Risks of seasonal extreme rainfall events in Bangladesh under 1.5 and 2.0 degrees' warmer worlds – How anthropogenic aerosols change the story?

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Abstract. Anthropogenic climate change is likely to increase ~~the frequency~~ risk of extreme weather events in the future. The term 'risk' here means the probability of occurrence of a hazard, e.g., an extreme rainfall event that can trigger sudden flash-flood, landslide or flood. Previous studies have robustly shown how and where climate change has already changed the risks of weather extremes. However, developing countries have been somewhat underrepresented in these studies, despite high vulnerability and limited capacities to adapt. How additional global warming would affect the future risks of extreme rainfall events in Bangladesh needs to be addressed to limit adverse impacts. Our study focuses on understanding and quantifying the relative risks of extreme rainfall events in Bangladesh under the Paris Agreement temperature goals of 1.5°C and 2°C warming above pre-industrial levels. In particular, we investigate the influence of anthropogenic aerosols on these risks given their likely future reduction and resulting amplification of global warming. Using large ensemble regional climate model simulations from weather@home under different forcing scenarios, we compare the risks of rainfall events under pre-industrial (natural), current (actual), 1.5°C, and 2.0°C warmer and greenhouse gas (GHG)-only (with pre-industrial levels of anthropogenic aerosols ~~removed~~) conditions. Analysis of percent change, standardized precipitation index and absolute change in seasonal mean rainfall revealed that there both GHGs and anthropogenic aerosols play important roles in determining the overall climate change impact over this region. For extreme rainfall events, we find that the risk of a 1 in 100 year rainfall event has already increased significantly compared with pre-industrial levels across parts of Bangladesh, with additional increases likely for 1.5 and 2.0 degree warming (of up to 5.5 times higher, with an uncertainty range of 3.5 to 7.8 times). Climate change impacts on the probabilities of extreme rainfall events ~~were observed~~ are found during both pre-monsoon and monsoon seasons, ~~periods~~ but ~~were~~ the level of impacts are spatially variable across the country. ~~in terms of the level of impact.~~ Results also show that reduction in anthropogenic aerosols plays an important role in determining the overall future climate change impacts; by exacerbating the effects of GHG induced global warming and thereby increasing the rainfall intensity. We highlight that the net aerosol effect varies from region to region within Bangladesh, which leads to different outcomes of aerosol reduction on extreme rainfall statistics, and must therefore be considered in future risk assessments. Whilst there is a substantial reduction in the impacts resulting from 1.5°C compared with 2°C warming, the difference is spatially and temporally variable, specifically with respect to seasonal extreme rainfall events.

1 Introduction

The 2015 Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC), on "Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C" (UNFCCC, 2015), needs strong support from research on the nature, benefits and feasibility of this challenging goal. This Agreement calls for the quantification and comparison between the impacts of 1.5°C versus 2.0°C warmer global temperatures on different climate related aspects such as extreme weather events. While assessing both risks and vulnerabilities to incremental increases in global mean temperature, the discrimination of the impacts of different radiative forcing contributions as well as the quantification of spatially varying changes in risk are crucially important. For example, highly unusual heat extremes that are virtually absent in the present climate in South Asia, would affect around 15% of land area of this region under 1.5°C and around 20% of land area under 2°C warming (The World Bank, 2012). The increase in heavy monsoon rainfall intensity for South Asia is projected to be 7% under 1.5°C and 10% under 2°C warming compared to pre-industrial conditions (Schleussner et al., 2016). Populations of this region largely depend on the stability of the monsoon, which provides water resources for agricultural production (The World Bank, 2012). It is projected that the years with above-normal monsoon rainfall will be more frequent (Endo et al., 2013; Kripalani et al., 2007). The seasonality of rainfall will be amplified with more rainfall during the wet season (Fung et al., 2011; Turner and Annamalai, 2012). The number of extreme rainfall events are projected to increase as well (Endo et al., 2012; Kumar et al., 2011 in Vinke et al., 2017). As a consequence of additional global warming, parts of East Asia and India are likely to have more frequent daily extreme rainfall events in monsoon season (Chevuturi et al., 2018). Here we assess whether these generalized projections are also valid using a large ensemble regional climate model framework focusing on Bangladesh.

Bangladesh is potentially a hotspot of climate change impacts as it is vulnerable to a combination of increasing challenges from record-breaking temperatures, extreme rainfall events, more intense river floods, tropical cyclones, and rising sea levels (The World Bank, 2012). Bangladesh has a tropical monsoon climate, flat and low-lying topography, and unique geographical location in the Ganges-Brahmaputra-Meghna Basin (Banglapedia, 2012; Rawlani and Sovacool, 2011). For these features, heavy rainfall events in the pre-monsoon (Mar-May) and monsoon (Jun-Sep) seasons are associated with a high risk of flooding and landslides almost every year. ~~In recent years, the frequency of high-intensity rainfall events has shown an increasing trend in the observations.~~ The frequencies of observed high-intensity rainfall events are increasing in the recent years (Murshed et al., 2011). For example, in 2017, heavy rainfall across the upstream Meghalaya hills in India and in Bangladesh caused pre-monsoon floods in March in the northeastern parts of the country. Consequently, vast areas of Haors (local name for lowland wetlands) and low-lying areas were inundated and most of the nearly-harvestable 'Boro' paddy crop (a local high yielding variety of paddy) was damaged (Nirapad, 2017). In June 2017, ~~heavy rain induced floods and landslides killed at least 156 people.~~ at southeastern parts of Bangladesh heavy rainfall caused devastating floods and multiple landslides killing at least 156 people (Paul and Hussain, 2017). National Aeronautics and Space Administration (NASA)'s near-real time Integrated Multi-satellitE Retrievals for Global Precipitation Measurement, GPM (IMERG) data estimated the heaviest rainfall accumulation of more than 510 mm in only 3 days (12-14 June 2017) ~~in southeastern Bangladesh~~ (Gutro, 2017).

Considering the unfolding change in risk of heavy rain in the region under present-day conditions how would a 1.5°C and a 2.0°C warmer world change the probability of extreme rainfall events in Bangladesh? If climate change is already playing a role, then similar events are likely to occur even more frequently as global warming continues in the future (Faust, 2017). Reliable information regarding the relative changes in future risks of extreme rainfall events can help ~~to provide~~ local decision makers to address the problem, develop appropriate adaptation strategies and allocate resources to minimize loss and damage associated with potential climate extremes. ~~A multi global climate model (GCM) ensemble based study conducted for northwestern part of Bangladesh reported ~9% and ~18% increase in mean seasonal rainfall during pre-monsoon (Mar-May) and monsoon (Jun-Sep) seasons respectively by 2090~~ According to global climate model (GCM) ensemble based study, by 2090, the north-western part of Bangladesh would experience ~9% and ~18% increase in the pre-monsoon and monsoon mean rainfall respectively (Kumar et al., 2014). Caesar et al., (2015) used the high resolution (25 km) regional climate model (RCM), HadRM3P that is nested in the global HadCM3 model and projected a large increase in the very heavy daily rainfall events (>99th percentile, i.e., >23.8mm/day) and a decrease in the light-moderate rainfall events (<75th percentile, i.e., <12.3mm/day) during monsoon season (Jun-Sep) over Bangladesh by 2099. According to PRECIS (Providing REgional Climates for Impact Studies) model projection for 2080, the north-eastern ~~parts of~~ Bangladesh would experience 0.42–75% more pre-monsoon rainfall compared to the baseline of 1971–2000

(Nowreen et al., 2015). While previous studies projected future changes in the seasonal mean or extreme rainfall events over a specific part or whole Bangladesh; none had the benefit of using very large model ensembles of high resolution ~~regional climate model~~ RCM to examine exceptionally rare extreme rainfall events (e.g., events with 100-1000 year of return periods); explained whether or not anthropogenic climate change played a role in changing the probabilities of those projected future rainfall events; and explored how anthropogenic aerosols changed the overall climate change impacts on rainfall events. The Fifth Phase Coupled Model Inter-comparison Project (CMIP5) models produced a broad range of temperature projections as a function of model sensitivity (van Vuuren et al., 2011). However, the specified warming targets set in the Paris Agreement were not addressed in those experiments. Hence the Half a degree additional warming, prognosis and projected impacts (HAPPI) framework has been developed, specifically targeted for 1.5°C and 2.0°C warming (Mitchell et al., 2016). There are only a few studies using CMIP5 (e.g., Fahad et al., 2017), or PRECIS (e.g., Nowreen et al., 2015) ~~runs~~ simulations that investigated future changes in ~~the~~ rainfall events over Bangladesh, but none of these have specifically addressed the warming targets of the Paris Agreement. The novelty of this study lies in meeting all these aforementioned challenges.

