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Defining and Predicting Heat Waves in Bangladesh

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1. Abstract

This paper proposes a heat wave definition for Bangladesh that could be used to trigger preparedness measures in a heat early warning system (HEWS) and explores the climate mechanisms associated with heat waves. A HEWS requires a definition of heat waves that is both related to human health outcomes and forecastable. No such definition has been developed for Bangladesh. Using a generalized additive regression model, a heat wave definition is proposed that requires elevated minimum and maximum daily temperatures over the 95th percentile for three consecutive days, confirming the importance of night-time conditions for health impacts. By this definition, death rates increase by about 20% during heat waves; this result can be used as an argument for public health interventions to prevent heat-related deaths. Furthermore, predictability of these heat waves exists from weather to seasonal timescales, offering opportunities for a range of preparedness measures. Heat waves are associated with an absence of normal pre-monsoonal rainfall brought about by anomalously strong low-level westerly winds and weak southerlies, detectable up to approximately ten days in advance. This circulation pattern occurs over a background of drier-than-normal conditions, with below-average soil moisture and precipitation throughout the heat wave season from April to June. Low soil moisture increases the odds of heat wave occurrence for 10 to 30 days, indicating that sub-seasonal forecasts of heat wave risk may be possible by monitoring soil moisture conditions.

2. Introduction

It is well-established that extreme heat poses a serious health risk, causing many excess deaths each year (IPCC, 2012; Smith et al., 2014). Heat waves were responsible for four of the ten deadliest natural disasters in 2015, with South Asian heat waves ranking third and fourth by mortality (UNISDR et al., 2015). However, heat-related deaths are largely preventable. Heat early warning systems (HEWSs, McGregor et al., 2014) are already in place in many cities in developed countries, and are known to save lives by facilitating improved preparedness (Ebi et al., 2004; McGregor et al., 2014). A successful HEWS consists of several components operating over a range of timescales: hazard forecasts, public awareness campaigns with well-considered communication strategies, training of key medical and social care personnel and finally disaster response and recovery (Public Health England et al., 2015).

Near the tropics, where hot weather is considered the norm, the perceived risk is often low, but recent heat waves in South Asia have caught the attention of the health community, policy-makers and the public, increasing motivation to develop HEWSs in the region (UNISDR et al., 2015; Wu, 2016). In recognition of the burgeoning heat-health problem, the first South Asian Climate Services Forum for Health was held in 2016 and focussed on heat health, convening representatives from national governments and climate and health sectors in the region. Work has already begun in India, where the first South Asian HEWS was adopted in the city of Ahmedabad and the policy is now expanding to include several cities across the country (Knowlton et al., 2014a; Natural Resources Defense Council, 2016). The motivation to build similar systems in other regional cities was evident, particularly in Bangladesh and Pakistan. However, the meeting also identified significant gaps in knowledge about the nature of heat risk in the region (WHO-WMO Joint Office for Climate and Health, 2016). These knowledge gaps are particularly stark in tropical regions and developing countries. Research is needed to better understand all aspects of the causes and impacts of heat waves in South Asia, including the climate hazard, societal exposure and population vulnerability.

Bangladesh is a country that is seriously threatened by climate change (Huq, 2001), which is expected to bring an increase in frequency and intensity of heat waves in the future (Kirtman et al., 2012). Evidence points to a substantial mortality increase during hot weather, with stronger heat effects found in cities, among the elderly, children and men (Burkart et al., 2014; Burkart et al., 2011a, 2014; Burkart et al., 2011b; Burkart & Endlicher, 2011). Given rising average temperatures, which are generally accompanied with even faster increases in the probability of heat extremes, developing early warning systems for extreme events like heat waves is a crucial component of a successful climate change adaptation strategy. Such a strategy should include interventions over different timescales and a mix of measures such as urban planning, improved infrastructure and health systems (IPCC, 2012; Smith et al., 2014).

The level of heat stress experienced by a person is a function of temperature, relative humidity, wind speed, solar radiation, clothing and many other factors (Blazejczyk et al., 2012; Nguyen & Dockery, 2015) and measures of heat stress used in HEWSs vary according to the local climate and vulnerability of the population. At a given temperature, high humidity increases the level of heat stress on a person. This effect can be accounted for with the heat index, which combines the effects of relative humidity and temperature to give an 'apparent' temperature, and is employed operationally in many countries (McGregor et al., 2015). There is substantial evidence that heat waves with hot conditions lasting through the night have a greater impact on human health than those with cooler nights, which offer people some respite from the hot weather (McGregor et al., 2015; Robinson, 2001). Increases in mortality during two of the most devastating heat waves of recent memory, in Chicago (1995) and France (2003), have been linked with high night-time temperatures (Karl & Knight, 1997; Laaidi et al., 2012). Many HEWSs therefore consider both day- and night-time conditions when defining a heat wave. Duration is another important factor, as mortality can increase non-linearly with persistence of hot weather (Tan et al., 2007), and most HEWSs accordingly impose minimum duration criteria or average (apparent) temperatures over two or more days (McGregor et al., 2015).

2.1. **Goals of this study**

The goals of this paper are twofold: 1) to provide a definition for heat waves in Bangladesh that is related to mortality and (2) to investigate the predictability of heat waves at a range of lead-times. While addressing the knowledge gaps specific to Bangladesh, we also contribute to the burgeoning global literature on heat wave thresholds and predictability.

(1) A heat wave definition for Bangladesh

A HEWS requires a clear trigger in order to issue a warning, which in turn requires an event definition that is both (a) related to human health outcomes and (b) forecastable using available weather and climate information. No such definition has been developed for Bangladesh. Lack of available data, inadequate models and limits on their spatial resolution mean the many factors contributing to a person's heat exposure cannot all be accounted for in forecasts. In this study, we test a suite of binary indicators for heat wave days against mortality data. The indices tested are based on criteria that have been identified as relevant for human health and used in heat wave early warning systems worldwide. In taking this approach, we strike a balance between fidelity (accurately describing the local conditions that impact upon health) and simplicity (quantities that are calculable given available data and likely to be related to synoptic climate conditions).

(2) Predicting Bangladeshi heat waves

It is widely recognised that extending forecast lead times could have important benefits for disaster preparedness (IFRC, 2008; Knowlton, 2014; Letson et al., 2007; Vitart et al., 2012). Many actions, such as replenishing stocks, revisiting contingency plans and refreshing training for health care and emergency providers, require more advanced warning than the few days commonly provided by weather forecasts (IFRC, 2008; Public Health England, 2015). Strong coupling between atmospheric temperatures and land surface conditions has been noted in several studies, with low soil moisture playing a role in Australia and in the major European and Russian heat waves of 2003 and 2010 (Hirschi et al., 2011; Miralles et al., 2014; Perkins et al., 2015; Quesada et al., 2012). In this paper, we focus on using atmospheric circulation, rainfall and soil moisture to harness heat wave predictability from weather to seasonal timescales.

3. Data

3.1. **Station data**

Daily minimum (*Tmin*) and maximum (*Tmax*) temperature data for 35 weather stations across Bangladesh were provided by the Bangladesh Meteorological Department (BMD) for the period 1948 to 2012. Figure 1 shows the locations of these weather stations. The data were quality controlled to check for missing values and outliers. Only data from 1989 to 2011 were used for the remaining analysis because of the high portion of missing data prior to 1989 and in 2012. During 1989-2011, fewer than 10% of data entries were missing. Anomalous values, identified by flagging repeated values and time steps where Tmin exceeded Tmax, were checked manually. Outliers were either replaced with missing values or corrected where obvious data-entry errors had occurred. The station values were then averaged to create daily time series of minimum and maximum temperature for Bangladesh.

3.2. **Gridded data**

Data from the ECMWF ERA Interim Reanalysis (Dee et al., 2011) were used to investigate the synoptic climate conditions associated with heat waves. Volumetric soil water content was integrated across the four soil layers in the ERA Interim/Land model. All variables used for this study were analysis fields. Precipitation is not an assimilated variable in the reanalysis, so gridded precipitation data were taken from the NOAA National Climatic Data Center's (NCDC) PERSIANN Climate Data Record (version 1, revision 1). This dataset provides daily precipitation for the global tropics and extra-tropics (60 S to 60 N) at a spatial resolution of 0.25 degrees, derived from satellite infrared data and merged with the Global Precipitation Climatology Project (GCPC) monthly product to ensure consistency (Ashouri et al., 2015; Sorooshian et al., 2014)

Where presented below, anomalies were calculated from smoothed daily climatologies, computed by fitting a sixth order harmonic function to the raw climatology of daily values from 1989-2011.

3.3. **Mortality data**

Nation-wide daily death counts collected within the Sample Vital Registration System (SVRS) were provided by the Bangladesh Bureau of Statistics (BBS). The SVRS surveys a sample population of approximately 1 million individuals, which is organized in primary sample units located across the country, and collects vital events, such as births and deaths in addition to other socio-economic information (Bangladesh Bureau of Statistics, 2008). Vital events are collected under a dual recording system by a local registrar at the time they occur (system 1), and in retrospect by an official from the BBS (system 2). Both datasets are then compared and unmatched cases are subject to further investigation by BBS officials. Cause of death is attributed, but is not medically certified and classification does not follow International Classification of Disease standards. Approximately 12% of deaths are not classified and 25% are classified as "old-age". Given this crude uncertified classification, we conducted no cause-specific analyses, but did exclude maternity- and accident-related deaths.

4. Methods

4.1. Defining heat wave days

Six indices of extreme heat were calculated for Bangladesh and are summarised in Table 1. These indices incorporate a range of conditions known to be important for heat stress: day- and night-time temperatures, humidity and duration (McGregor et al., 2015). According to all indices, a heat wave day is declared on the third consecutive day on which one (or two) variables exceed the 95^{th} percentile of daily values. In an operational setting, three-day weather forecasts could be used to determine the likelihood of reaching this threshold. Percentiles are indicated by a subscript '95' and defined over all days between 1989 and 2011. Indices are produced from country-averaged meteorological observations to correspond to the country-aggregated mortality data.

The heat index was calculated according to the formulation used by the United States National Weather Service, based on temperature and relative humidity (National Weather Service, 2016). In absence of verified station observations, relative humidity data from ERA Interim were used to compute the heat index. Inconsistencies were found between 2 m ERA Interim temperatures and dew point temperatures, resulting in some excessive near-surface supersaturation values. These errors would affect calculations of the highest heat index values of interest to this study, so relative humidity at 950 hPa was used instead. Daily cycles of ERA Interim temperature at 2 m elevation and 950 hPa relative humidity were examined to determine the appropriate time step to use with the daily maximum and minimum station temperature data, as no information about the timing of these observations was available. Average daily minimum and maximum ERA Interim temperatures were reached at 06:00 and 12:00. Relative humidity exhibited a negative correlation with temperature, with minimum and maximum values reached at 18:00 and 6:00. Relative humidity data were extracted at 6:00 and 12:00 to correspond to the station observations and averaged across the country before being used with the country-averaged station temperature data for the heat index calculations.

