Assessment of future rainfall for the Brahmani-Baitarani river basin – practical implications of limited data availability

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ABSTRACT

Severe floods are common in the Brahmani-Baitarani river basin in India. Insights into the implications of climate change on rainfall extremes and resulting floods are of major importance to improve flood risk analysis and water system design. A wide range of statistical and dynamical downscaling and bias-correction methods for the generation of local climate projections exists. Yet, the applicability of these methods highly depends on availability of meteorological data. In developing countries, data availability is often limited, either because data do not exist or because of restrictions on use. We here present a climate change analysis for the Brahmani-Baitarani river basin focusing on changes in rainfall using data from three GCMs from the Fifth Coupled Model Intercomparison Project (CMIP5) that were selected based on their performance. We apply and compare two widely used and easy to implement bias-correction methods. These were selected because reliable open historical meteorological datasets required for advanced methods were not available. The results indicate likely increases in monsoon rainfall especially in the mountainous regions and likely increases in the number of heavy rain days. We conclude with a discussion on the gap between state-of-the-art downscaling techniques and the actual options in regional climate change assessments.

Key words | bias-correction, Brahmani-Baitarani river basin, climate change, data availability, downscaling, India

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INTRODUCTION

In the past, extreme rainfall over India has resulted in landslides, flash floods, severe river floods, and crop damage that have severely impacted society, the economy and the environment (Goswami *et al.* 2006). Increases in rainfall extremes have quantifiable impacts on intensity–duration–frequency relations (Kao & Ganguly 2011) and are expected to enhance coastal and river flood risks and will, without adaptive measures, substantially increase flood damage. Climate adaptation strategies for emergency planning, the design of structures, reservoir management, pollution control and risk calculations rely on knowledge of the frequency of these extreme rainfall events (Goswami *et al.* 2006; Guhathakurta *et al.* 2011).

Several studies have already investigated the trends in rainfall extremes over India (e.g., Goswami *et al.* 2006; Chatuverdi *et al.* 2012; Paul & Birthal 2016). Goswami *et al.* (2006) found significant positive trends in the frequency and the magnitude of heavy rain events and a significant negative trend in the frequency of moderate events over central India during the monsoon seasons from 1951 to 2000. Climate change is

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expected to further alter the intensity and frequency of extreme rainfalls (Kharin *et al.* 2007; Chatuverdi *et al.* 2012). Globally, the intensity of extreme rainfall is projected to increase even in regions where mean rainfall decreases (Semenov & Bengtsson 2002). Moreover, future climate studies based on climate model simulations suggest that greenhouse warming is likely to intensify the monsoon rainfall over a broad region encompassing South Asia (Lal *et al.* 2000; Meehl & Arblaster 2003; May 2004). However, precise assessments of future changes in regional monsoon rainfall have remained ambiguous due to wide variations among the model projections (Kripalani *et al.* 2007; Sabade *et al.* 2011). The simulated rainfall response to global warming by climate models is, in fact, accompanied by a weakening of the large-scale South-West (SW) monsoon flow (Ueda *et al.* 2006; Krishnan *et al.* 2013). Nonetheless, the recently released CMIP5 projections confirm significant reduction in return times of annual extremes of daily rainfall for the late 21st century in India (Ramesh & Goswami 2014) and local increases in summer mean rainfall amounts (Menon *et al.* 2013; Maity *et al.* 2016). In addition, Chatuverdi *et al.* (2012) found a steady increase in the number of days with extreme rainfall for the period of 2060 and beyond.

Within this paper we try to assess future climate-induced changes in several rainfall indices of relevance to water resources and flood risk management in the Brahmani-Baitarani river basin. The basin is located in the eastern part of India, see Figure 1. It has experienced severe floods in the years of 2001, 2003, 2006, 2008, 2011 and 2013. The basin is of special interest because it encompasses both coastal and mountainous areas and there will likely be spatial variation in the response to climate change as has also been observed for the historical period (Paul & Birthal 2016). Moreover, climate change assessments for the Brahmani and Baitarani River basins exist (Gosain *et al.* 2006; Mitra & Mishra 2014) but none of these are based on a set of GCMs.