We considered anthropogenic aerosols in addition to greenhouse gases (GHGs) as a potential contributing factor in changing the risks of extreme rainfall events. Because aerosols can influence regional climate and change the risks of rainfall events by radiative forcing and microphysical effects (Guo et al., 2013; Li et al., 2016). Furthermore, extreme rainfall events have higher sensitivity to aerosols removals, per degree of surface warming, in particular over the major aerosol emission regions like Asia (Samset et al., 2018). Therefore it is important to explore aerosol impacts while assessing the changes in the risks of extreme rainfall events under additional global warming scenarios of 1.5 and 2.0 degrees' of Paris Agreement.

Drawing on the large ensemble of regional climate model (RCM) runs generated with the weather@home system (Guillod et al., 2017; Massey et al., 2015) within the HAPPI experimental framework, ~~here~~ we quantify changing rainfall risks for Bangladesh during MAM and JJAS ~~pre-monsoon (Mar-May; MAM) and monsoon (Jun-Sep; JJAS) seasons. In order to look at local sub-regional scale rainfall risks within Bangladesh, we use sub-regions 1-4 located at north-west (88°-90°E, 24°-26°N), north-east (90.5°-92.5°E, 24°-25.5°N), south-west (89°-91°E, 21.5°-23.5°N) and south-east (91°-93°E, 20.5°-24°N) respectively.~~ The risk of extreme rainfall events is evaluated for a counterfactual 'natural', current 'actual' and future 1.5 and 2.0 degrees warmer climate scenarios, ~~a counterfactual 'natural' scenario as well as~~ a ~~current climate with no anthropogenic aerosols (GHG-only) scenario~~. In particular, ~~the~~ The impact of anthropogenic aerosol emissions is quantified and discussed based on the GHG-only scenario.

We first introduce data and methods in Section 2, whilst a summary of model performance is presented in Section 3.1. ~~2.2. Further details on model evaluation are provided in Rimi et al. (under review).~~ We then assess percentage changes and standardized changes in the seasonal mean rainfall within five forcing scenarios (Natural, Actual, 1.5°C, 2.0°C and GHG-only) in Section 3.2. Finally, in Section 3.3 we ~~explore~~ detect the relative shifts in the probabilities of MAM and JJAS daily and 5-day rainfall extremes ~~during the pre-monsoon and monsoon seasons using return times over the four sub-regions, and identify the relative shifts in the probabilities of extreme rainfall events~~ between the different forcing scenarios. The results are discussed in context of regional vulnerabilities and observed changes in Section 4.

2 Data and Methods

2.1 Observational data

~~Two~~ The daily observational ~~dataset~~ data sets that are used as a comparison against model results include:~~, observational~~ (i) Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) ~~daily rainfall data for the duration of 2006-2015~~ (Yatagai et al., 2012) and (ii) NOAA's Climate Prediction Center (CPC) global 0.5°

analysis ~~of daily rain gauge measurements covering 2006-2015~~ (Chen et al., 2008a). APHRODITE is a ~~the only long-term continental-scale, daily gridded rainfall dataset (available for 1951-2007) with high-resolution grids for Asia;~~ high-resolution daily gridded rainfall dataset for Asia (V1901, available for 1998-2015); created primarily with data obtained from a rain-gauge-observation network. CPC global daily rainfall dataset (available from 1979 to present) is constructed through a unified analysis of gauge-based daily rainfall over global land (Chen et al., 2008b). Basic facts about these two observational data sets are presented in ~~the~~ Table S1 in the supplementary information. ~~APHRODITE and CPC were also used in the model evaluation conducted by Rimi et al., (2019).~~ Both model and observation data is re-gridded using bi-linear interpolation method to have similar and comparable grid structures.

2.2 Model setup and experimental design

The weather@home is part of the climateprediction.net programme (Stainforth et al., 2005) ~~programme~~ and is able to generate very large ensembles of climate model simulations by harnessing spare CPU time on a network of volunteers' personal computers (Allen, 1999; Stott et al., 2004; Massey et al., 2015; Otto, 2017). For this study, we use the high resolution (50 km) RCM, ~~of~~ HadRM3P (over South Asia region) that is nested in the global atmosphere-only HadAM3P model of weather@home system and is driven by prescribed sea surface temperatures (SSTs) and radiative forcing (Massey et al. 2015; Guillod et al. 2017) to generate the required model ensembles with initial condition perturbations. ~~of present-day actual climate conditions (denoted as 'ACT'); the counterfactual world with natural climate conditions of pre-industrial period with no anthropogenic warming influences (denoted as 'NAT'); and the hypothetical world with the GHG-only climate condition where the anthropogenic aerosols are reduced to pre-industrial levels (denoted as 'GHG-only'). Evaluation of the model for the region was conducted by Rimi et al (Rimi et al., 2018), and demonstrated a reasonable agreement between model results and observational datasets for extreme rainfall events. The model is therefore considered fit for purpose in evaluating the potential impacts of climate change.~~

HAPPI experiments are designed to address ~~the~~ research questions relating to 1.5°C and 2.0°C warming and as part of the experiments weather@home system is used to generate large model ensembles (Massey et al., 2015; Otto, 2017; Stainforth et al., 2005). Following the experimental set up of the HAPPI framework (for details see Mitchell et al., 2017), this study uses experiments of three decadal model ensembles:

1. Actual climate (denoted as 'ACT') ~~ACT~~ model ensemble with 98 members per year representing the current decade (2006–2015) with ~~the actual climatic conditions, using~~ observed SST data from the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) dataset (Donlon et al., 2012; Stark et al., 2007) and present-day atmospheric GHG and aerosol concentration.
2. HAPPI 1.5 model ensemble (2091–2100) with 98 members per year representing 1.5°C warmer than pre-industrial (1861–1880) climatic conditions, and
3. HAPPI 2.0 model ensemble (2091–2100) with 98 members per year representing 2.0°C warmer than pre-industrial (1861–1880) climatic conditions.

For the HAPPI 1.5 model ensemble, the RCP 2.6 scenario is used to provide the model boundary conditions. In RCP 2.6 scenario, the mean global temperature reaches to ~1.55°C by 2100 (Mitchell et al., 2017). Since there is no analogous CMIP5 simulation available which results in ~2°C warmer temperatures relative to preindustrial levels, a weighted combination of RCP2.6 and RCP 4.5 is used to provide the model boundary conditions of SST and sea ice for the HAPPI 2.0 model ensemble. The global mean temperature response reaches to ~2.05°C by the end of century in the HAPPI 2.0 model ensemble (Mitchell et al., 2017).

Following the RCP2.6 protocol, anthropogenic aerosol concentrations are approximately ~~1/3th~~ one-third of the current levels (IPCC, 2013) in both HAPPI scenarios.

In addition, we use two model ensembles of hypothetical ~~world~~ climate conditions:

4. Natural ('NAT') ~~NAT~~ model ensemble with 98 members per year representing the current decade (2006–2015) climatic conditions, but here the modelled SST patterns of anthropogenic forcing (ΔSSTs ~~hereinafter~~) are removed from the OSTIA observed SSTs to simulate a counterfactual world. ΔSSTs are generated from the CMIP5 archive.