The *day* index represents the hottest days, while *day-and-night* selects the days on which both day- and night-time temperatures are high. Accounting for the influence of relative humidity, the *humid-day* and *humid-day-and-night* indicators identify days on which only the day-time or both day- and night-time heat indices are high. The *average-temperature* and *average-heat-index* indicators select days with high values of average day- and night-time temperature and heat index, respectively.

Our choice of indicators incorporates a fixed minimum duration of three days, but does not distinguish among events of longer duration; for example, five consecutive days exceeding the threshold will count as three heat wave days, with the conditions met on the third, fourth and fifth days. Consequently, we distinguish between 'heat wave days' and 'heat waves' as follows: 'heat wave days' are days that meet the criteria for an index (the third day of conditions exceeding the threshold), irrespective of whether these occur consecutively. A 'heat wave' consists of any number of consecutive heat wave days, and heat waves must be separated from each other by at least one day. For example, there are 39 *day-and-night* heat wave days between 1989 and 2011, but these days occur as part of only 13 separate heat waves, each lasting for different lengths of time (Table 1).

4.2. **Regression methodology**

We used generalized additive regression models (Wood, 2006), adjusting for the long- and short-term confounding effects of day of the week and month, seasonal cycle and long-term trend, to determine the relative risk of dying on a heat wave day compared with a non-heat wave day. The binary heat wave indicators in Table 1 were used as predictor variables, and the regression models were used to determine the percentage increase in mortality associated with each indicator. We adjusted for long-term trends and the seasonal cycle by including a variable counting each day from the beginning of the time series until its end. Smoothing parameters for trend adjustment were based on the minimization of the Unbiased Risk Estimator (Wood, 2006) and the partial autocorrelation of model residuals. Final models were fitted using five degrees of freedom per year with three to seven degrees of freedom serving as sensitivity analyses. Additionally, models were adjusted for day of the month and week as well as age. Three age groups were formed with children between the age of 1-15 years, adults between 16 and 64 years, and the elderly above the age of 65 years. Infants below the age of 1 year were excluded from the analyses as birth generally exhibits a seasonal pattern. In order to test the sensitivity of age adjustment, we fitted models adjusting for 2 age groups (1-64 yrs. and 65+ yrs.) and 4 age groups (1-15 yrs., 16-44 yrs., 45-64 yrs. and 65+ yrs.). Models were fitted including daily death counts of the same day as well as sums of the same day and two previous days as dependent variables. Given data limitations, established methods used to investigate decreases in heat-related mortality in the weeks and months following a heat wave are not feasible for Bangladesh, so this "harvesting" effect could not be accounted for. The models were robust to different degrees of freedom in trend adjustment as well as the alteration in age adjustment. Equation (1) shows the final regression model:

$$\log(E_i) = f(x_1) + f(x_2) + \beta_3 x_3 + \beta_4 x_4 + \beta_{hw} x_{hw} \quad (1)$$

with E_i being the observed daily death counts across the country; $f(x_1)$ the spline function for long-term and seasonal trend; $f(x_2)$ the spline function for day of the month; $\beta_3$and $\beta_4$are the model estimates for day of the week and age; $x_{hw}$is the nation-wide binary heat wave indicator; and β_{hw} is the model estimate for heat wave days.

The relative risk (RR_{hw}) of dying during a heat wave and the associated percentage increase in country-aggregated mortality during heat wave days were derived from the model parameters through equations (2) and (3):

$$RR_{hw} = e^{\beta_{hw}} \quad (2)$$

$$\%change = (RR_{hw} - 1) \cdot 100 \quad (3)$$

5. Results

5.1. **Heat wave definition**

Table 2 displays the percentage increase in mortality during heat wave events as defined by the six indices. Regardless of the heat wave definition, we observed an increase in country-wide mortality for all indices. Strongest effects were observed when defining heat wave days on the third consecutive day surpassing the 95th percentiles of day- and night-time temperatures (*day-and-night)* or the same condition applied to the day- and night-time heat index (*humid-day-and-night)*. Mortality increased by 22% (95% CI: 8-38%) on *day-and-night* heat wave days, and by 24% (95%CI: 10-40%) on *humid-day-and-night* heat wave days. Increases in mortality were smaller when defining heat periods by the exceedance of the 95th percentile of maximum temperatures (*day),* neglecting night-time conditions. Mortality increased by 10% (95%CI: 2-19%) when using the *day* indicator and 17% (95%CI: 3-30%) when using the *humid-day* indicator. When defining heat wave episodes by the exceedance of the 95th percentile of daily mean values, mortality increased by 18% (95%CI: 7-29%) for temperature (*average-temperature* indicator) and by 11% (2-21%) for heat index (*average-heat-index* indicator). Mortality increases were estimated for deaths occurring on heat wave days as well as for the sum of deaths occurring on heat wave days plus the two preceding days, since a heat wave day is defined to occurs on the third day of hot weather. Effect estimates varied between these two methods, but the general trends and conclusions remain consistent (Table 2).

Based on these regression results, we conclude that *day-and-night* and *humid-day-and-night* indicators are the best predictors of mortality from the six indices tested, and we focus on these for the remaining analyses. Where results for both heat wave indicators were similar, only those for the *day-and-night* index are presented below. This index was preferred because it could be calculated from station temperature data alone, while the calculation of the *humid-day-and-night* index required relative humidity data from ERA Interim at 950 hPa as a proxy for local data and so is less representative of near-surface conditions. Furthermore, online media reports of heat waves in Bangladesh suggest that severe heat waves do occur in April (online Google search using the keywords ‘Bangladesh heat wave’, 28th Oct 2016), and these would not be captured by the *humid-day-and-night* indicator (Figure 3b), since relative humidity is low in April (Figure 2b).

5.2. **Climate drivers of heat waves**

5.2.1. Climatology of heat in Bangladesh

Bangladesh has a monsoon climate, characterised by three distinct seasons: cool, dry winters (approximately mid-October to late-February), hot pre-monsoon summers (March to May/early June) and a rainy monsoon season (June - late September/early October). Continental heating increases throughout the pre-monsoon period, producing a low-pressure monsoon trough that is anchored by the Tibetan Plateau and the Himalaya, which extend the heating throughout the troposphere. The resulting cross-equatorial pressure gradient, reinforced by convective activity over the region, triggers the arrival of the monsoon in southeast Bangladesh in early June. The monsoon progresses towards the northwest later in the month and retreats from the northeast to the southwest in late September or early October (Ahmed & Karmakar, 1993).

The average seasonal cycles of temperature, rainfall and relative humidity in Bangladesh are shown in Figure 2. Rainfall reaches an annual minimum in December/January and then increases until the onset of the monsoon in June, peaking in late June/July, and again in September (Figure 2b). Day-time temperatures (daily maxima) reach their highest values (close to 35^{o}C on average) in April and May, decreasing markedly as rainfall increases with the start of the monsoon season in early June and remaining roughly constant until the monsoon retreats in September/October (Figure 2a & b). Night-time temperatures (daily minima) do not show the same peak in the pre-monsoon season as day-time temperatures, reaching their highest values in the mid-monsoon season (Figure 2a). Relative humidity peaks at approximately 90% during the early part of the monsoon season, later than the peak in maximum temperature, and then decreases towards the end of the rainy season (Figure 2b).

Figure 3a shows the seasonality of heat-wave occurrence according to our two definitions: *day-and-night* heat waves and *humid-day-and-night* heat waves. When only temperature is considered (*day-and-night*), almost all heat waves occur between April and June (hereafter AMJ), with most in May and one in September. Most *humid-day-and-night* heat waves still occur in May and June, but this indicator suggests that heat waves continue throughout the monsoon months until September.

Figure 4 shows the interannual variability in frequency of heat wave days. With a few exceptions, *day-and-night* and *humid-day-and-night* heat waves occur in the same years. Linear trends in heat wave frequency were not significant over this period (0.01 [95% CI: -0.14 to 0.15] yr^{-2} for *day-and-night* and 0.1 [95% CI: -0.07 to 0.27] yr^{-2} for *humid-day-and-night* indices). Similarly, non-significant trends were found for AMJ-averaged daily minimum (0.02 [95% CI: -0.01 to 0.05] yr^{-2}), maximum (0.03 [95% CI: -0.01 to 0.06] yr^{-2}) and average (0.03 [95% CI: -0.01 to 0.06] yr^{-2}) temperatures. However, significant trends were found in annual average daily minimum (0.02 [95% CI: 0.01 to 0.04] $C^{o}yr^{-1}$), maximum (0.03 [95% CI: 0.01 to 0.05] $C^{o}yr^{-1}$) and average (0.03 [95% CI: 0.01 to 0.04] $C^{o}yr^{-1}$) temperatures, so a longer time series may reveal discernible temperature trends during the heat wave season.

5.2.2. Synoptic climate conditions during heat waves

In this section, we examine the average prevailing meteorology during heat waves in Bangladesh, presenting results as anomaly composites from smoothed daily climatologies calculated over the period 1989-2011. All composites are weighted by heat wave duration.

Figures 5a & b show the climatological circulation patterns at mid- (500 hPa) and low- (850 hPa) levels of the atmosphere between April and June, when most heat wave days occur (Figure 3). The pre-monsoon season is a transition period between the northerly winter circulation and the south to south-easterly summer monsoon circulation. During these months, winds are weak and variable. A “zone of discontinuity” (Huq, 1974) separates the hot, dry north-westerly air mass from the moist, southerly flow arriving from the Bay of Bengal. This season is characterised by hot temperatures and highly variable thunderstorms and convective rain, which depend on southerly winds for their moisture supply (Sanderson & Rafique, 2009).

Anomaly composites of the wind circulation on *day-and-night* heat wave days, relative to the smoothed daily wind climatology, are also shown at the same atmospheric levels (Figure 5c & d). An anomalous anticyclonic pattern centred over central-eastern India occurs at the mid-atmospheric level. Nearer the surface, strong northerly anomalies occur over most of India and offshore in the Bay of Bengal on heat wave days. In Bangladesh, westerly winds arriving from northern India are stronger than normal for this time of year, while south-westerly flow from the Bay of Bengal is considerably weaker. Heat wave days are also associated with anomalous subsidence in the mid- to upper-atmosphere (Figure 6). A region of low relative humidity is collocated with the anomalous westerly flow from India (Figure 7a), and anomalous moisture flux divergence across the whole area is positive, indicating drier than normal conditions (Figure 7b). Similar conditions occur during heat wave days defined according to the *humid-day-and-night* indicator and are not shown.