To enable a quantitative climate change analysis, we use global climate model (GCM) data. GCM rainfall data normally have biases from observations and need to be corrected to ensure their applicability at the local scale (Christensen *et al.* 2008; Sperna Weiland *et al.* 2012; Teutschbein & Seibert 2012). There is a wide range of statistical and dynamical downscaling and bias-correction methods available to generate local climate projections that also consider changes in rainfall extremes. Yet, the applicability of these methods highly depends on

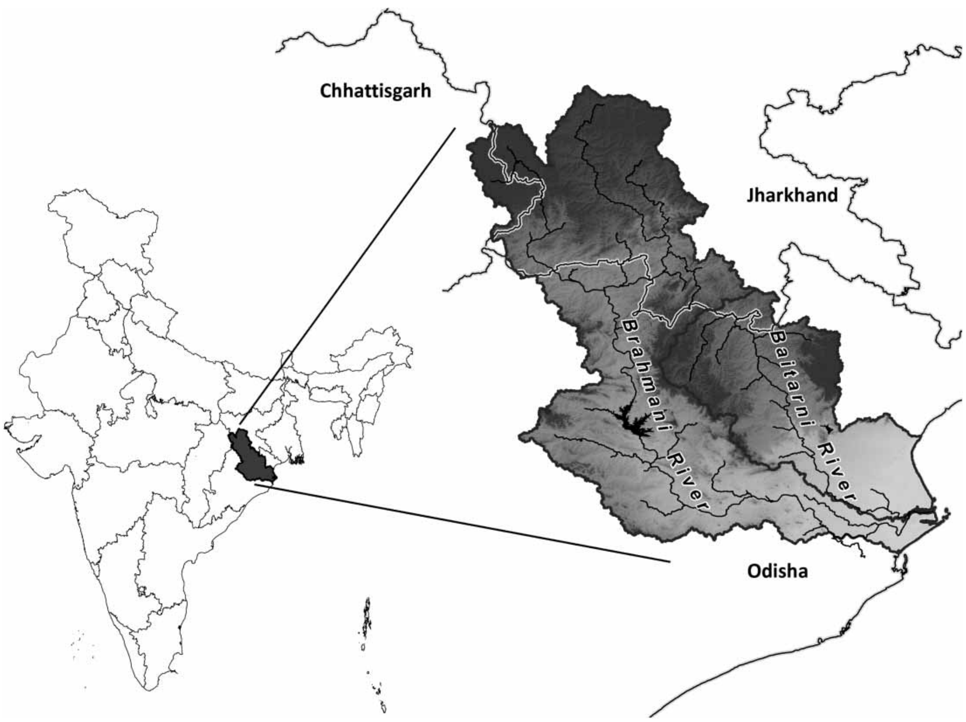

Figure 1 | Map showing location of the Brahmani-Baitarani river basin as study area and the boundaries of the three surrounding Indian states.

availability of meteorological observations at local scale. With this paper, we do not want to make a scientific contribution in terms of the use of advanced state-of-art bias-correction techniques, yet we want to illustrate the consequences of limited availability of open affordable high resolution gridded data products or long records of *in-situ* measurements. Most peer-reviewed papers on advanced downscaling and bias-correction methods address the ideal situation where long historic observational records are available. In this study, only data from a limited number of rain gauges with incomplete time-series and a gridded rainfall product – the APHRODITE dataset (Yatagai *et al.* 2012) – could be accessed and used. Due to this data quality issue, we concentrate on two widely used and easy to implement bias-correction procedures – linear scaling (LS) and delta change (DC). We evaluate the influence of the simplicity of these procedures on resulting changes in rainfall indices. Instead of using a large ensemble of GCMs, we focus on three models that nearly span the full range of seasonal mean rainfall projections available for India – analysing in more detail the locally relevant variation between these GCMs and their projected changes.

This paper is organized as follows. The section immediately below presents an overview of the selected GCMs, reference dataset, bias correction methods, the impact analysis framework applied and the study area. This is followed by a section in which we report the main findings of our study and present the range of rainfall indices under climate change. Here, we are specifically concerned with an inter- and intra-comparison of the GCMs and downscaling methods. Next, the limitations experienced for bias-correction techniques experienced in this study are discussed. The paper ends with a summary of our main conclusions and provides an outlook for future work.

METHODS

The method adopted in this study for the analysis of climate change impact on four rainfall indices is based on four steps described in subsequent sub-sections:

1. GCM selection by comparing observed (gauge and gridded time series) and simulated (GCM) variability of monthly rainfall.
2. A description of the selected reference rainfall dataset.
3. Bias correction of daily rainfall time series from the selected GCMs for the baseline and future projections using LS and DC method.
4. Rainfall indices analysis for the baseline and future projections focusing on water resources and flood risk management.