   ~~**Anthropogenic forcing/signals, ΔSSTs = CMIP5 Historical SSTs – CMIP5 Natural SSTs……(i)**~~

   ~~**Counterfactual World's SSTs = OSTIA Observed SSTs – ΔSSTs………………………………(ii)**~~

   In this case, HistoricalNat simulations are subtracted from the Historical simulations as described in Schaller et al. (2016), thereby generating a representation of human influences on the SSTs that can be removed from the OSTIA SSTs. GHG and aerosol concentrations are set to pre-industrial levels.

5. 'GHG-only' model ensemble with 98 members per year representing the current decade (2006–2015) climatic conditions, but with anthropogenic aerosol concentrations reduced to pre-industrial levels to simulate a hypothetical climate, where impacts of aerosols are removed. The difference between ACT and GHG-only conditions simulates the net aerosol effect under current conditions assuming additive behaviour of different radiative ~~forces~~ forcing. The GHG-only model ensemble with anthropogenic aerosols reduction scenario in the HadRM3P model is satisfactorily representative when compared with the other GCMs (Haustein et al., in progress). Based on the very limited sample of CMIP5 aerosol only (AA) experiments, we found that the resulting ΔSST patterns are reasonably similar compared with ΔSSTs from ACT minus GHG-only (not shown).

2.3 Methods

To understand how seasonal mean rainfall changes from one climate condition to another, we looked at percent change (PC) and standardized precipitation index (SPI) change between different two forcing scenarios (from pre-industrial NAT to current ACT, ACT to HAPPI 1.5, HAPPI 1.5 to 2.0 and from ACT to GHG-only). For brevity, the supplementary text includes the details of the calculation methods for PC and SPI changes.

Return time (or, return period) plots are used to explore the relative risks of rare events (like those with probabilities of <= 1 in 1000 years). To construct the return time plots ~~of~~ for MAM and JJAS ~~the~~ daily and ~~five~~ 5-day ~~mean~~ rainfall events ~~in pre-monsoon and monsoon seasons~~, we use 98 plausible model realizations ~~with initial condition perturbations~~ for the 10-year period of each model ensemble ~~within 2006-2015~~. For each year, three (MAM) ~~or,~~ and four (JJAS) months of data are used for pre-monsoon and monsoon season, respectively. The model uses a 360-day calendar with all 12 months spanning for 30 days. Therefore, we have ~~90x10x98~~ 3x30x10x98 = 88,200 simulated values to calculate the return periods of pre-monsoon rainfall events. Whereas, for ~~the~~ monsoon season, we have ~~120x10x98~~ 4x30x10x98 = 117,600 simulated values ~~to calculate the return periods~~. Such large sample size allows us to estimate a range of physically plausible climate conditions with focus on the tails of the distribution, which can be robustly determined.

The return time plots are done for local sub-regional scale rainfall risks within Bangladesh. And for this purpose, we use sub-regions 1-4 located at north-west (88°-90°E, 24°-26°N), north-east (90.5°-92.5°E, 24°-25.5°N), south-west (89°-91°E, 21.5°-23.5°N) and south-east (91°-93°E, 20.5°-24°N) respectively. The two eastern sub-regions 2 and 4 are the rainier parts of the country compared to the other two western sub-regions of 1and 3.

To add a qualitative representation of the year-to-year natural variability from the ~~present-day actual climate simulated in the~~ ACT model ensemble, we use two ~~of the~~ wettest and two ~~of the~~ driest years during the decade of 2006-2015. The spatiotemporal average for the corresponding sub-region and season over the 10-year simulation period has been used to determine the wettest and driest year. ~~; see also Table S2).~~ By comparing these two subsampled model ensembles with the ensembles of different forcing scenarios, we can estimate the signal-to-noise ratio in the return period plots. The supplementary material of Table S2 lists the wettest and driest years for pre-monsoon and monsoon seasons over the four different sub-regions.

~~We presented the change in the occurrence probability of rainfall event, Risk Ratio (RR) (NAS, 2016) quantified as~~

~~***RR = P_f / P_{cf}.............................(iii)***~~

In order to quantify changes in the probability of occurrence of extreme rainfall event, we use Risk Ratio (RR), which is calculated as RR = P_f / P_{cf} (NAS, 2016). Here P_f denotes the probability of the event in factual climate including climate change (ACT, HAPPI 1.5 and HAPPI 2.0) and P_{cf} denotes the probability of an event of the same magnitude in a counterfactual climate without anthropogenic climate change (NAT).~~Where probability of the event in the factual climate including climate change (here in ACT, HAPPI 1.5 and HAPPI 2.0 scenarios) is denoted by P_f and the probability of the same event in a counterfactual climate without anthropogenic climate change (here in NAT scenario) is denoted by P_{cf}.~~ But, in case of RR for GHG-only scenario, it is calculated with regard to ACT instead of NAT. We ~~provided~~ quantified the changes in the RRs for four event thresholds ~~in pre-monsoon~~ during MAM and ~~monsoon seasons~~ JJAS with return period of 10, 20, 50 and 100 year over the four sub-regions of Bangladesh.

3 Results and Discussion

3.1 Model Evaluation ~~for Five Day Mean Rainfall~~

~~To explore how pre-monsoon and monsoon rainfall is likely to change in Bangladesh over the four sub-regions, We investigate the annual cycles of five day mean 5-day rainfall under different forcing scenarios in comparison to observations. Five day mean rainfall is used to represent the timescale responsible for river flooding as opposed to daily extremes that cause flash floods primarily in the pre-monsoon season.~~ In Figure 1, ~~annual~~ seasonal cycles of ~~five day mean~~ 5-day rainfall as in the simulations of model ensembles under five different forcing scenarios (ACT, NAT, GHG-only, HAPPI 1.5 and HAPPI 2.0) and two observations (APHRODITE and CPC) are shown. The coloured lines represent the ensemble means, with light-coloured shading representing the 10-90% percentile ranges (only shown for ACT model ensemble and the observations). The ~~annual~~ seasonal cycles are based on 5-day rainfall, which is used to represent the timescale responsible for river flooding as opposed to daily extremes that cause flash floods primarily in the pre-monsoon season.

The ~~annual~~ seasonal cycles of ~~five day mean~~ 5-day rainfall from the different model ensembles are adequately representative of the observed ~~annual~~ seasonal cycles. However, ~~the monsoon~~ JJAS rainfall ~~during JJAS months~~ is underestimated by ~~25-65~~ 25-50% depending on the observational dataset ~~it is compared with~~ and sub-regions. This ~~the monsoon rainfall~~ bias is higher (up to 50% dry bias) ~~at~~ in the wetter sub-regions of 2 and 4 (~~see~~ Figs. 1b & d) and lower (up to 30% dry bias) ~~at~~ in the drier sub-regions of 1 and 3 (~~see~~ Figs. 1a & c). ~~We note that~~ The bias is apparently present in all model scenarios; hence it is unlikely to affect the comparison between model scenarios. We also note that the signal of the change due to the changing climate is relatively small in comparison to the total rainfall. Evaluation of the model simulations for the four sub-regions of Bangladesh conducted by Rimi et al (2019) demonstrated a reasonable agreement between model and observations for extreme rainfall events. The model is therefore considered fit for purpose in assessing the potential impacts of climate change. ~~More details regarding the model's~~

~~performance over can be found in Rimi et al. (under review)~~. The differences between the forcing scenarios throughout the ~~annual~~ seasonal rainfall cycle are discussed below.

3.2 Impact of Climate Change and Aerosol Reduction on Seasonal Mean Rainfall

Our results suggest that changes in mean rainfall due to global warming are significant for both ~~the pre-monsoon~~ MAM and JJAS ~~monsoon periods~~, and that aerosols play an important role in determining the magnitude of future changes (Figs. 2 & 3). Based on PC, these changes are particularly evident ~~in the pre-monsoon season~~ during MAM ~~based on PC~~, yet a smaller PC during ~~the monsoon season~~ JJAS can still have a ~~significant~~ major impact given the magnitude of rainfall. Relative changes between pairs of forcing scenarios show large spatial variability over Bangladesh and the wider central South Asia region, although they suggest a general wetting trend across Bangladesh for both 1.5°C and 2.0°C ~~degree~~ warmer worlds.

