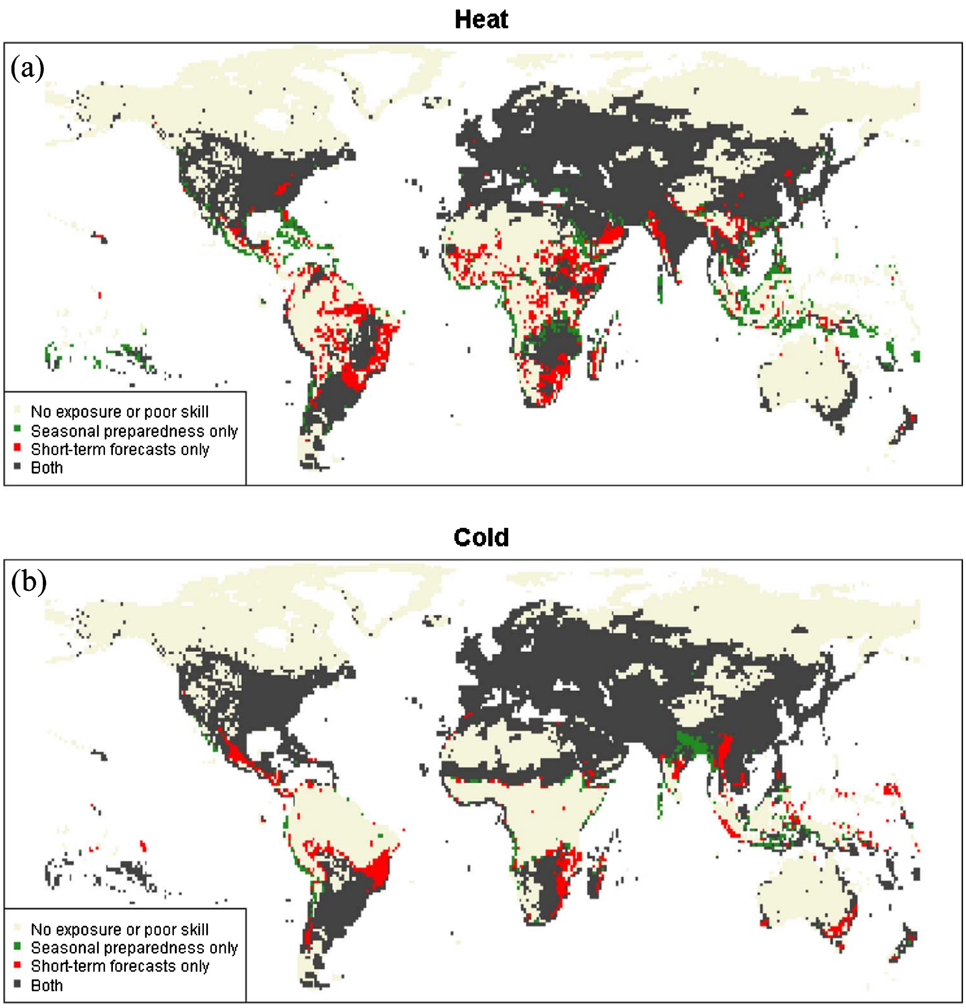

Figure 5. Compilation of figures 1-4, indicating what type of preparation could be possible for (*a*) heatwaves and (*b*) coldwaves around the world. Black areas offer both skillful short-term forecasts and seasonality of heatwaves/coldwaves in either the NOAA or ECMWF models. Green areas are regions where only seasonality could be used for preparation. Red areas are regions where only skillful short term forecasts can be used for preparation. Cream colored areas have no exposure or have neither distinct climatology nor forecast skill.

In much of India and Bangladesh, there is a strong seasonality and predictability for heatwaves. Heatwaves tend to be confined to the pre-monsoon summer season, before the rains arrive, which suppresses high temperatures. Predictability on weather timescales arises from a characteristic atmospheric circulation pattern and a deficit of normal rainfall at the beginning of the monsoon, which is reflected in anomalously low soil moisture for this time of the year (Nissan *et al* 2017). Models that better represent land-surface interaction are likely to perform better in predicting heatwaves in this region.