Global circulation model selection

Datasets from three GCMs of the Fifth Coupled Model Intercomparison Project (CMIP5 – Taylor *et al.* 2012; Knutti & Sedláček 2013) for RCP6.0 were downloaded. These are HadGEM2-ES, GFDL-CM3 and MIROC-ESM. Data were downloaded for 1961–1990 (baseline), 2030–2059 (short-term projections) and 2070–2099 (long-term projections).

Almost all CMIP5 models show good performance for surface air temperature simulations averaged over South Asia and the Indian subcontinent (Chatuverdi *et al.* 2012), with MIROC5 being one of the models closest to the observations. Yet, for area-averaged annual and seasonal rainfall, the models significantly deviate from observations over India (Chatuverdi *et al.* 2012). Here, GFDL-CM3 is one of the best performing models. In addition, HadGEM2-ES is selected because it is one of the most commonly used GCMs. For India, the three selected GCMs nearly span the uncertainty band for annual mean rainfall that was obtained with 18 Earth system models (ESMs) used in a validation exercise (Mondal & Mujumdar 2014; Ramesh & Goswami 2014). Interpreting Menon *et al.* (2013), HadGEM2-ES could be regarded as 'too dry', GFDL-CM3 as 'representative' and MIROC-ESM as 'quite wet'.

Representative concentration pathway (RCP) selection

The RCPs as considered in IPCC AR5 (Van Vuuren *et al.* 2011) are compatible with a wide range of stabilization, mitigation and baseline emission scenarios, and span a full range of socio-economic driving forces (Hibbard *et al.* 2011). In this study, we focus on RCP6.0 as it follows a stabilizing CO_2 concentration close to the median range of all four policy pathways and will give us a not too extreme indication of what might change. The spread and uncertainty in projections will increase when including additional RCPs and changes may become more pronounced when using RCP8.5 (Hibbard *et al.* 2011).

Observed rainfall

Observed rainfall was obtained for three rain gauges from the Central Water Commission of India (CWC). Locations of these rain gauges are shown in Figure 2. Ideally, we would use the CWC observations for the analysis, but we have only 11 gauges with complete records in a basin of 51,822 km^2 which does not result in a sufficient spatial grid coverage for planned future modelling work. Moreover, CWC gauges cover the period 1990–2012 whereas we have historic GCM data for the period 1961–1990. Differences in rainfall distributions for the two datasets may occur due to increasing trends in both frequency and intensity of heavy rain events over Central India of 10% per decade since 1950 (Goswami *et al.* 2006). To be reliable, bias-corrections should be based on long-term data records, ideally more than 20 years, this to include the natural variability sufficiently with anomalous wet and dry periods (Rajczak *et al.* 2015).

The Indian Meteorological Department has developed a daily gridded rainfall dataset (1901–2010) in high spatial resolution of $0.25^\circ \times 0.25^\circ$ (Pai *et al.* 2014). The IMD gridded data would have been the ideal dataset for this analysis as they contain data from 6,955 gauges over India and cover the period 1901–2010. However, the IMD dataset is not to be used freely for all applications. We therefore used the APHRODITE

Figure 2 | Locations of the GCMs center points (in black): HadGEM2-ES (square), MIROC-ESM (triangle) and GFDL-CM3 (circle). The nearest APHRODITE centre points have the same markers (grey). CWC rain gauges are shown with the station name (black star).

(Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources, Japan) long-term daily gridded precipitation dataset (version V1101) developed for Monsoon Asia (Yatagai *et al.* 2012). The APHRODITE dataset is a long-term (1951–2007) continental-scale product that contains a dense network of daily rain gauge data for Asia including the Himalayas, South and South-east Asia. The APHRODITE dataset consists of $0.25^\circ \times 0.25^\circ$ resolution gridded daily precipitation derived from the Global Telecommunication System, precompiled datasets and APHRODITE's individual data collection. The data are quality controlled and corrected for orographic effects. The dataset includes over 2,000 stations over India and captures the large-scale features of monsoon rainfall over the Indian region well. Pai *et al.* (2014) showed the comparability of the APHRODITE dataset with the climatological and rainfall variability over all India. Prakash *et al.* (2015) listed APHRODITE together with the Global Precipitation Climatology Center (GPCC) product as the best performing among four rain gauge-based land-only rainfall datasets when compared to the IMD gridded dataset.