During MAM ~~the pre-monsoon season (Fig. 2)~~, results show a non-linear response to temperature change in the PC over the eastern part of South Asia (Figs. 2a, b, & c) that is likely to be caused at least in part by the response for aerosols in ~~the~~ Fig. 2d. The present-day ~~(~~ACT~~)~~ PC relative to ~~the pre-industrial period (~~NAT~~)~~ indicates that ~~the~~ mean ~~pre-monsoon~~ MAM rainfall is reduced by 15-30% over the eastern parts of South Asia and increased by 15-25% over the northern parts Bangladesh (Fig. 2a). Figure 2d shows the spatial distribution of the "omitted" aerosol induced rainfall over the South Asia region. Once aerosol levels drop to ~~1/3th~~ one-third of its current values (following the RCP2.6 protocol, IPCC, 2013), an increase of up to 20% in ~~the pre-monsoon~~ MAM rainfall is very likely to happen over most parts of South Asia~~n~~ region. Associated with this increased rainfall, ~~the~~ PC relative to ~~present-day (~~ACT~~)~~ in ~~a 1.5°C warmer world (~~HAPPI 1.5~~)~~ increases up to 20% over South Asia (Fig. 2b), with Bangladesh being the region where the aerosol effect dominates the total change (Figs. 2f & h). Across Bangladesh, our results indicate that ~~the pre-monsoon~~ MAM rainfall increases approximately linearly with temperature, suggesting a ~~primary~~ relevant role for thermodynamic effects and ~~only a secondary~~ perhaps a smaller role for dynamic changes as far as our HadRM3P model results are concerned. The additional warming effects in ~~a 2.0°C world~~ of ~~(~~HAPPI 2.0~~)~~ increase the mean ~~pre-monsoon~~ MAM rainfall by an extra 10-20% over Bangladesh (Fig. 2g), in contrast to other parts of Asia. We note that our conjectures are speculative at this point, yet likely based on established research into monsoon dynamics (e.g., Bollasina et al. 2011).

Using other RCM projections (based on RCP8.5), Fahad et al. (2017) pointed out that ~~pre-monsoon seasonal~~ MAM mean rainfall may ~~significantly~~ increase by up to 20% relative to their baseline period (1971–2000) over the eastern mountainous region of Bangladesh, in line with our results for 1.5 and 2.0°C warming. However, the fact that the northern parts of India show very non-linear behaviour with regard to rainfall PC in response to the combined GHG and aerosol-related radiative forcing (Figs. 2a-d) is indicative of circulatory, dynamic shifts with stronger warming. ~~This is opposed to a more linear thermodynamic response which usually scales with 20-40% of Clausius-Clapeyron for non-extreme rainfall.~~

The PC of mean ~~monsoon seasonal~~ JJAS rainfall (Fig. 3a) in ~~the present-day climate (~~ACT~~)~~ relative to ~~pre-industrial period (~~NAT~~) (Fig. 3a)~~ indicates a weakening monsoon over central India and strengthening of the monsoon over Bangladesh and north-east India (10-15% increase ~~in mean monsoon seasonal rainfall~~). Evidence for reduced ~~monsoon~~ JJAS rainfall amounts over the last few decades in ~~the~~ South Asia~~n~~ region is also found in the observational records (Bollasina et al., 2011; Srivastava et al., 2010; Turner and Annamalai, 2012; Wang et al., 2012). In contrast, the CMIP5 models simulate about 2.3% increase in rainfall per degree of warming for the Indian summer monsoon (Menon et al., 2013) due to an increase in moisture availability in a warmer world. These conflicting results can be attributed to an underestimated aerosol effect in many CMIP5 models. Subsampling those models that include indirect aerosol effects helps to resolve the discrepancy (Bollasina et al., 2011; Turner and

Annamalai, 2012). ~~We highlight that HadRM3P model estimates the aerosol effects satisfactorily (Haustein et al., in progress); besides the results are largely consistent with observed rainfall trends.~~

The most ~~significant~~ important change in the PC occurs in ~~the~~ ~~1.5°C warmer world~~ HAPPI1.5 relative to ACT ~~the current actual world~~ (Fig. 3b). Comparing HAPPI 1.5 and 2.0~~°C~~, we find an additional increase in ~~the~~ mean ~~monsoon~~ JJAS rainfall but of lower magnitude (a further 10 to 20% increase; Fig. 3c). We find a very strong drying tendency during JJAS due to ~~the presence of~~ anthropogenic aerosols ~~relative to ACT~~ over most parts of South Asia (Fig. 3a). Correspondingly, the "committed" rainfall increase, which will be realised once aerosol emissions are reduced (Fig. 3d), is in the order of 15-30%. This means that the observed drying is entirely caused by the aerosols that have overcompensated~~, and hence efficiently masked,~~ the GHG induced rainfall increase. In Bangladesh (Figs. 3e-h), the aerosol effect is less strong and GHG induced intensification of summer monsoon rainfalls have already increased the risk of more intense rain. The Standardized Precipitation Index (SPI) ~~index~~ analysis for the pre-monsoon and monsoon seasons (Supplementary Figs. S1 & 2) corroborates our results from the PC analysis.

In addition to PC and SPI analyses, we looked at the absolute rainfall (Figs. 4 & 5) for all five forcing scenarios during MAM and JJAS (median, as well as the 25-75th percentiles of seasonal mean rainfall) to explain the variability in the mean of absolute rainfall relative to the change between scenarios over the four sub-regions in Bangladesh (for locations of the sub-regions, see boxes in Figs. 2e & 3e). ~~Changes in the mean absolute rainfall are much more pronounced over sub-region 1 and 2 during pre-monsoon season (see Fig. 4 a & c), whereas smaller absolute changes occur in sub-region 3 and 4 during monsoon season only (Fig. 5 b & d).~~ The magnitude of the mean absolute rainfall change is higher over sub-regions 1 and 2, where both MAM and JJAS rainfall exhibit pronounced shifts from one forcing scenario to another (Fig. 4). On the other hand, over sub-regions 3 and 4, only JJAS rainfall exhibited a robust shift towards more rainfall (Fig. 5 b & d). The absolute aerosol effect is strongest in summer during JJAS, yet the relative change is smaller which is in line with lower rainfall PC as discussed above. Most importantly, ~~however,~~ aerosols play a dominant role in all sub-regions and seasons, except for MAM rainfall over sub-region 3 and 4. Despite more effective aerosol removal from the atmosphere by means of wet deposition during JJAS ~~the monsoon season~~, high regional emission rates prevent drastic reductions of the aerosol optical depth. ~~As a result~~ Consequently, direct and indirect aerosol effects, accompanied by feedbacks such as reduced lapse rate, ~~increased atmospheric stability,~~ reduced boundary layer turbulence, or a modified land-sea circulation, remain to be a potent driver for changing monsoonal rainfall amounts.

For future warming scenarios of ~~(~~HAPPI 1.5 and HAPPI 2.0~~)~~ compared to ~~current actual climate conditions (~~ACT~~)~~, we find robust linear (absolute) increase in rainfall in almost all sub-regions and seasons. We notice a persistent change with increase in absolute mean rainfall from ACT to HAPPI 1.5 and HAPPI 1.5 to HAPPI 2.0. Conversely, we find no clear ~~trend~~ shifts between NAT, ACT and HAPPI 1.5 ~~in~~ during MAM ~~in~~ over sub-region 3 and 4 (Figs. 5a & c). While aerosol effects are consistent with those in other regions, the GHG induced rainfall is hampered, likely due to dynamic changes such as a delayed onset of the monsoon in response to warming. The proximity to the Indian Ocean may also be a contributing factor. While the atmosphere can hold more moisture, the slower ocean warming stabilises the atmosphere over sea in the same way aerosols stabilise the atmosphere over land.