5.2.3. Sources of predictability

ERA Interim soil moisture content was analysed to determine whether any advanced warning could be discerned in the days to months leading up to a heat wave. Soil moisture exhibits lower variance than atmospheric fields, retaining the memory of recent events for longer. Detecting a signal in soil moisture would therefore suggest that extended range predictability may be achievable beyond that afforded by atmospheric conditions alone (Vitart et al., 2014).

In subsequent figures, lead-time indicates the number of days before the first day of a heat-wave, with a lead time of 0 days corresponding to the first day of a heat wave.

Weather and Sub-Seasonal Prediction

Anomaly composites reveal that heat wave days defined by high day- and night-time temperatures (*day-and-night)* are associated with a soil moisture deficit that can be seen at least thirty days in advance (Figure 8). Country-wide, the total soil moisture deficit increases sharply approximately ten days prior to the occurrence of a heat wave (Figure 9a). This dry soil signal can be attributed to declining negative daily precipitation anomalies over the same period and to low relative humidity, which increases the rate of potential evaporation from the surface (Figure 9b and c). A shift in the low-level wind circulation is also observed about ten days prior to the occurrence of heat waves: the pattern of stronger westerly winds and weaker southerlies shown in Figure 5c emerges with a lead time of between 10 and 8 days, and then persists until the heat wave begins (Figure 10).

Heat wave days defined by high day- and night-time heat indices (*humid-day-and-night*) also follow several days of below-normal and sharply declining soil moisture in Bangladesh. However, the anomaly is weaker and the signal is not clearly discernible more than ten days in advance (not shown).

The existence of soil moisture deficits in the run-up to heat wave days does not in itself imply greater predictability of these events, because it may be the case that soil moisture deficits also occur frequently in the absence of heat waves. To isolate the additional predictability afforded by negative soil moisture anomalies we computed the relative odds (Agresti, 1996) of a heat wave given soil moisture deficits of varying duration, as compared to climatological heat wave odds during the heat wave season. We focus on the thirty-day period prior to a heat wave as this time-frame has important implications for improving early warning and preparedness (Vitart et al., 2012).

Percentiles of soil moisture were calculated for each day of the year across the 23 years of data (1989-2011). Annual values were sorted and assigned cumulative probabilities evenly across the range (0,1) and linear interpolation was used to construct a cumulative distribution function (CDF). Each value of soil moisture in the data series was thus converted to a percentile based on the CDF for the appropriate day of the year. This calculation was performed for 5- to 30-day soil moisture totals. It would be desirable to explore the influence of the magnitude of soil moisture deficit on heat wave predictability, but the 23-year series available for this study limits the accuracy of the percentile estimations. Instead, we use the 20th percentile of accumulated soil moisture as the cut-off threshold to indicate dry soil moisture conditions.

The climatological probability of a heat wave day, defined by either the temperature (*day-and-night)* or heat index (*humid-day-and-night)* definitions during the main heat wave season (April to June) is 2%; these events do not occur often, but have serious impacts on human health (Table 2). The relative odds of a heat wave following periods of dry soil moisture lasting between 5 and 30 days are shown in Figure 11. The odds of a temperature-only *day-and-night* heat wave are more than 3 times higher following a 5-day period of dry soil moisture than under normal climatological conditions between April and June. The heightened heat wave risk decreases with increasing lead-time, but the relative odds remain close to 3 for soil moisture deficits lasting up to 30 days. The odds of a *humid-day-and-night* heat wave are more than 3 times higher than normal following a 5-day soil moisture deficit and remain greater than normal on average at longer lead times, though this result is not significant beyond 5 days. Given the higher humidity of *humid-day-and-night* days, the reduced association with drier-than-normal soil conditions is expected. A permutation test was performed to check whether the observed increase in odds was likely to have arisen by chance. The observed heat waves were randomly redistributed within the heat wave season according to a fitted kernel distribution and randomly across all years, and the relative odds were recomputed. On average, the odds of a heat wave following periods of soil moisture deficit were no greater than climatology for the randomly generated distributions and the relative odds observed following 5-day soil moisture deficits were reproduced by chance in fewer than 0.2% of the simulated distributions for *day-and-night* and 0.1% for *humid-day-and-night* heat waves.

Seasonal prediction

While average daily total precipitation over the country fluctuates considerably (Figure 9b), we would expect the clear soil moisture deficit shown in Figure 9a to be reflected in the accumulated precipitation anomalies. To reduce this noise, anomalous daily rainfall totals were accumulated backwards in time from the occurrence of a heat wave (Figure 12). The negative accumulated precipitation anomaly continues to increase up to about sixty days before a heat wave and then becomes approximately constant, consistent with lower-than-normal soil moisture over the same period.

The long persistence of these anomalies suggests that the relationship between drier-than-normal conditions and higher heat wave frequencies may be discernible on interannual timescales. Time series comparing total precipitation, soil moisture and number of *day-and-night* heat wave days between April and June (AMJ) are shown in Figure 13. Both AMJ-total soil moisture and AMJ-total precipitation are negatively correlated with the AMJ number of *day-and-night* heat wave days between April and June, though the correlation is stronger with total soil moisture ($r = -0.6$ ($p=0.0$) vs. -0.3 ($p=0.1$) for precipitation). This negative correlation is confirmed for *humid-day-and-night* heat waves, despite the lower persistence and magnitude of the observed soil moisture anomaly (correlations with total number of heat waves were -0.5 and -0.4 for soil moisture and precipitation, respectively).

6. Discussion

6.1. Defining heat waves

The improved performance of day- and night-time indicators as compared with day-time only indicators (Table 2) demonstrates that night-time conditions are important determinants of mortality during hot weather in Bangladesh. While both *day-and-night* and *humid-day-and-night* indices were significant predictors of mortality, we suggest that the temperature-only index (*day-and-night)* is the more useful definition of heat waves. Both indices showed similar statistical performance, but the temperature-only indicator (*day-and-night)* is easier to compute and only requires daily minimum and maximum temperature data. Furthermore, while the regression results suggest that relative humidity is important for heat stress in Bangladesh, this would need to be confirmed using verified near-surface observations. Station data for relative humidity were unavailable for this study, so reanalysis data at 950 hPa were used as a substitute in the heat index calculations. However, water vapour is a greenhouse gas, trapping radiation emitted from the land surface and mitigating heat-loss during the night. As a result, high night-time temperatures tend to occur in conjunction with high relative humidity. We therefore propose *day-and-night* as a suitable catchall indicator for heat wave events in Bangladesh, combining the effects of day- and night-time temperatures, relative humidity and duration.

However, we note that this definition is based on nationally-aggregated mortality and country-averaged climate data. Further work would be needed to establish district or city-level thresholds. The relative spatial coherence of the temperature field and the small size of the country made aggregation possible in this case. Aggregation was necessary to achieve a similar spatial scale between the meteorological and mortality datasets, but this approach would not be advisable over larger countries with distinct climate zones. Cluster analyses on daily (Burkart et al., 2014) and AMJ-averaged data revealed no large scale structures in the temperature field (not shown). A temperature gradient of approximately 3°C across the country was discernible after interpolating among stations, with higher temperatures in the Northwest, corresponding with the region of highest seasonal rainfall totals (Sanderson & Rafique, 2009) and the region of strongest negative soil moisture anomalies during heat waves (Figure 8). However, the urban heat island effect, which is not resolved by the sparse set of meteorological stations, combined with the concentration of human exposure and vulnerability in cities, suggests that heat-related risk is likely to be high in cities.

A global heat wave definition remains elusive. A proposed reference set of climate extremes indices (Tank et al., 2009) includes the monthly maximum of the daily minimum and maximum temperatures and the number of days with minimum/maximum temperatures above the 90th percentile. These indices are useful for long term monitoring and prediction of changing frequencies in extremes under climate change. The thresholds are chosen to identify moderate extremes, not the most severe events, and do not incorporate vulnerability information. Their usefulness for operational forecasting and early warnings is therefore limited. Moreover, the coincidence of high day- and night-time temperatures is not accounted for, despite evidence that both are important for health outcomes.

Operational heat wave definitions vary substantially, with each country (or city) determining their own index and thresholds according to the local climate and the vulnerability of their population. However, in general there are many commonalities, and this recommendation is consistent with definitions used elsewhere (McGregor et al., 2015). In France for example, daily minimum and maximum temperatures must remain elevated for three days to declare a heat wave, but temperature thresholds are determined for each sub-region according to local mortality data (McGregor et al., 2015). Regional or city-scale thresholds should be pursued in Bangladesh if sufficient mortality and temperature data are available. For a regional comparison, the operational heat wave definition employed in neighbouring India does not consider night-time temperatures (National Disaster Management Authority, 2016). However, this definition is based on meteorological criteria and is not tailored for public health issues.

6.2. **Predicting heat waves**

The climate analyses presented here paint a coherent picture of heat wave occurrence in Bangladesh. Circulation during heat waves is characterised by stronger-than-normal low-level westerly winds bringing hot, dry air from Northern India, and weaker-than-normal southerlies. This wind pattern develops up to 10 days in advance of a heat wave and is consistent with the occurrence of northwesterly “loo” winds, which advect heat from Pakistan and have been associated with heat waves in northern India (Pattanaik, Mohapatra, Srivastava, & Kumar, 2016). This synoptic circulation limits the import of moisture from the Bay of Bengal and reduces relative humidity, resulting in a suppression of normal pre-monsoon rainfall in the days immediately prior to a heat wave, evidenced by sharply declining negative daily anomalies of soil moisture and precipitation. An anticyclonic anomalous circulation in the mid-level atmosphere (500hPa) is also associated with heat wave days. Heat wave predictability on the weather timescale therefore arises from a combination of an absence of rainfall that normally falls at this time of year, and a characteristic and related circulation anomaly.

The weather pattern associated with heat wave days (stronger dry westerly winds and weaker moist southerlies) occurs over a background of drier-than-normal conditions, with below-average soil moisture and accumulated rainfall for as long as sixty days in advance of a heat wave (Figure 9 and Figure 12). Heat wave days are more frequent during years with lower total rainfall and soil moisture between April and June, and less frequent in the reverse case (Figure 13). Dry conditions are conducive to high temperatures, as low surface water availability reduces latent heating, shifting the partition of surface heat fluxes in favour of sensible over latent heat and allowing temperatures to rise further than when surface moisture is high. In drier-than-normal years, very hot conditions thus arise more easily once the characteristic circulation pattern develops.