Bias correction

There is often a clear bias from observations in the statistics of variables produced by GCMs, such as temperature and rainfall due to limitations, in among others, the incorporation of local topography and non-stationary phenomena within the GCMs. GCM outputs can, therefore, often not be directly applied for impact studies at the catchment scale (Kay *et al.* 2006; Christensen *et al.* 2008; Fan *et al.* 2010). Dynamic downscaling, statistical downscaling and bias correction are the most commonly used methods to generate locally applicable climate data (Fowler *et al.* 2007). Dynamic downscaling includes nesting of high resolution regional climate models (RCMs) with GCM outputs at boundaries which ensures consistency between climatological variables. However, they are computationally expensive, their skill strongly depends on GCM boundary and for India there are no ready to use RCM scenarios for the RCP emission scenarios at hand. Statistical downscaling models are based on statistical relationships between large-scale climate variables (predictors) and local-scale climate variables (predictant) and hence require less computational time. However, for the establishment of reliable statistical relationships, long historical observed records of both predictor and predictant variables should be available.

Simpler bias correction procedures consisting of general transformation techniques for adjusting the GCM output are often used. They assume a stationary bias between GCM output and observations for the baseline period and future climate (Teutschbein & Seibert 2012). With the more advanced quantile mapping method (Camici *et al.* 2014), changes in mean and extreme rainfall are corrected individually – however this method requires reliable CDFs of observed rainfall. From the comparison between the APHRODITE dataset and station observations (Rana *et al.* 2014), we know that large biases in rainfall extremes exist. The deviations in the extremes seem more pronounced than the differences in monthly average conditions (see Results section) and would require the quantile mapping transfer functions to make large adjustments in the tails of the distribution making the end result less reliable. Therefore, we restrict ourselves to two simple methods: (1) the DC method and (2) the LS method (Christensen *et al.* 2008), realizing that these methods only concentrate on the correction of monthly mean rainfall amounts and can thus affect our analysis of changes in rainfall indices, especially for the extremes.

Delta change method

The DC method transforms historical observations into future projections using monthly average correction factors that are derived from the GCM simulations for the baseline and future climate (Teutschbein & Seibert 2013; Camici *et al.* 2014) according to:

$$\Delta P_m = \frac{\overline{P\_GCM_m^{fut}}}{\overline{P\_GCM_m^{BL}}} \tag{1}$$

$$P\_OBS^{fut} = \Delta P_m \, . \, P\_OBS^{BL} \tag{2}$$

where *fut* refers to future climate, *BL* refers to baseline climate (i.e., 1961–1990), *GCM* refers to GCM simulations and *OBS* refers to either observations (*BL period*) or future projections (*fut*), *P* refers to daily rainfall values and P_m refers to monthly long-term mean rainfall values.

The disadvantage of this method is that the future and baseline scenarios differ only in terms of their means and intensity while all other statistics of the data, such as the skewness and number of wet days (WD), remain almost unchanged (Camici *et al.* 2014). This will hamper the assessment of change in extreme rainfall frequency as the change in return period is essentially a derivative of the multiple factors.

Linear scaling method

Within the LS method, the long-term average monthly bias between the baseline (i.e., 1961–1990) GCM simulations and observations is derived and this bias is applied to correct the future GCM simulations assuming a stationary bias over time, according to:

$$BIAS_m = \frac{\overline{P\_OBS_m^{BL}}}{\overline{P\_GCM_m^{BL}}} \tag{3}$$

$$P\_OBS^{fut} = BIAS_m \, . \, P\_GCM^{fut} \tag{4}$$

where $BIAS_m$ is the monthly average bias for the baseline climate and the correction factor for the future GCM simulations. The advantage of this method is that the variability of the corrected data, for both baseline and future climate, is more consistent with the GCM data, which implies that changes in wet day frequencies and intensities can be derived, although they are not individually corrected as all events are adjusted with the same monthly average correction factor (Teutschbein & Seibert 2013).

Impact analysis framework

To study the impact of climate change on rainfall and associated fields like water resources and flood risk management, we selected the following four indices.

1. Mean annual and seasonal rainfall.
2. Frequency of seasonal WD. According to the definition followed by the India Meteorological Department (IMD), a day with rainfall is considered a 'wet day' if the rainfall equals or exceeds 2.5 mm.
3. Seasonal frequency of days with light, moderate and heavy up to extremely heavy rainfall (LRD, MRD and HRD, respectively). Table 1 shows the IMD classification for rainfall intensities. We clustered all 'heavy rain' classifications into one group to examine climate change-induced alterations in potential flood inducing events.
4. One-day extreme rainfall return periods to investigate the potential impact of climate change on rainfall intensities. In this study, we applied the Gumbel extreme value type-1 distribution to derive rainfall intensities for different return periods (2, 5, 10, 25, 30, 50 and 100 years).