Impact of climate change and aerosol reduction on seasonal mean rainfall (as in PC, SPI and absolute) is in agreement with the findings in the ~~annual~~ seasonal cycles (Fig. 1) presented before. As shown in Fig. 1, the monsoon onset in sub-region 3 and 4 (Figs. 1c & d) does not change notably under different forcing scenarios as far as 5-day ~~mean~~ rainfall is concerned. Otherwise, the aerosol and GHG induced response is consistent with the conclusions based on the spatial maps across the four sub-regions. Sub-regions 1 and 2 show considerable changes in rainfall strength during MAM ~~the pre-monsoon season~~, with an earlier onset in the HAPPI 2.0 scenario ~~in~~ over sub-region 2. The most pronounced change is simulated ~~during~~ at the peak of ~~the~~ monsoon season, in early June ~~in~~ over sub-region 2, with an associated increase in magnitude of almost ~~1/3~~ one-third between NAT and HAPPI 2.0. It is noteworthy that this increase in rainfall is very linear with progressively warmer climate conditions (Fig. 1b).

3.3 Extreme Rainfall Events

An analysis of changes in extreme rainfall events suggests that Bangladesh is likely to experience significantly higher ~~frequencies of occurrence~~ magnitude ~~for~~ of 1 and 5-day rainfall events (Figs. 6-9 and S3-S6) during both pre-monsoon and monsoon seasons across all sub-regions ~~(Figs. 6-9)~~ for a 1.5°C change. ~~with~~ The only exceptions ~~of~~ included ~~pre-monsoon~~ MAM rainfall events over sub-region 4 (Fig. 7b)~~;~~ and ~~monsoon~~ JJAS rainfall events over sub-region 3 ~~and 4~~ (Figs. 9a ~~& b~~). In contrast, changes between HAPPI 1.5 and HAPPI 2.0 are only significant in JJAS over sub-regions 1 and 2 ~~in summer monsoon season~~ (Figs. 8a & b). ~~The signal-to-noise ratio is higher in the monsoon season across all sub-regions with the lowest and highest ratio in sub-region 1 and 3, respectively (Figs. 8a & 9a).~~ Overall, the signal-to-noise ratio is higher across all sub-regions, during JJAS compared to that during MAM. During MAM, the highest and lowest signal-to-noise ratio is over sub-region 1 and 3, respectively (Figs. 6a & 7a). On the other hand, during JJAS, we find the highest and lowest signal-to-noise ratio is over sub-region 3 and 1, respectively (Figs. 9a & 8a). The lower the ratio, the more difficult it is to establish causality as natural variability due to ENSO or circulation anomalies is higher.

~~In summary, the~~ The most linear rainfall response to warming is simulated in sub-region 2 in MAM and JJAS (Figs. 6b & 8b), with aerosols masking approximately 50% of the increased risk with regard to 1-in-100-year NAT return time. Hence future rainfall in sub-region 2 continues to increase, with accelerated pace once aerosol levels drop significantly. Sub-region 1 is likely to receive more extreme rainfall as well with continued warming, with strong increases once aerosol levels drop. Sub-regions 1 and 2 are equally sensitive to aerosols, yet dynamic feedback processes ~~appear to~~ might partially counter the thermodynamic increase in rainfall risk with continued warming.

Figures 10 and 11 give simple illustration for the change in risk ratios, which remarkably vary with seasons (pre-monsoon and monsoon) as well as locations (sub-regions of 1-4) and also indicate how aerosols impact risk ratios. Supplementary material of Table S3 presents the risk ratios with associated uncertainty ranges for both seasons over four sub-regions. Figure 10 demonstrates that there is noticeable masking effect of aerosols during MAM that repress the change between NAT and ACT worlds at sub-region 1. Hence, present-day risk for MAM rainfall event has not changed (see RR for ACT/NAT in Fig. 10a). But then the risk of extreme rainfall event with respect to 1-in-100-year NAT return time increase by a factor of 4 (with uncertainty range 2.0-7.0) in a 1.5°C world (see RR for HAPP1.5/NAT in Fig. 10a). In contrast, the aerosol masking effect during MAM is minimal at sub-region 2; leading to a robust change between NAT and ACT worlds (see RR for ACT/NAT in Fig. 10b).

We find persistent increase in the RRs for JJAS extreme rainfall events at the sub-regions 2 and 4. At sub-region 2, risk of JJAS extreme rainfall event with respect to 1-in-100-year NAT return time increases 3-fold (with uncertainty range 1-4) in a 1.5°C world and then 4.6-fold (with uncertainty range 2.9-7.2) in a 2.0°C world (see RRs for HAPP1.5/NAT and HAPP2.0/NAT in Fig. 10d). At sub-region 4 (Fig. 11d), where current risks of JJAS extreme rainfall events are already increased 3.9 times (with uncertainty range 2.6-5.8) with respect to 1-in-100-year NAT return time; the risk for similar event increases 4.1 times (with uncertainty range 2.2-5.3) in a 1.5°C world and 5.5 times in a 2.0°C world (with uncertainty range 3.5-7.8).

4 Conclusions

Results of the weather@home HadRM3P South Asia regional model suggest that both, 1.5°C and 2.0°C warming are projected to increase seasonal mean and extreme rainfall probabilities during the pre-monsoon and monsoon seasons across Bangladesh. These increases are likely to be amplified by a reduction in aerosols, consistent with previous findings (e.g., Samset et al., 2018). These projected changes have important implications for agricultural yields and associated economic losses, particularly during the pre-monsoon season. In contrast, property damage is more likely to occur during the monsoon season when large inhabited areas are inundated on a regular basis. We find that there are large spatial variations in the patterns of changes in the relative risks of extreme rainfall in Bangladesh.

~~In conclusion, the drier~~ ~~s~~ Sub-regions 1 and 2 shows ~~a greater masking effect from the aerosols~~ an enhanced susceptibility to aerosols during the pre-monsoon season; whereas, ~~the wetter~~ sub-regions 3 and 4 ~~have~~ show a smaller aerosol ~~effect~~ sensitivity ~~particularly~~ during the monsoon season. Aerosols have reduced the absolute daily rainfall amount by up to 1mm (~ 5-10%) during the monsoon season in sub-region 1 and 2, comparable to the simulated rainfall change in a future 2.0°C warming scenario. This is in line with a growing array of research that has shown that anthropogenic aerosols play a substantial role in modulating the strength of the monsoon in South Asia (Bollasina et al., 2011, 2013; Lau and Kim, 2010; Ramanathan et al., 2005). As far as other regions in South Asia are concerned, our results imply that the present-day decline in the mean monsoon seasonal rainfall can be explained by the existing atmospheric aerosols impacts, which offsets the GHG-induced global warming effects. Future aerosol removal from the atmosphere will unmask the GHG induced rainfall increase with surprisingly fast changes in risk due to the non-linear nature of the imposed external forcing contributions (e.g., over sub-region 1 in pre-monsoon season). For that reason we emphasize that the impacts of aerosol reductions on the changing risks of extreme rainfall events should be considered for future risk assessments.

Finding of this study implies that policy-makers and relevant stakeholders not only need to take distinctively different regional responses in extreme rainfall into account, but also the non-linearity in the response. Relying on observed changes can be deeply misleading, creating an unwarranted sense of security. Our study highlights that preparedness for more frequent extremes is key in the northern part of Bangladesh during both the pre-monsoon and the monsoon season. The magnitude of change exceeds the current internal year-to-year variability in the associated sub-regions 1 and 2 during both pre-monsoon ~~MAM~~ and monsoon ~~JJAS~~ seasons. While additional regional model experiments are needed to confirm the weather@home model results, available data from other HAPPI GCMs point in the same direction (Chevuturi et al., 2018; Lee et al., 2018). However, since they do not allow for a quantification of the aerosol effect, we call for more nuanced experiments in that regard in the future.