The strong persistence of negative soil moisture and accumulated precipitation anomalies before heat waves suggests that seasonal heat wave predictions may be possible. However, even without accurate seasonal rainfall forecasts, monitoring soil moisture conditions could enable extended range forecasts of heat wave risk on sub-seasonal timescales. Soil moisture is less variable than precipitation and changes are easier to detect above the noise of daily variations.

With only 23 years of data, the estimation of soil moisture percentiles used to define dry soil moisture conditions is approximate. The general pattern is clear, but the exact numbers should not be relied upon. Moreover, the 20th percentile of soil moisture would be crossed too frequently to act a sensible trigger for a sub-seasonal early warning system, and would lead to many false alarms. A longer time series of temperature observations would enable the computation of increases in heat wave risk following more extreme soil moisture deficits.

Forecasts provided further than about two weeks in advance cannot pinpoint the precise location or day on which an event may occur (Letson et al., 2007). Rather, such forecasts can only indicate the chance of occurrence at some point over an area (Vitart et al., 2014). For now, weather forecasts may be the appropriate basis for most preparatory measures, with soil moisture monitoring providing indications of increased risk in the near-term.

To rule out the possibility of the anomaly composites being dominated by a few days with strong signals, and to allow a closer comparison with the monthly climatology to aid interpretation, the analyses were repeated for separate months. This did not affect our conclusions. The decision to weight the composites by heat wave duration is justified given the important role that duration plays in heat wave impacts, contributing non-linearly to total mortality in some cases (McGregor et al., 2015; Tan et al., 2007). Repeating the analyses including only the first day of each heat wave produced soil moisture and precipitation anomalies of the same sign, but lower in magnitude and showing less persistence, than those with all heat wave days. We therefore infer that longer-duration heat waves are associated with more extreme dry conditions than shorter events.

7. Conclusions

This study proposes a definition for heat waves that is associated with increases in mortality in Bangladesh. We recommend using the *day-and-night* index, which defines a heat wave as elevated day- and night-time temperatures above the 95th percentile for three consecutive days. This definition results in 39 heat wave days (13 separate heat waves) in 23 years, from 1989-2011. Almost all heat waves occur during the hot pre-monsoon summer season, between April and June, with most in May. An early warning system requires a threshold for triggering heat wave warnings that is both related to human health outcomes and predictable using available weather and climate information. The recommended heat wave index (*day-and-night,* Table 1) is a statistically significant predictor of mortality in Bangladesh. Mortality increased by about 20% during heat waves defined by this indicator, a result which can be used to motivate public health interventions to prevent heat-related deaths. The index is simple to calculate, with minimal data requirements, and results indicate the potential for extreme heat forecasts from weather to seasonal timescales.

At present, weather forecasts for heat wave risk are not issued in Bangladesh, and such forecasts would be an obvious first step. At the lead times needed for weather forecasts (several days), this study has revealed the strengthening of dry low-level westerly winds from India and the weakening of moisture-laden southerly winds during the pre-monsoon season as precursors of heat wave occurrence. The low-level circulation pattern occurs in conjunction with anomalous anticyclonic circulation in the mid-atmosphere, centred over central-eastern India.

Extending the lead-time of forecasts beyond the weather timescale offers valuable additional time to implement disaster preparedness measures. This study has demonstrated that heat wave predictability in Bangladesh exists on sub-seasonal to seasonal timescales. Predictability arises from the absence of pre-monsoonal rainfall and can be harnessed through monitoring or forecasting soil moisture. Sub-seasonal forecasts based on below-normal soil moisture could raise the alert for heightened risk of extreme heat in the coming month, prompting closer monitoring of weather forecasts with more detailed spatial and temporal information about the hazard. More investigation is needed to predict where the impacts will be greatest and to target preparedness measures appropriately, but the concentration of human exposure and vulnerability in cities gives a logical focal point for such interventions.

A thorough understanding of exposure and vulnerability to heat is an important component of a successful heat early warning system. Further work is needed to demonstrate the human cost of extreme heat in Bangladesh, including in specific locations and especially urban contexts. However, this should not limit the ambition of policy makers wishing to take action to prevent unnecessary mortality during periods of hot weather. It has already been shown that high temperatures lead to increased mortality in Bangladesh, and that the elderly, children, men and urban populations are most at risk (Burkart et al., 2011a,b, 2014a,b; Burkart & Endlicher, 2011). Experience from heat early warning systems developed recently in India has shown that many common sense measures can be taken with relatively little advanced warning (Indian Institute of Public Health Ganghinagar et al., n.d.).

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Tables

Index name	Condition(s)	Minimum duration	Number of heat wave days	Number of heat waves
Day	$Tmax > Tmax_{95}$	3 consecutive days	218	59
Day-and-night	$Tmax > Tmax_{95}$ and $Tmin > Tmin_{95}$	3 consecutive days	39	13
Humid-day	$HImax > HImax_{95}$	3 consecutive days	111	40
Humid-day-and-night	$HImax > HImax_{95}$ and $HImin > HImin_{95}$	3 consecutive days	43	17
Average-temperature	$Tav > Tav_{95}$	3 consecutive days	174	57
Average-heat-index	$HIav > HIav_{95}$	3 consecutive days	145	47

Table 1 Definitions of the six binary indicators tested. Tmax (Tmin) and HImax (HImin) are daily maximum (minimum) temperature and heat index, respectively, and the subscript '95' indicates the 95th percentile of daily values defined over all days between 1989 and 2011. $Tav = 0.5 \times \sum[Tmin + Tmax]$ and $HIav = 0.5 \times \sum[HImin + HImax]$. Heat wave days are days that meet the criteria for an indicator given in the table, irrespective of whether these occur consecutively, while a heat wave consists of any number of consecutive heat wave days, and must be separated from other heat waves by at least one day.

Indicator	Mortality increase on heat wave days (%)	p-value	Mortality increase on heat wave days plus the two preceding days (%)	p-value
Day-and-night	22.3 (8.2-38.2)	0.001	18.8 (10.7-27.5)	<0.001
Day	10.4 (2.3-19.1)	0.010	11.8 (10.7-16.8)	<0.001
Humid-day-and-night	24.0 (9.8-40.2)	<0.001	16.8 (8.7-25.5)	<0.001
Humid-day	16.8 (3.2-29.7)	0.004	10.1 (3.8-17.1)	0.002
Average-temperature	17.8 (7.3-29.4)	<0.001	14.1 (8.0-20.5)	<0.001
Average-heat-index	10.8 (1.6-20.8)	0.102	8.5 (3.2-14.1)	0.001

Table 2 Percentage increases in mortality during heat wave days compared with non-heat wave days. Estimates including 95% confidence intervals (displayed in parentheses) and p-values are determined for the mortality increase associated with heat wave days only as well as for the mortality increase associated with the sum of deaths occurring on heat wave days plus the two previous days, since a heat wave day is defined on the third consecutive day of hot weather.

Figure Captions

Figure 1 Locations of the 35 Bangladesh Meteorological Department weather stations

Figure 2 Smoothed seasonal cycle of country-averaged daily a) minimum/maximum (grey lines) and mean (black line) temperatures, from BMD station data, and (b) NCDC precipitation (solid line, mm) and ERA Interim relative humidity (dotted line, %) at 950hPa. During the hot season (April to June), average minimum and maximum temperatures across the country ranged from 23.0 to 25.8°C and from 31.3 to 35.3°C, respectively. During this season, temperatures tend to be highest in the west, while precipitation occurs throughout the country but is strongest in the northeast (Sanderson & Rafique, 2009).

Figure 3 Seasonality of heat-wave occurrence according to the a) day-and-night and b) humid-day-and-night indicators. Black circles show the average number of heat wave days, with whiskers indicating the maximum/minimum numbers per month across all years (1989-2011).

Figure 4 (a) Annual number of day-and-night (black bars) and humid-day-and-night (grey bars) heat waves from 1989 to 2011. (b) Duration of day-and-night (black bars) and humid-day-and-night (grey bars) heat waves in days. Only heat waves lasting three days or longer are counted in the analyses presented in this study (Table 1). Most hot days occur in isolation rather than as part of a heat wave lasting several days.

Figure 5 Average wind climatology (1989-2011) between April and June at (a) 850hPa and (b) 500hPa levels. Anomaly composites of wind vectors during day-and-night heat waves at (c) 850hPa and (d) 500hPa levels. Wind data are from the ECMWF ERA Interim reanalysis, anomalies are relative to smoothed daily climatology in each grid and the anomaly composites are weighted by heat wave duration.

Figure 6 ERA Interim vertical wind anomaly composites during day-and-night heat waves at (a) 500 hPa, (b) 600 hPa and (c) 700 hPa levels. Units are $hPas^{-1}$, with positive values indicating subsidence. Anomalies are relative to smoothed daily climatology (1989-2011) in each grid and anomaly composites are weighted by heat wave duration. For reference, the standard deviation of the country-averaged daily vertical wind anomaly between 500 and 700 hPa is 0.06 $hPas^{-1}$, from April to June 1989-2011.

Figure 7 Anomaly composites of (a) vertically integrated moisture flux divergence ($kgm^{-2}s^{-1}$) and (b) relative humidity (%) during day-and-night heat waves. Anomalies are relative to smoothed daily climatology (1989-2011) in each grid and anomaly composites are weighted by heat wave duration. Data are from the ECMWF ERA Interim reanalysis. For reference, the standard deviation of the country-averaged daily (a) vertically integrated moisture flux divergence anoamly is $4x10^{-4}$ $kgm^{-2}s^{-1}$ and (b) relative humidity anomaly is 8%, from April to June 1989-2011.

Figure 8 Soil moisture anomaly composites (m^3m^{-2}) at different lead times from 0 to 30 days in advance of day-and-night heat waves. Anomalies are relative to smoothed daily climatology (1989-2011) in each grid and anomaly composites are weighted by heat wave duration. Data are from the ECMWF ERA Interim reanalysis. For reference, the standard deviation of the country-averaged daily soil moisture anomaly is 0.03 m^3m^{-2}, between April and June 1989-2011.

Figure 9 Anomalous values of Bangladesh total (a) soil moisture (m^3m^{-2}), (b) precipitation (mm) and c) relative humidity (%) at 950 hPa, shown as a function of lead-time before the first day of a day-and-night heat wave. Data are from the ECMWF ERA Interim reanalysis. Anomalies are relative to smoothed daily climatologies (1989-2011) and anomaly composites are weighted by heat wave duration. Confidence intervals were computed using bootstrap sampling of heat wave days with replacement, with 1000 samples. For reference, the standard deviations of the country-averaged daily soil moisture, precipitation and relative humidity anomalies are 0.03 m^3m^{-2}, 9 mm, and 8 %, between April and June 1989-2011.