For coldwaves, however, Bangladesh does not see predictability in either model. Coldwave patterns that are associated with large-scale variability such as the El Niño Southern Oscillation do not extend eastward to Bangladesh (Ratnam *et al* 2016). Diagnostic climate research is needed to understand the possible reasons for this discrepancy, which may pertain to dynamic weather patterns responsible for coldwaves in the Ganges Delta that are not well-captured by the models.

Areas for further research

While the maps produced here provide a first indication of regions in which seasonal preparedness and/or early warning systems could be beneficial, our hazard definitions were generalized over large areas, and should be tested with local morbidity and mortality data where possible. In particular, it would be important to assess the differential vulnerability of at-risk groups. For example, migrants are not necessarily adapted to the same temperatures as the local population, and they may be both vulnerable and exposed to hazardous weather. In addition, climate change could increase or decrease risk in many locations, particularly for regions that currently have low risk (Forzieri *et al* 2017). These regions should use local temperature data to monitor any changes to temperature distributions in a changing climate.

In addition, current forecast skill of these two global models does not represent the full predictability that could be realized with further research in many regions. For example, soil moisture is known to improve predictability in many regions of the world, such as Bangladesh, but reliable initialization of soil moisture in the models is not straightforward. Africa, the Maritime Continent, and South Asia saw patchy and inconsistent skill between the models; further research is needed to understand the limits and drivers of predictability of temperature extremes in these regions. Targeted research in areas where there are clear drivers of predictability but poor model skill could enable the development of early warning systems in less-served areas.

While global models tend to be the only information available for the world's most vulnerable locations, locally-calibrated models that combine local observations with forecasts are likely to increase skill in locations that can implement this technology. Improvements in temperature observation systems will be necessary in many places to enable this verification and calibration, and post-processing and multi-model ensembles could further improve local skill. These results should be treated as a first approximation of global patterns in skill and should be verified locally.

The model evaluation carried out here focused on current model skill, which would be achieved by using these models without alteration. Operational skill on the ground could be more limited than this, as ECMWF forecasts, for example, are not freely available in many countries, and operational forecasts could be derived from unverified or hedged forecasts that do not reach the skill levels found here.

While we do evaluate seasonality as a tool for preparedness, we do not evaluate seasonal temperature forecasts in this study. With a few exceptions, most seasonal forecasts do not estimate the probability of extreme heat or cold events during the season, but focus on seasonal average temperatures. Seasonal forecasts of extreme events, however, could be developed, evaluated, and integrated into early warning systems where useful.

Conclusions

Extreme temperatures remain responsible for significant spikes in morbidity and mortality, yet we have shown that, for much of the world, information on seasonality and/or short-term forecasts can help to anticipate extreme events with enough time to take action. Nearly 5 billion people can take advantage of this for heatwaves and for coldwaves. For these regions, policies to build resilience and adaptation to (changing) extremes should not be confined to structural adaptation, but also build the capacity to act on seasonality and early warnings.

As the climate warms, increased impact from heat extremes is expected in much of the Earth's land surface, even while taking into account gradual acclimatization to higher temperatures (Huang *et al* 2011, IPCC 2012). Early warning systems are a powerful tool to adapt to a potential rise in risk. The development of heat-health early warning systems should be considered for implementation at scale in the regions with predictability (see figure 5(*a*)). Such systems have the potential to save many lives. These should be underpinned by an evidence base on the efficiency of different preparedness measures for heatwaves and coldwaves in different climates and levels of urbanization, as well as research on the success factors for well-functioning early action systems. Here, we indicate where early warning systems may potentially work, but many localities might require resources or capacity to take action on these warnings. Investment in such capacity, such as the establishment of Forecast-based Financing systems (Coughlan de Perez *et al* 2015), can ensure that early action is taken when an extreme event is predicted.

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