Author contributions

Ruksana H. Rimi’s contribution towards this work was performed as part of her DPhil research project. All results were analysed and plotted by Ruksana H. Rimi with advice from Myles R. Allen, Karsten Haustein, and Emily Barbour. Sihan Li and Sarah N. Sparrow prepared and distributed the computational simulations to generate the data used in the study onto the weather@home system. David C.H. Wallom manages operation of the weather@home/climateprediction.net infrastructure which was used to generate the data. The paper was written by Ruksana H. Rimi, with edits from all co-authors.

Acknowledgments

We would like to thank the Met Office Hadley Centre PRECIS team for their technical and scientific support for the development and application of weather@home. We would like to thank our colleagues at the Oxford eResearch Centre for their technical expertise. We acknowledge the use of the observation datasets of APHRODITE and CPC. Finally, we would like to thank all the volunteers who have donated their computing time to climateprediction.net and weather@home. The authors declare that they have no conflict of interest.

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Figure captions:

Figure 1. ~~Annual~~ Seasonal cycles of five day mean rainfall under different forcing scenarios over the four sub-regions of Bangladesh. The ~~HadRM3P~~ ACT (black), NAT (green) and GHG-only (orange), ~~and~~ HAPPI 1.5 (blue) and 2.0 (red) ensembles are compared with the observations from APHRODITE (dark purple) and CPC (dark purple). ~~The model can represent the annual cycles as in the observations but monsoon (JJAS) rainfall is underestimated in all sub-regions. A clearly distinguishable shift in the annual cycles of five day mean rainfall from NAT to ACT, from ACT to GHG, from ACT to HAPPI 1.5 and from HAPPI 1.5 to 2.0 forcing scenarios can be seen in sub-region2 only.~~ The model adequately captures the ~~annual~~ seasonal cycle of rainfall compared to observation but underestimates monsoon rainfall. Only over sub-region 2, rainfall is clearly shifting from NAT to ACT, from ACT to GHG-only, from ACT to HAPPI 1.5 and from HAPPI 1.5 to 2.0 forcing scenarios.

Figure 2. Percentage change (PC) in ~~the pre-monsoon (MAM)~~ MAM ~~seasonal~~ mean rainfall between different forcing scenarios. The top row (panels a-d) shows the regional PC over central parts of the South Asia. ~~(SA) while, bottom row (panels e-h) shows the PC over Bangladesh. The four boxes (1-4) on top of the panel e approximately represent the four sub-regions of Bangladesh. These four sub-regions 1-4 are used later for the relative quantification of risks of extreme pre-monsoon rainfall events.~~ a. ~~present-day rainfall PC relative to natural pre-industrial climate~~ ACT rainfall PC relative to NAT over SA b. ~~present-day~~ ACT rainfall PC relative to HAPPI 1.5°C ~~world~~ over SA c. HAPPI 1.5°C ~~world~~ rainfall PC relative to HAPPI 2.0°C ~~world~~ over SA d. ~~present-day~~ ACT rainfall PC relative to GHG-only ~~climate over SA~~. Bottom row (panels e-h) shows PC in the same way but over Bangladesh. The four boxes (1-4) on top of the panel e represent the four sub-regions of Bangladesh.

Figure 3. ~~Percentage change (PC) in the monsoon (JJAS) seasonal mean rainfall between different forcing scenarios. The top row (panels a-d) shows the regional PC over central parts of the South Asia (SA) while, bottom row (panels e-h) shows the PC over Bangladesh. The four boxes (1-4) on top of the panel e approximately represent the four sub-regions of Bangladesh. These four sub-regions 1-4 are used later for the relative quantification of risks of extreme monsoon rainfall events. a. present-day rainfall PC relative to natural pre-industrial climate over SA b. present-day rainfall PC relative to 1.5°C world over SA c. 1.5°C world rainfall PC relative to 2.0°C world over SA d. present-day rainfall PC relative to GHG-only climate over SA.~~ Same as Fig. 2, but for JJAS rainfall PC. ~~The~~ This figure shows that the apparently non-linear response between panels of a, b, and c (or, e, f, g) can be explained by the response for ~~aerosols~~ GHG-only (anthropogenic aerosols reduced to pre-industrial levels) in the panel d (or, h).

Figure 4. ~~Mean~~ Seasonal mean rainfall in ~~pre-monsoon~~ MAM (left column) and ~~monsoon~~ JJAS (right column) ~~seasons during MAM and JJAS months~~ over the sub-regions ~~of~~ 1 and 2 (top and bottom row) of Bangladesh. Green, orange, grey, blue and red colours represent ~~the natural (~~NAT~~)~~, ~~actual climate with aerosols reduced to the pre-industrial level (AR)~~ GHG-only, ~~Actual (~~ACT~~)~~, HAPPI 1.5 ~~(1.5)~~ and HAPPI 2.0 ~~(2.0)~~ ensembles respectively. Each panel has different y-scale range to clearly indicate the details of changes in the median values between different model ensembles. The horizontal black line in each box indicates the median value, the bottom and top limits of the box represents the 25^{th} and 75^{th} percentiles respectively. ~~The figure shows that aerosol impacts are distinguishable between the dry sub-region 1 and the wet sub-region 2. There is noticeable masking effect of aerosols that repress the change between NAT and ACT worlds at sub-region 1. In contrast, at sub-region 2, where highest amounts of observed rainfall can clear most of the pollution from the atmosphere, the masking effect in minimal hence, a robust change between NAT and ACT worlds can be seen. In future with additional warming the mean seasonal rainfall increases over both sub-regions but then again over the sub-region 2, we see larger~~

~~changes in the seasonal mean rainfall~~. The figure shows that aerosol impacts over both sub-regions 1 and 2 are larger in MAM dry season than that in JJAS wet season.

Figure 5. ~~Mean rainfall in pre-monsoon (left column) and monsoon (right column) seasons during MAM and JJAS months over the sub-regions of 3 (top row) and 4 (bottom row) of Bangladesh. Green, orange, grey, blue and red colours represent the natural (NAT), actual climate with aerosols reduced to the pre-industrial level (AR), Actual (ACT), HAPPI 1.5 (1.5) and HAPPI 2.0 (2.0) ensembles respectively. Each panel has different y-scale range to clearly indicate the details of changes in the median values between different model ensembles. The horizontal black line in each box indicates the median value, the bottom and top limits of the box represents the 25th and 75th percentiles respectively. There is noticeable masking effect of aerosols that repress the change between NAT and ACT worlds at both sub-region 3 and 4 during pre-monsoon season. On the contrary, in monsoon season, large amounts of rainfall can clear most of the pollution from the atmosphere; so, the masking effect is minimal, hence, a clear change between NAT and ACT worlds is happening. In future with additional warming the mean seasonal rainfall increases over both sub-regions but, larger changes occur in the mean rainfall in monsoon season.~~ Same as Fig. 4, but for sub-regions 3 and 4. During MAM over both sub-regions 3 and 4, aerosol effects repress the mean rainfall change between NAT and ACT (i.e., ACT rainfall is lower than NAT). On the other hand, during JJAS over both sub-regions 3 and 4, with lesser aerosol masking effects, ACT has higher mean rainfall than NAT and GHG-only would have noticeably much higher mean rainfall.

Figure 6. Return time plots for MAM daily rainfall ~~during pre-monsoon (MAM) season in~~ under different forcing scenarios over the sub-regions ~~of~~ 1 and 2 of Bangladesh. The ~~HadRM3P~~ ACT (black), ACT highest (~~upper grey with upward triangles~~ sky-blue), ACT lowest (~~lower grey with downward triangles~~ grey), NAT (green) and GHG-only (orange) ensembles are compared with the HAPPI 1.5 (blue) and HAPPI 2.0 (red) ensembles. ~~Anthropogenic warming effects have not strongly influenced the present-day risks of extreme pre-monsoon rainfall in the sub-region1. With a 1.5 or 2.0 degrees' world, this sub-region might see extreme rainfall events with four-fold higher risks.~~ Anthropogenic warming effects have not strongly influenced the present-day risks of extreme MAM rainfall over sub-region 1 (Fig. 6a). With a 1.5 or 2.0 degrees' world, this sub-region might see extreme rainfall events with four-fold higher risks.