Figure 10 Daily ERA Interim 850 hPa wind anomaly composites (m/s) shown (a) on the first day of a day-and-night heat wave, and (b) 5 days, (c) 8 days and (d) 10 days before the heat wave starts. Anomalies are relative to a smoothed daily climatology (1989-2011) of wind vectors and anomaly composites are weighted by heat wave duration. For reference, the standard deviations of the country-averaged daily 850 hPa wind speed is 2 ms^{-1}, between April and June 1989-2011.

Figure 11 Relative odds of (a) a day-and-night and (b) a humid-day-and-night heat wave occurring following 5 to 30-day soil moisture deficits between April and June. Soil moisture deficits are defined when total soil moisture summed over 5-30 days is below the 20th percentile of annual values for each day of the year, and relative odds were weighted by heat wave duration. Error bars show the 5th and 95th percentiles from 1000 heat wave distributions generated by bootstrap sampling.

Figure 12 Accumulated country-total NCDC precipitation anomaly (mm), shown as a function of lead time before the first day of a day-and-night heat wave. Anomalies are relative to smoothed daily climatology (1989-2011) and are weighted by heat wave duration. Confidence intervals were computed using bootstrap sampling of heat wave days with replacement, with 1000 samples.

Figure 13 Total April to June (AMJ) number of heat wave days (bars) for (a) day-and-night and (b) humid-day-and-night heat waves, and total AMJ precipitation (mm, solid line) and soil moisture (m^3m^{-2}, dashed line). Soil moisture and precipitation in (a) and (b) are the same. Correlations between total AMJ number of heat wave days and total AMJ precipitation and soil moisture were -0.3 (p=0.1) and -0.6 (p=0.0), respectively, for day-and-night heat waves. For humid-day-and-night heat waves these correlations were -0.4 (p=0.1) and -0.5 (p=0.0), respectively.

Figures

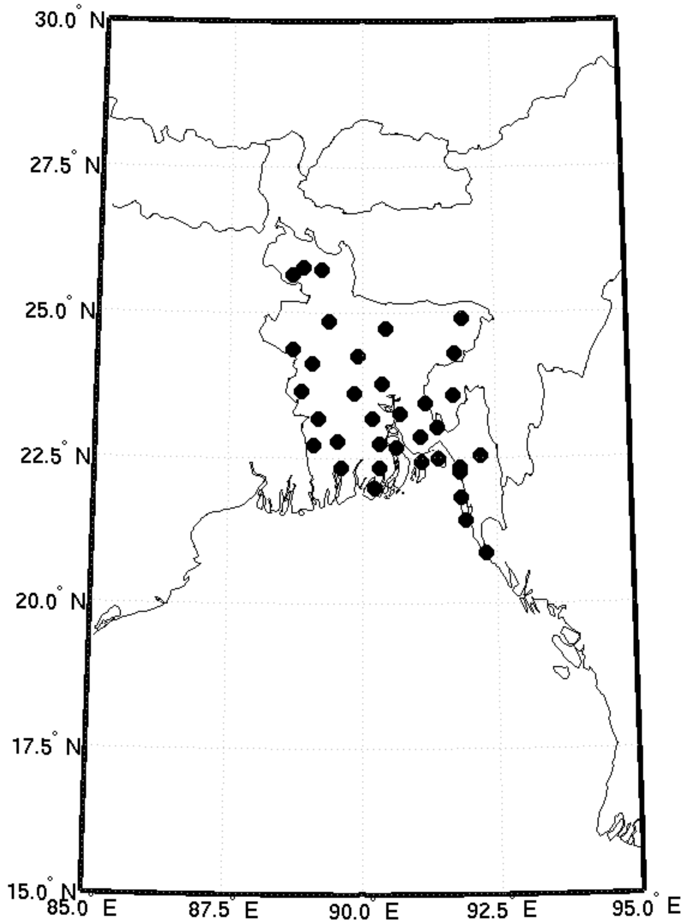

Figure 1 Locations of the 35 Bangladesh Meteorological Department weather stations

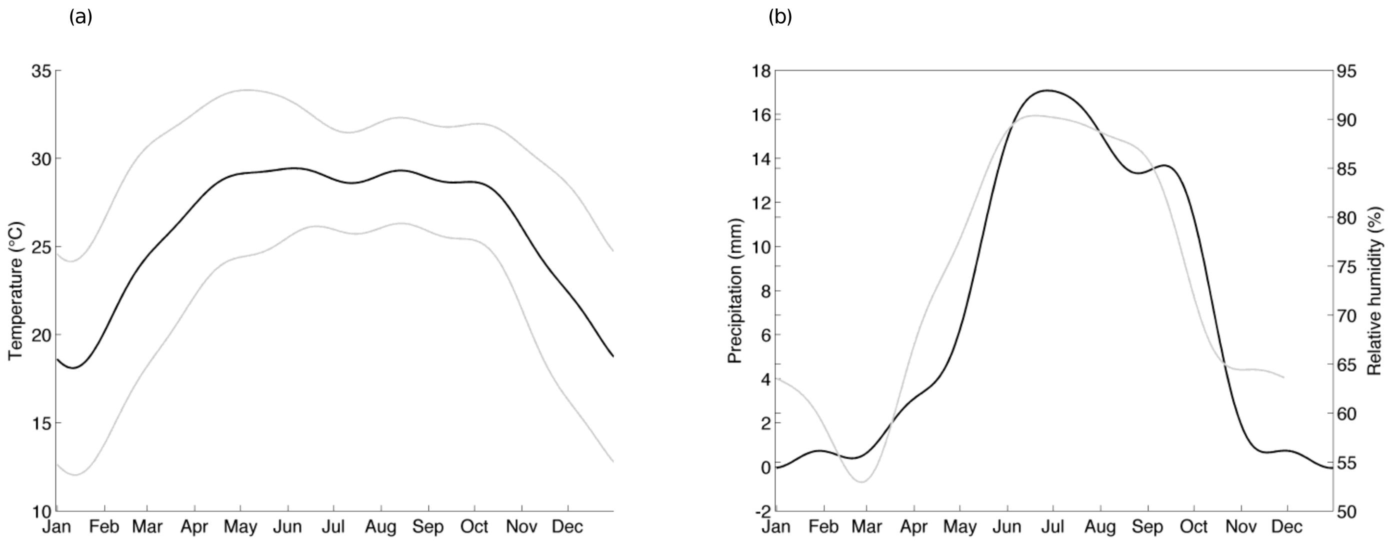

Figure 2 Smoothed seasonal cycle of country-averaged daily a) minimum/maximum (grey lines) and mean (black line) temperatures, from BMD station data, and (b) NCDC precipitation (solid line, mm) and ERA Interim relative humidity (dotted line, %) at 950hPa. During the hot season (April to June), average minimum and maximum temperatures across the country ranged from 23.0 to 25.8°C and from 31.3 to 35.3°C, respectively. During this season, temperatures tend to be highest in the west, while precipitation occurs throughout the country but is strongest in the northeast (Sanderson & Rafique, 2009).

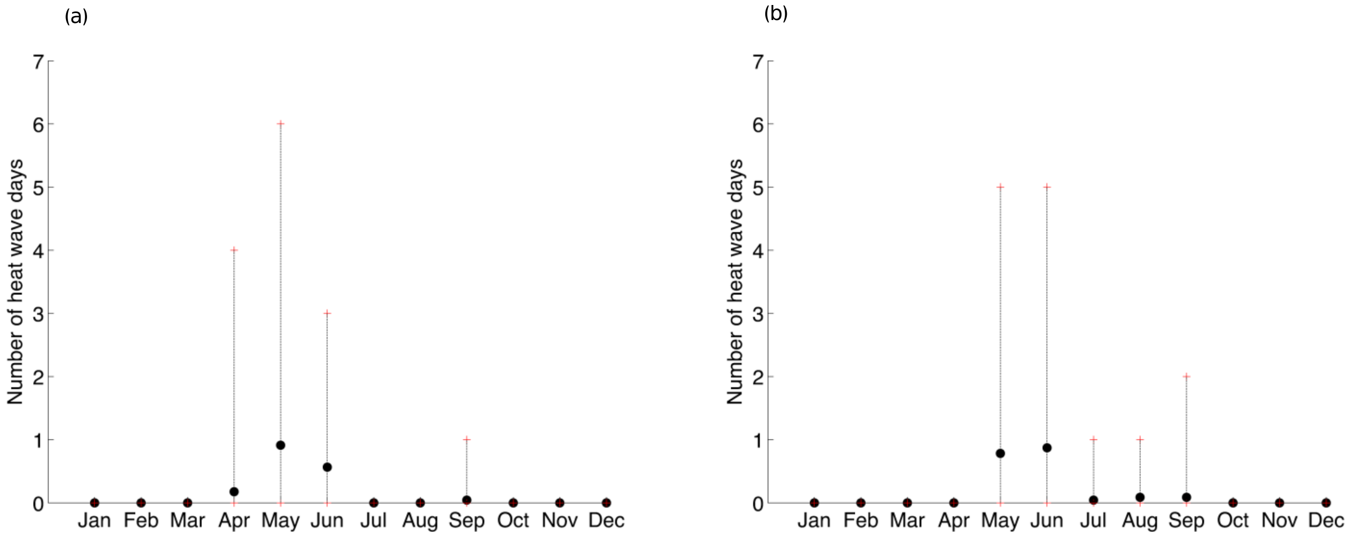

Figure 3 Seasonality of heat-wave occurrence according to the a) day-and-night and b) humid-day-and-night indicators. Black circles show the average number of heat wave days, with whiskers indicating the maximum/minimum numbers per month across all years (1989-2011).

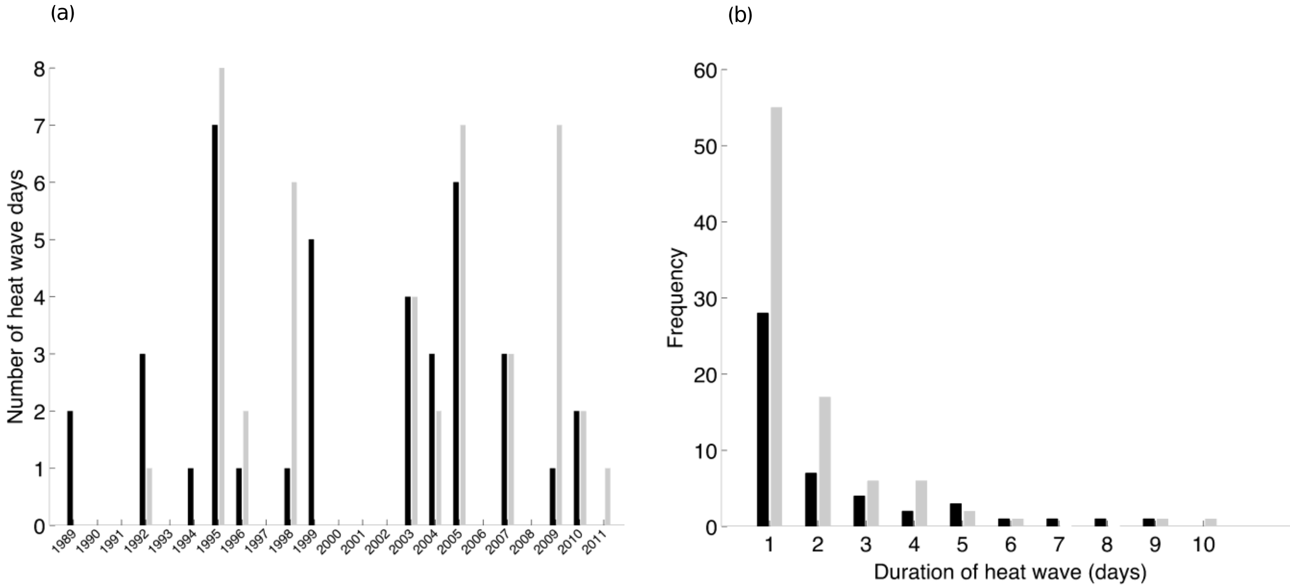

Figure 4 (a) Annual number of day-and-night (black bars) and humid-day-and-night (grey bars) heat waves from 1989 to 2011. (b) Duration of day-and-night (black bars) and humid-day-and-night (grey bars) heat waves in days. Only heat waves lasting three days or longer are counted in the analyses presented in this study (Table 1). Most hot days occur in isolation rather than as part of a heat wave lasting several days.

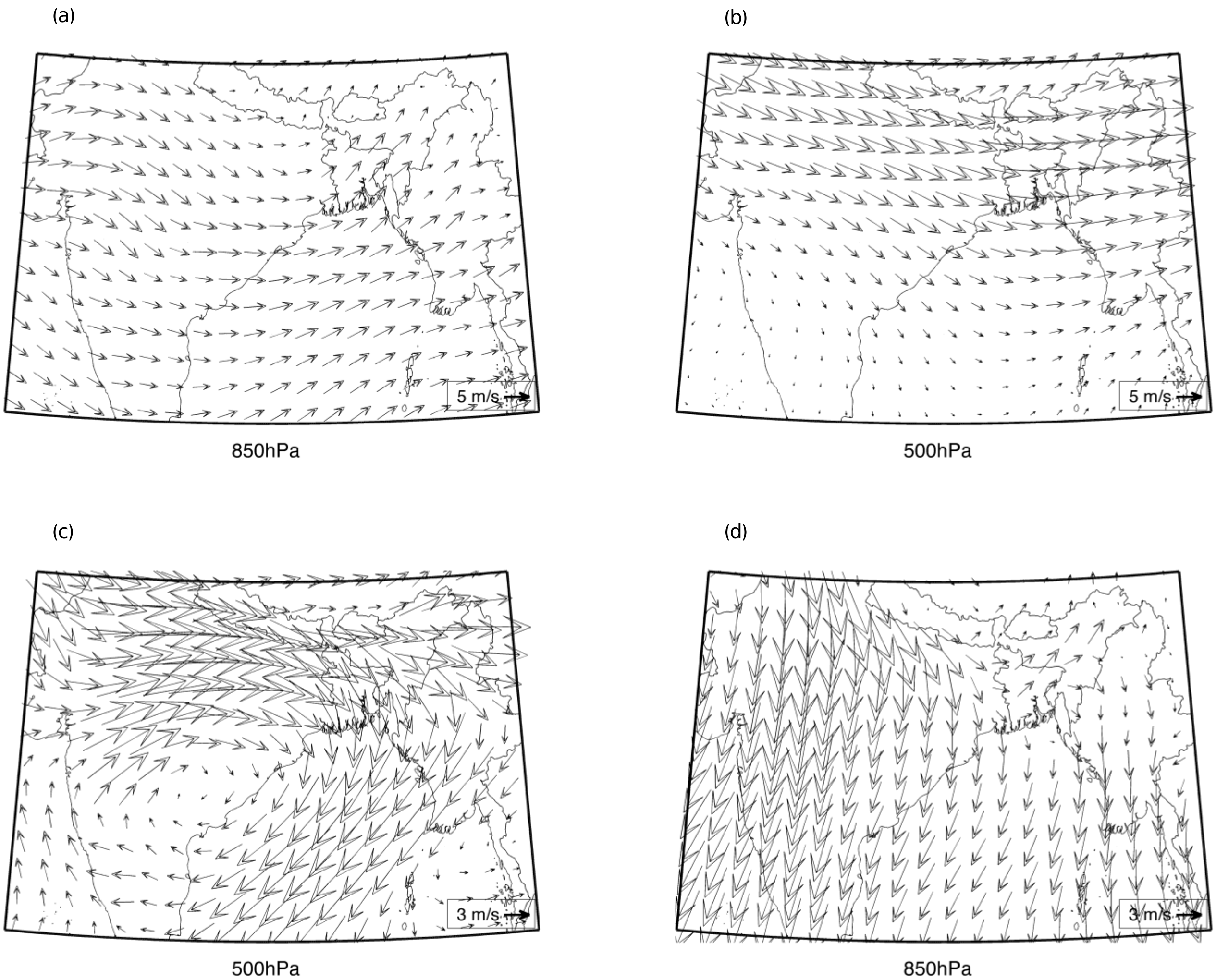

Figure 5 Average wind climatology (1989-2011) between April and June at (a) 850hPa and (b) 500hPa levels. Anomaly composites of wind vectors during day-and-night heat waves at (c) 850hPa and (d) 500hPa levels. Wind data are from the ECMWF ERA Interim reanalysis, anomalies are relative to smoothed daily climatology in each grid and the anomaly composites are weighted by heat wave duration.

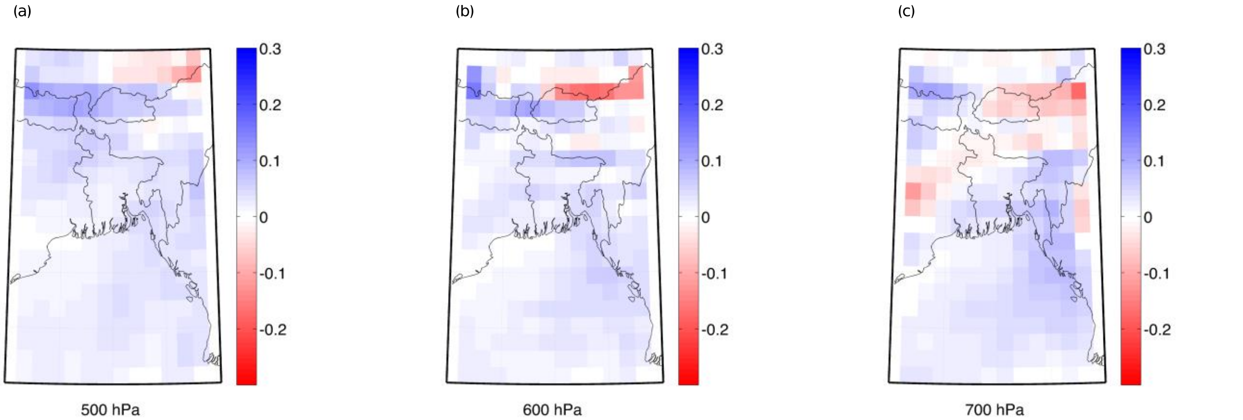

Figure 6 ERA Interim vertical wind anomaly composites during day-and-night heat waves at (a) 500 hPa, (b) 600 hPa and (c) 700 hPa levels. Units are hPas^{-1}, with positive values indicating subsidence. Anomalies are relative to smoothed daily climatology (1989-2011) in each grid and anomaly composites are weighted by heat wave duration. For reference, the standard deviation of the country-averaged daily vertical wind anomaly between 500 and 700 hPa is 0.06 hPas^{-1}, from April to June 1989-2011.

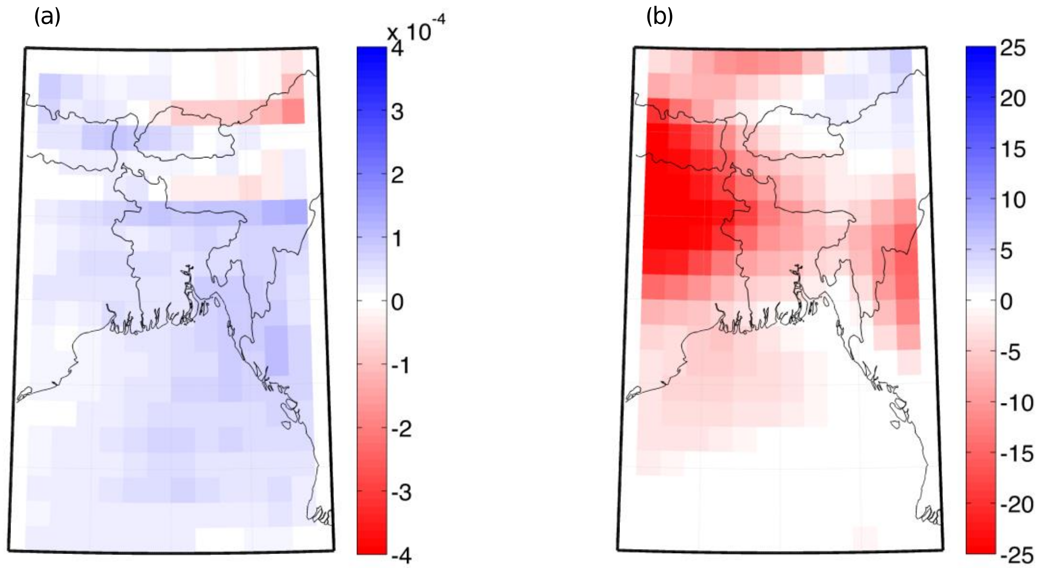

Figure 7 Anomaly composites of (a) vertically integrated moisture flux divergence (kgm^{-2}s^{-1}) and (b) relative humidity (%) during day-and-night heat waves. Anomalies are relative to smoothed daily climatology (1989-2011) in each grid and anomaly composites are weighted by heat wave duration. Data are from the ECMWF ERA Interim reanalysis. For reference, the standard deviation of the country-averaged daily (a) vertically integrated moisture flux divergence anoamly is 4x10^{-4} kgm^{-2}s^{-1} and (b) relative humidity anomaly is 8%, from April to June 1989-2011.