Figure 7. Same as Fig 6, but showing return time plots for MAM daily rainfall ~~during pre-monsoon (MAM) season in~~ under different forcing scenarios over the sub-regions ~~of~~ 3 and 4 of Bangladesh.

Figure 8. Return time plots for daily rainfall during monsoon (JJAS) season in different forcing scenarios over the sub-regions of 1 and 2 of Bangladesh. The HadRM3P ACT (black), ACT highest (upper grey with upward triangles), ACT lowest (lower grey with downward triangles), NAT (green) and ~~GHG~~ GHG-only (orange) ensembles are compared with the HAPPI 1.5 (blue) and 2.0 (red) ensembles. The most significant changes in the risks of extreme monsoon rainfall take place in the sub-region2, which is already the wettest part of Bangladesh.

Figure 9. Same as Fig 8, but showing return time plots for daily rainfall during monsoon (JJAS) season in different forcing scenarios over the sub-regions of 3 and 4 of Bangladesh.

Figure 10. The risk ratios of four specific rainfall events with return periods of 10, 20, 50, and 100 years between ~~Actual/Natural~~ ACT/NAT, HAPPI 1.5/NAT ~~Natural~~, HAPPI 2.0/NAT ~~Natural~~ and ~~GHG~~ GHG-only /ACT ~~Actual~~ over the two northern sub-regions ~~of~~ 1 and 2 during ~~of Bangladesh in pre-monsoon (~~MAM~~)~~ (~~shown in~~ top two panels of a. ~~and~~ & b.) and ~~monsoon (~~JJAS~~)~~ (~~shown in~~ bottom two panels of c. ~~and~~ & d.) ~~seasons~~. The error bars indicate the associated uncertainty range with 95% confidence level for individual event. ~~This figure demonstrates that the uncertainty range increases with the increase of the return periods of rainfall events (i.e., rarer events) in most of the cases, which should be considered in the risk assessment process. While there is no discernible climate change impacts on the current risks (i.e., all four risk ratios are ~1), in a1.5°C world there would be 4 (with uncertainty range 2.0-7.0) times increase in the risks of extreme rainfall events of 100 years return period over sub-region 1 during pre-monsoon season (top left panel a.).~~

Figure 11. ~~The risk ratios of four specific rainfall events with return periods of 10, 20, 50, and100 years between Actual/Natural, HAPPI 1.5/Natural, HAPPI 2.0/Natural and GHG/Actual over the two southern sub-regions of 3 and 4 of Bangladesh in pre-monsoon (MAM) (shown in top two panels of a. and b.) and monsoon (JJAS) (shown in bottom two panels of c. and d.) seasons. The error bars indicate the associated uncertainty range with 95% confidence level for individual event.~~ Same as Fig 10, but for MAM and JJAS risk ratios over the two southern sub-regions 3 and 4. ~~The risk ratios over sub-region 4 in monsoon (bottom right panel d.) indicate that the extreme rainfall events with 100 years return period are already made 3.9 (with uncertainty range 2.6-5.8) times likely in the actual climate compared to the events of natural climate. With additional global warming effects the same event will become 4.1 (with uncertainty range 2.2-5.3) and 5.5 (with uncertainty range 3.5-7.8) times likely in a 1.5 and 2.0 degrees' worlds.~~

Supplement of

"Risks of extreme rainfall in Bangladesh under 1.5 and 2.0 degrees' warmer worlds"

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Table S1: Basic information about the two observation data sets

Product Name	Product version	Spatial Resolution	Time Scale	Source/reference
APHRODITE	Monsoon Asia (MA) ~~V1003R1~~ V1901	0.5°X 0.5°	~~1951-2007~~ 1998-2015	Yatagai et al., 2012. Available at: http://journals.ametsoc.org/doi/pdf/10.1175/BAMS-D-11-00122.1
CPC	CPC daily rainfall	0.5°X 0.5°	1979- 2016	Chen, M. and Xie, P. 2008. Available at: ftp://ftp.cpc.ncep.noaa.gov/precip/CPC_UNI_PRCP/GAUGE_CONUS/DOCU/Chen_et_al_2008_Daily_Gauge_Anal.pdf

Table S2: As per actual climate model ensemble during 2006-2015 - the wettest and driest two years over the four sub-regions.

	pre-monsoon season (MAM)		monsoon season (JJAS)	
Sub-regions	Wettest years	Driest years	Wettest years	Driest years
Sub-region 1 (north-west region)	2008, 2011	2009, 2014	2008, 2009	2013, 2014
Sub-region 2 (north-east region)	2008, 2015	2009, 2014	2008, 2012	2006, 2013
Sub-region 3 (south-west region)	2008, 2012	2009, 2014	2008, 2014	2011, 2013
Sub-region 4 (south-east region)	2008, 2015	2009, 2013	2008, 2014	2011, 2013

Table S3: The risk ratios with associated uncertainty ranges (in brackets) for four rainfall events.

Return periods	Sub-region 1 (north-west region) – pre-monsoon season				Sub-region 2 (north-east region) – pre-monsoon season			
	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT
10 years	1.1 (0.9-1.2)	1.5 (1.2-1.6)	1.8 (1.5-2.0)	1.4 (1.2-1.6)	1.6 (1.3-1.9)	1.9 (1.5-2.3)	2.5 (2.0-2.9)	1.1 (1.0-1.2)
20 years	1.2 (0.9-1.5)	2.1 (1.6-2.8)	2.5 (1.9-3.4)	1.9 (1.6-2.2)	1.5 (1.2-2.0)	2.1 (1.6-2.8)	3 (2.2-3.9)	1.4 (1.0-1.9)
50 years	1.1 (0.7-1.5)	2.5 (1.8-3.8)	3.1 (2.0-4.5)	2.5 (1.9-3.8)	1.7 (1.1-2.2)	2.4 (1.7-3.4)	2.8 (1.9-4.0)	1.2 (0.9-1.9)
100 years	1.1 (0.6-2.1)	**4 (2.0-7.0)**	**3.9 (2.1-6.8)**	**3.3 (1.9-5.9)**	1.9 (1.1-3.1)	**3.2 (2.0-5.3)**	**2.9 (1.9-4.5)**	1.9 (1.0-3.2)
Return periods	Sub-region 3 (south-west region) – pre-monsoon season				Sub-region 4 (south-east region) – pre-monsoon season			
	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT
10 years	1 (0.9-1.1)	1.1 (1.0-1.3)	1.4 (1.2-1.6)	1.1 (1.0-1.3)	1.1 (1.0-1.3)	1.4 (1.2-1.5)	1.5 (1.3-1.6)	1.3 (1.0-1.5)
20 years	1.1 (0.9-1.2)	1.3 (1.1-1.8)	1.6 (1.3-2.1)	1.2 (0.9-1.4)	1.3 (1.0-1.6)	1.9 (1.3-2.3)	1.7 (1.2-2.1)	1.4 (1.0-1.6)
50 years	1.2 (0.9-1.8)	1.5 (1.2-2.1)	2.5 (1.9-3.8)	1.5 (1.0-2.0)	2.1 (1.4-3.0)	2.2 (1.5-3.2)	2.2 (1.6-3.2)	1.6 (1.0-2.2)
100 years	1.5 (0.9-2.8)	2 (1.0-3.0)	3.1 (1.9-5.2)	1.5 (0.9-2.4)	1.7 (0.9-2.9)	2.5 (1.6-4.0)	2.1 (1.2-3.3)	(0.9-2.3)
Return periods	Sub-region 1 (north-west region) – monsoon season				Sub-region 2 (north-east region) – monsoon season			
	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT
10 years	1.7 (1.5-2.0)	2.5 (2.1-2.9)	2.3 (2.0-2.6)	1.3 (1.0-1.5)	1.8 (1.5-2.1)	2.5 (2.1-3.1)	3.1 (2.6-4.0)	1.1 (1.0-1.2)
20 years	2.3 (1.9-2.9)	3.7 (2.9-4.5)	3.2 (2.5-4.0)	1.5 (1.1-1.9)	1.5 (1.1-1.9)	2.2 (1.8-2.9)	2.9 (2.2-3.8)	1.1 (0.9-1.2)
50 years	2.1 (1.5-2.9)	3.8 (2.8-4.9)	3.3 (2.6-4.6)	1.5 (1.1-2.1)	1.3 (0.9-1.9)	2.1 (1.5-3.0)	3.2 (2.2-4.8)	1.5 (1.0-1.9)
100 years	1.6 (1.0-2.5)	**4** (2.5-6.3)	**3.8** (2.3-6.0)	2 (1.2-3.7)	1.8 (1.0-3.0)	**3 (1.0-4.0)**	**4.6 (2.9-7.2)**	1.8 (1.0-2.9)
Return periods	Sub-region 3 (south-west region) – monsoon season				Sub-region 4 (south-east region) – monsoon season			
	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT	ACT/NAT	HAPPI1.5/NAT	HAPPI2.0/NAT	GHG/ACT
10 years	1.6 (1.4-1.9)	1.5 (1.3-1.7)	2 (1.7-2.2)	1 (0.8-1.2)	1.9 (1.6-2.1)	2.1 (1.9-2.5)	2.3 (2.0-2.8)	1 (0.9-1.2)
20 years	2 (1.8-2.2)	1.9 (1.4-2.3)	2.5 (2.0-3.0)	1.1 (0.8-1.8)	2 (1.5-2.5)	2.3 (1.8-2.8)	2.9 (2.2-3.8)	1.1 (0.9-1.5)
50 years	2.1 (1.7-2.5)	1.9 (1.2-2.6)	2.1 (1.5-2.8)	1.2 (0.7-1.9)	2.5 (1.9-3.5)	2.6 (1.9-3.7)	3.9 (2.9-5.5)	0.9 (0.5-1.2)
100 years	2.2 (1.6-3.1)	2.3 (1.3-3.6)	2.2 (1.3-3.8)	1.3 (0.5-2.2)	**3.9 (2.6-5.8)**	**4.1 (2.2-5.3)**	**5.5 (3.5-7.8)**	0.9 (0.3-1.8)

Supplementary Figure captions:

Figure S1. Relative change~~s~~ in ~~the~~ SPI of ~~pre-monsoon (~~MAM~~)~~ ~~seasonal~~ mean rainfall between different forcing scenarios. The top row (panels a-d) shows the regional SPI changes over central parts of the South Asia (SA) while, bottom row (panels e-h) shows the SPI changes over Bangladesh. The four boxes (1-4) on top of the panel e ~~approximately~~ represent the four sub-regions of Bangladesh. ~~These four sub-regions (1-4) are used later for the relative quantification of risks of extreme monsoon rainfall events.~~ a. ~~present-day~~ ACT rainfall ~~PC~~ SPI relative to ~~natural pre-industrial climate~~ NAT over SA b. ~~present-day~~ ACT rainfall ~~PC~~ SPI relative to HAPPI1.5~~°C world~~ over SA c. HAPPI1.5~~°C~~ ~~world~~ rainfall ~~PC~~ SPI relative to HAPPI 2.0~~°C world~~ over SA d. ~~present-day~~ ACT rainfall ~~PC~~ SPI relative to GHG-only ~~climate~~ over SA.

Figure S2. ~~Relative changes in the SPI of monsoon (JJAS) seasonal mean rainfall between different forcing scenarios. The top row (panels a-d) shows the regional SPI over central parts of the South Asia (SA) while, bottom row (panels e-h) shows the SPI over Bangladesh. The four boxes (1-4) on top of the panel e approximately represent the four sub-regions of Bangladesh. These four sub-regions (1-4) are used later for the relative quantification of risks of extreme monsoon rainfall events. a. present-day rainfall PC relative to natural pre-industrial climate over SA b. present-day rainfall PC relative to 1.5°C world over SA c. 1.5°C world rainfall PC relative to 2.0°C world over SA d. present-day rainfall PC relative to GHG-only climate over SA.~~ Same as Fig. S1, but for SPI changes in JJAS mean rainfall. ~~The~~ This figure shows that the apparently non-linear response between panels of a, b, and c (or, e, f, g) can be explained by the response for aerosols in the panel d (or, h).

Figure S3. Return time plots for MAM five day mean rainfall ~~during pre-monsoon (MAM) season in~~ under different forcing scenarios over the sub-regions ~~of~~ 1 and 2 of Bangladesh. The ~~HadRM3P~~ ACT (black), ACT highest (~~upper grey with upward triangles~~ sky-blue), ACT lowest (~~lower grey with downward triangles~~ grey), NAT (green) and GHG-only (orange) ensembles are compared with the HAPPI 1.5 (blue) and HAPPI 2.0 (red) ensembles.

Figure S4. Same as Fig. S3, but for ~~showing~~ return time plots for MAM five day mean rainfall ~~during pre-monsoon (MAM) season in~~ under different forcing scenarios over the sub-regions ~~of~~ 3 and 4 of Bangladesh.

Figure S5. Return time plots for JJAS five day mean rainfall ~~during monsoon (JJAS) season in~~ different forcing scenarios over the ~~four~~ sub-regions ~~of~~ 1 and 2 of Bangladesh. The ~~HadRM3P~~ ACT (black), ACT highest (~~upper grey with upward triangles~~ sky-blue), ACT lowest (~~lower grey with downward triangles~~ grey), NAT (green) and GHG-only (orange) ensembles are compared with the HAPPI 1.5 (blue) and HAPPI2.0 (red) ensembles. The risks of extreme rainfall events are evidently increasing between different forcing scenarios over sub-region 2.

Figure S6. Same as Fig. S5, but for ~~showing~~ return time plots for JJAS five day mean rainfall ~~during monsoon (JJAS) season in~~ under different forcing scenarios over the sub-regions ~~of~~ 3 and 4 of Bangladesh.

Supplementary Text

Analysis methods:

1. **Percentage Change (PC)** in seasonal mean precipitation is calculated for one forcing scenario relative to another forcing scenario to indicate the magnitude of change between the scenarios across the study region. This approach enables the identification of areas at risk of becoming wetter or drier. For instance, the PC for ACT relative to NAT in monsoon (JJAS) season is calculated as:

$$PC_{\text{ACT relative to NAT}} = \left[\frac{\text{JJAS precipitation in ACT} - \text{JJAS precipitation in NAT}}{\text{Mean JJAS precipitation in ACT}}\right] \times 100$$

The multi-year monthly means of JJAS months for each decadal model ensemble is used to calculate the PC in all cases. The PC for pre-monsoon (MAM) season is calculated using the same approach.

2. The **Standardized Precipitation Index (SPI)** (Mckee et al., 1993; McKee et al., 1995) is a simple, flexible index which is powerful to effectively analyse both wet and dry periods. SPI is widely used for assessing wetting/drying effects (e.g., Du et al., 2013; Li et al., 2015, 2008; Mahfouz et al., 2016). Precipitation data is the only required input parameter to calculate the SPI and this can be computed for multiple timescales from 1 to 24 months (WMO, 2012). For example, SPI for monsoon precipitation during JJAS months in GHG only climate model ensemble (denoted as GHG-only) relative to actual climate model ensemble (denoted as ACT) is calculated by the following equation:

$$\text{SPI}_{\text{GHG-only relative to Act}} = \frac{\text{JJAS precipitation in GHG-only} - \text{JJAS precipitation in ACT}}{\text{Standard deviation of JJAS precipitation in ACT}}$$

The multi-year monthly means of JJAS months for each model ensemble is used to calculate the SPI in all cases. An SPI index value greater than 2.0 indicates areas are extremely wet, 1.5 to 1.99 indicates very wet; 1.0 to 1.49 moderately wet; -0.99 to 0.99 near normal; -1.0 to -1.49 moderately dry; -1.5 to -1.99 severely dry; and -2 and less indicate areas to be extremely dry (WMO, 2012).