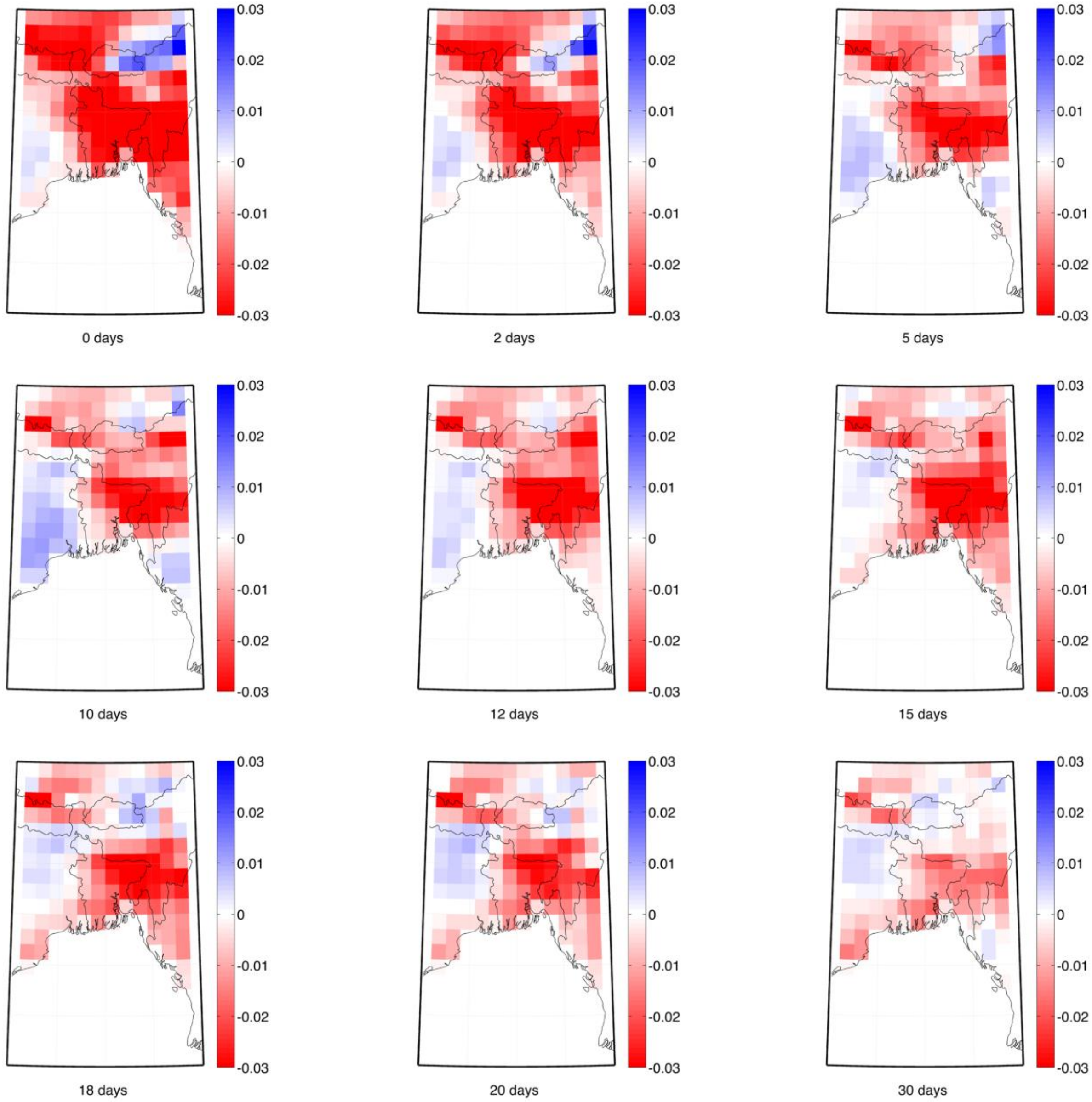

Figure 8 Soil moisture anomaly composites (m^3m^{-2}) at different lead times from 0 to 30 days in advance of day-and-night heat waves. Anomalies are relative to smoothed daily climatology (1989-2011) in each grid and anomaly composites are weighted by heat wave duration. Data are from the ECMWF ERA Interim reanalysis. For reference, the standard deviation of the country-averaged daily soil moisture anomaly is 0.03 m^3m^{-2}, between April and June 1989-2011.

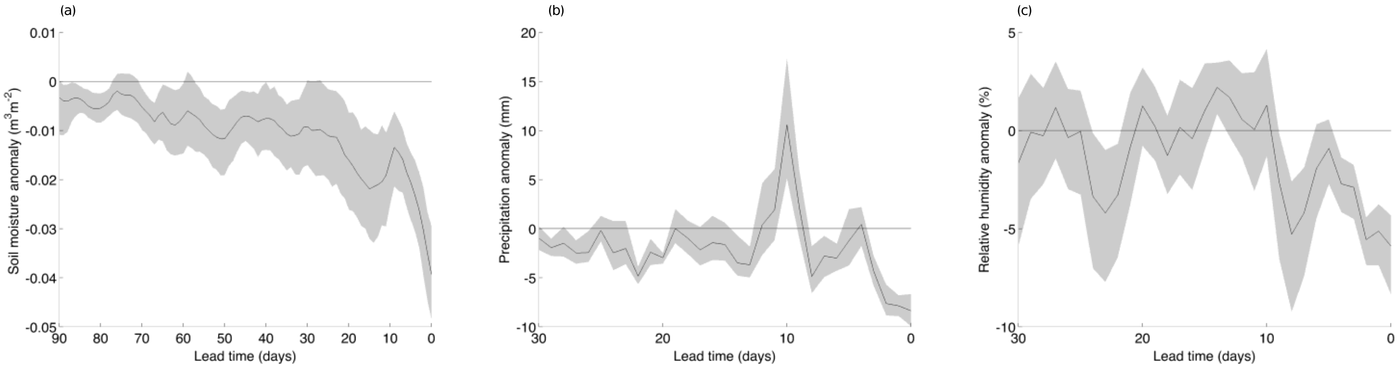

Figure 9 Anomalous values of Bangladesh total (a) soil moisture (m^3m^{-2}), (b) precipitation (mm) and c) relative humidity (%) at 950 hPa, shown as a function of lead-time before the first day of a day-and-night heat wave. Data are from the ECMWF ERA Interim reanalysis. Anomalies are relative to smoothed daily climatologies (1989-2011) and anomaly composites are weighted by heat wave duration. Confidence intervals were computed using bootstrap sampling of heat wave days with replacement, with 1000 samples. For reference, the standard deviations of the country-averaged daily soil moisture, precipitation and relative humidity anomalies are 0.03 m^3m^{-2}, 9 mm, and 8 %, between April and June 1989-2011.

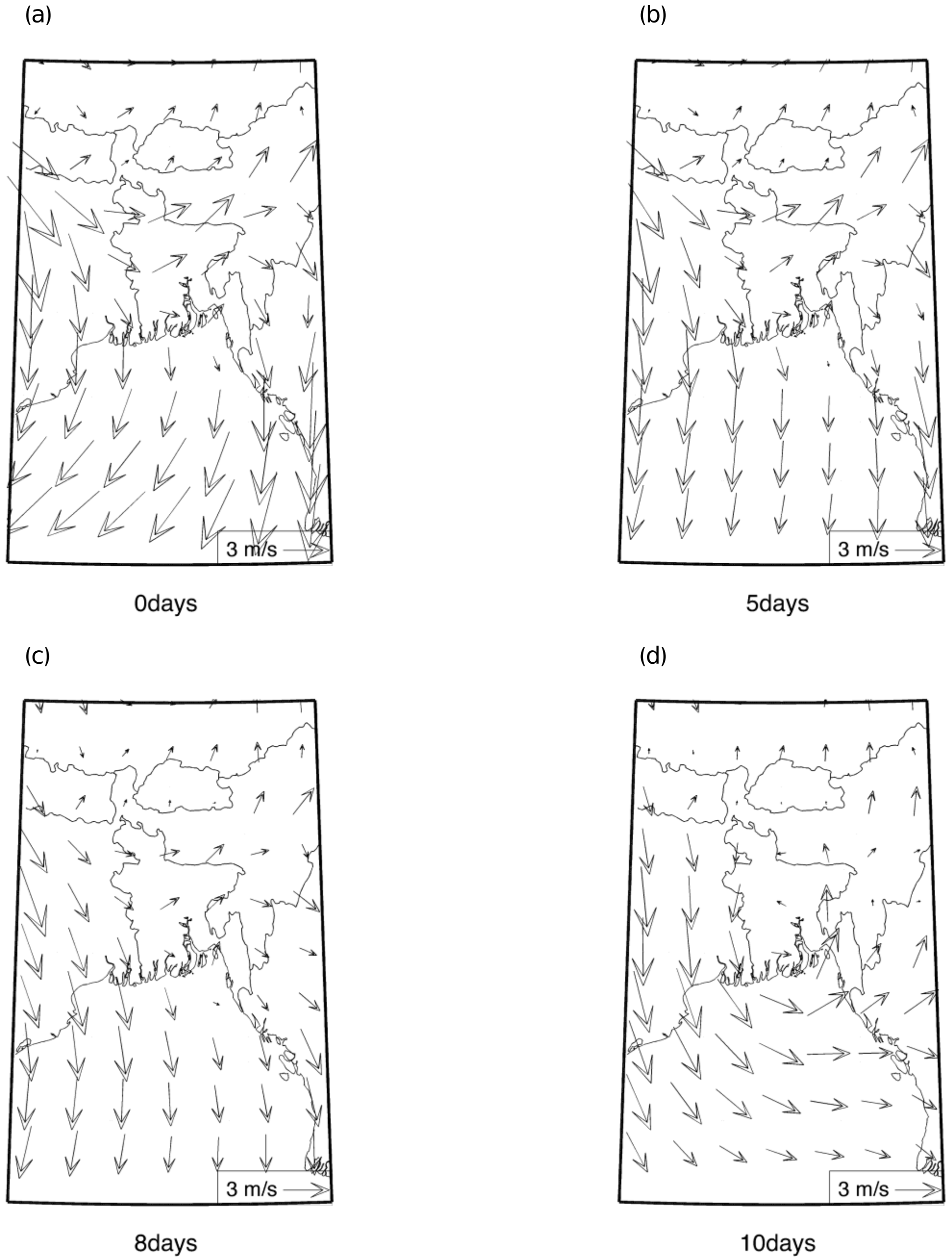

Figure 10 Daily ERA Interim 850 hPa wind anomaly composites (m/s) shown (a) on the first day of a day-and-night heat wave, and (b) 5 days, (c) 8 days and (d) 10 days before the heat wave starts. Anomalies are relative to a smoothed daily climatology (1989-2011) of wind vectors and anomaly composites are weighted by heat wave duration. For reference, the standard deviations of the country-averaged daily 850 hPa wind speed is 2 ms^{-1}, between April and June 1989-2011.

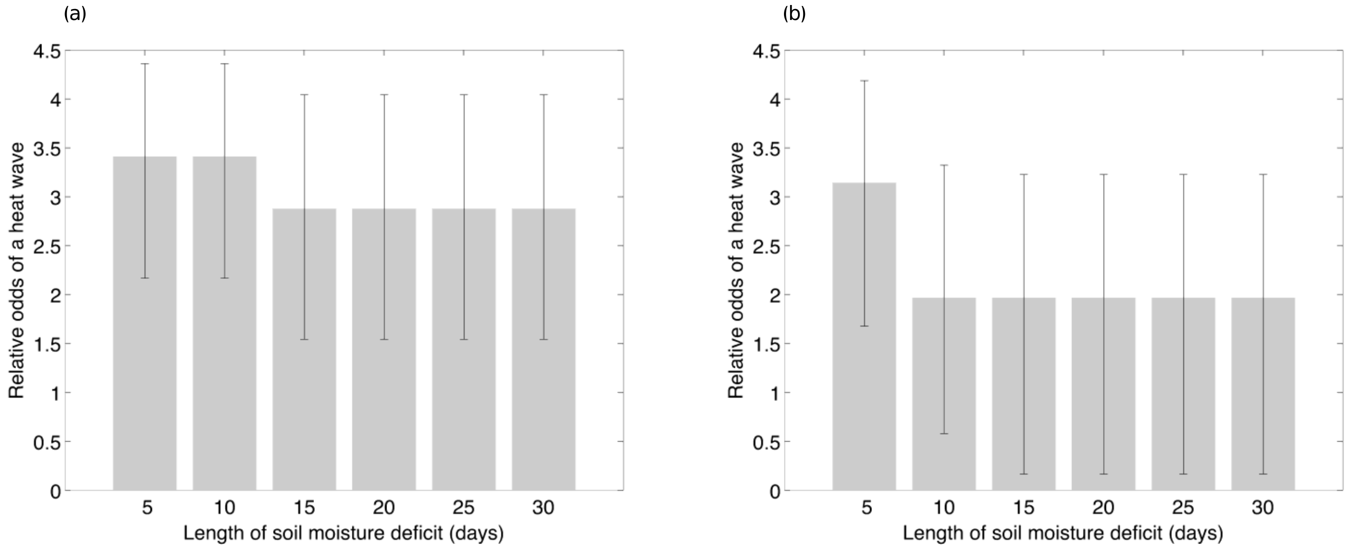

Figure 11 Relative odds of (a) a day-and-night and (b) a humid-day-and-night heat wave occurring following 5- to 30-day soil moisture deficits between April and June. Soil moisture deficits are defined when total soil moisture summed over 5-30 days is below the 20th percentile of annual values for each day of the year, and relative odds were weighted by heat wave duration. Error bars show the 5th and 95th percentiles from 1000 heat wave distributions generated by bootstrap sampling.

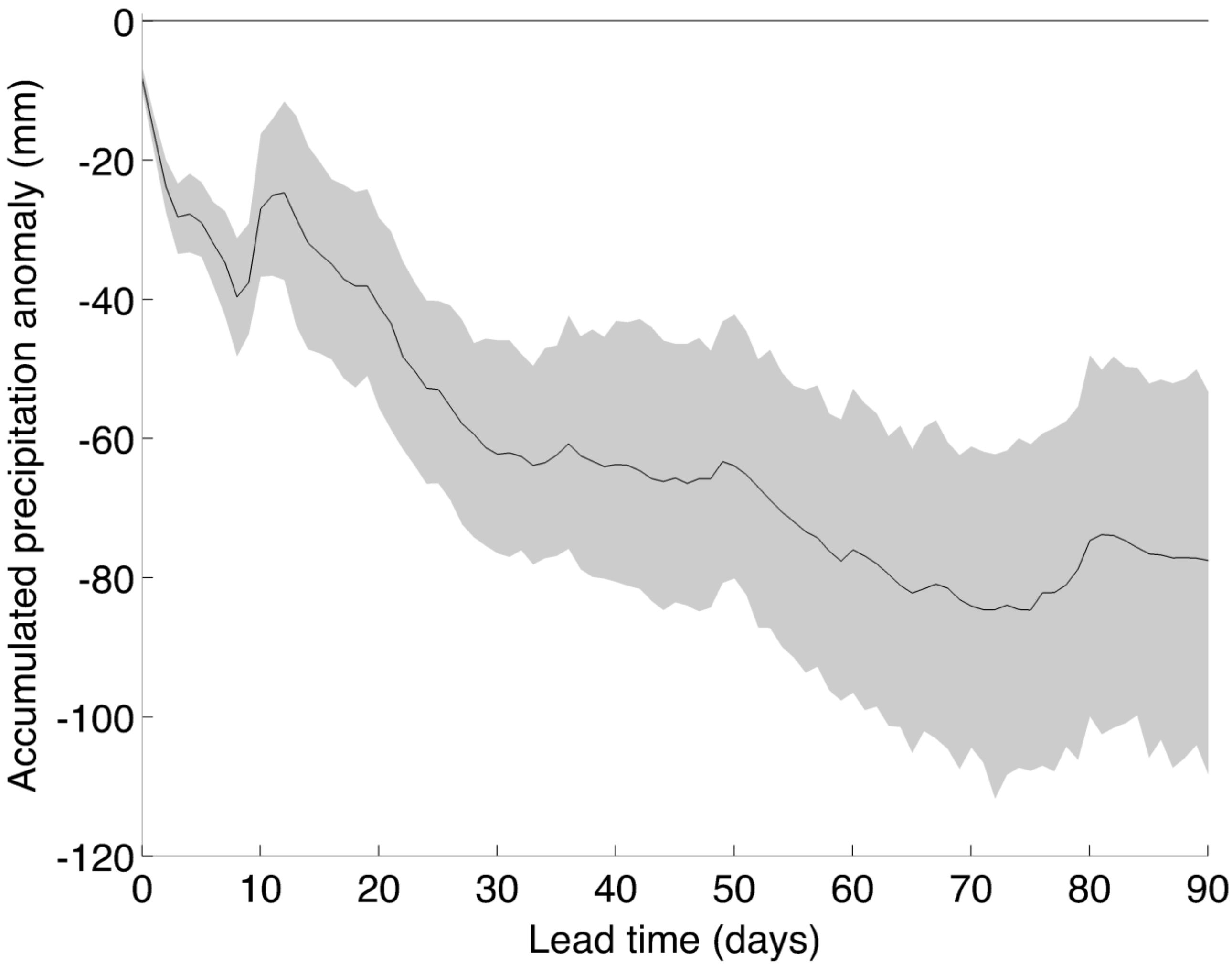

Figure 12 Accumulated country-total NCDC precipitation anomaly (mm), shown as a function of lead time before the first day of a day-and-night heat wave. Anomalies are relative to smoothed daily climatology (1989-2011) and are weighted by heat wave duration. Confidence intervals were computed using bootstrap sampling of heat wave days with replacement, with 1000 samples.

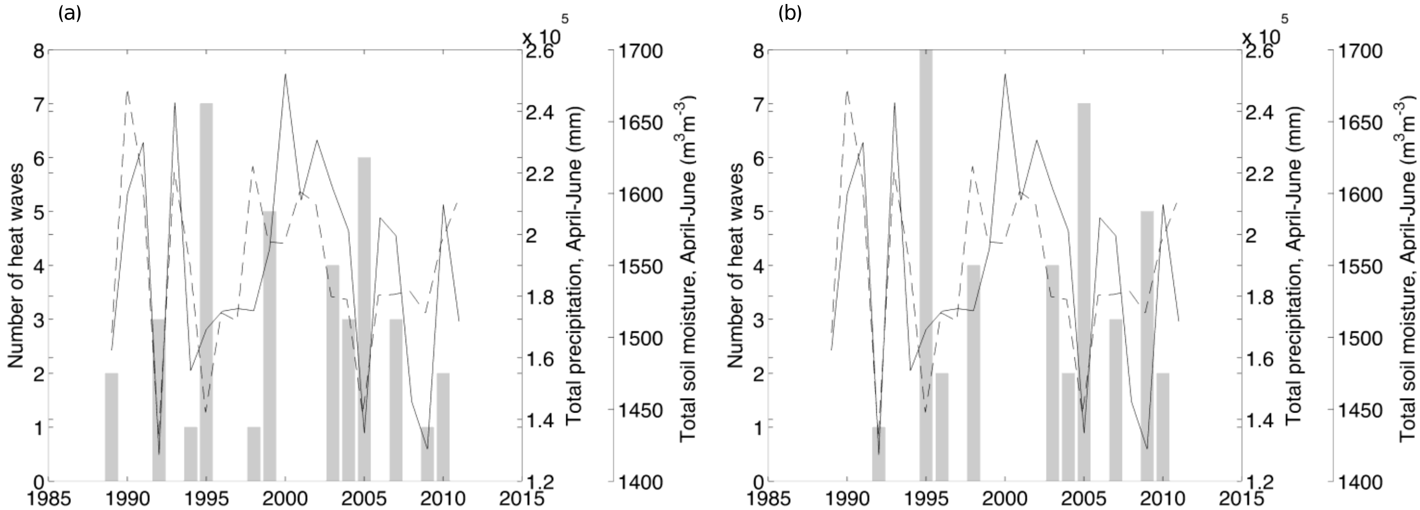

Figure 13 Total April to June (AMJ) number of heat wave days (bars) for (a) day-and-night and (b) humid-day-and-night heat waves, and total AMJ precipitation (mm, solid line) and soil moisture (m^3m^{-2}, dashed line). Soil moisture and precipitation in (a) and (b) are the same. Correlations between total AMJ number of heat wave days and total AMJ precipitation and soil moisture were -0.3 (p=0.1) and -0.6 (p=0.0), respectively, for day-and-night heat waves. For humid-day-and-night heat waves these correlations were -0.4 (p=0.1) and -0.5 (p=0.0), respectively.