Table 1 | Indian meteorological department classification of rainfall intensity

Event	Abbreviation	Rainfall
Wet day	WD	Daily rainfall ≥2.5 mm
Light rain	LRD	Daily rainfall between 2.5 mm and 7.5 mm
Moderate rain	MRD	Daily rainfall between 7.6 mm and 35.5 mm
Rather heavy rain	HRD	Daily rainfall between 35.6 mm and 64.4 mm
Heavy rain	HRD	Daily rainfall between 64.5 mm and 124.4 mm
Very heavy rain	HRD	Daily rainfall between 124.5 mm and 244.4 mm
Extremely heavy rain	HRD	Daily rainfall >244.5 mm

Part of the analysis focuses on single seasons. Here, the year is divided into four seasons: winter (December, January, February (DJF)), pre-monsoon (March, April, May (MAM)), SW monsoon (June, July, August, September (JJAS)) and post-monsoon (October, November (ON)).

Study area

This study focuses on the Brahmani-Baitarani river basin located in the eastern part of India (see Figure 1). The Brahmani-Baitarani river basin and neighbouring Mahanadi river basin experienced serious floods in the years 2001, 2003, 2006, 2008, 2011 and 2013. During September 2011, heavy rainfall together with high sea levels led to the flooding of large parts of the delta. It affected about 3.4 million people, of which, 45 people lost their lives. In 2013, cyclone Phailin created havoc along the coastal districts of Odisha state. Due to storm surge up to 3.5 m, large areas were inundated. The

Baitarani River, along with other rivers, experienced floods as a result of torrential downpour. No less than 13 million people were affected, of which, 44 people lost their lives.

The basin is an inter-state basin and spreads across the states of Chhattisgarh, Jharkhand and Odisha. The elevation ranges from >750 m in the north-western part of the basin to approximately 10 m in the delta region. The Baitarani River enters the Brahmani River in the deltaic region before it drains into the Bay of Bengal. The catchment area is 51,822 km^2. The region is characterized by a sub-tropical monsoon climate zone with mean annual rainfall of approximately 1,450 mm (CWC 2011), most of which occurs during the SW monsoon season (June to September).

The basin is exposed to orographic effects with a positive elevation-rainfall depth slope during monsoon season and an inverse slope in the post-monsoon season when cyclones hit the coast of Odisha. Due to the size and shape, the Brahmani-Baitarani river basin is captured by approximately one GCM grid cell in the deltaic region and one grid cell in the mountainous region. This allows study of possible orographic effects present in the future projections (Prokop & Walanus 2015). GCM and APHRODITE observed rainfall values were taken from the grid cell with centre coordinates closest to these regions. It was decided not to resample the APHRODITE observed and GCM datasets to one common grid, since this would result in spatial smoothening of rainfall extremes.

RESULTS

We focus our discussion on the SW monsoon season only, as mainly changes in monsoon rainfall will affect water resources and flood risk management in the basin. The figures contain results for all seasons.

Comparison of APHRODITE and gauge rainfall data

The APHRODITE dataset covers the full GCM baseline period, whereas the gauge observations are more recent and only available for a limited time-span, and can therefore not be used as baseline reference. We here verify the quality of the APHRODITE dataset compared to gauge observations for the overlapping period 1990–2007. Overall the APHRODITE dataset resembles the CWC rain gauges quite well (see Figure 3).

However, during pre-monsoon and monsoon season, APHRODITE data underestimate the rainfall in comparison to the gauge observations (averaged for the three gauge stations 17% and 12% less rain during the pre-monsoon and monsoon period, respectively). APHRODITE data underestimate the occurrence of 'heavy rain' events during the 1990–2007 period with 68% (24 instead of 74 events), 61% (17 instead of 44 events) and 90% (5 instead of 48 events) for Akhuapada, Anandpur and Tilga gauge, respectively, with an average 0.3–1.3 of such events per year (a frequency of less than 1 and changes therein will affect the analysis of extreme value return periods). This underestimation is most likely caused by the smoothening introduced when interpolating point observations to the grid. Differences in rainfall extremes between the two datasets can clearly be seen from their respective CDFs (see Figure 4). Still, based on this analysis and the period covered by the APHRODITE dataset, we conclude that the dataset is suitable as a gridded reference dataset for the Brahmani-Baitarani river basin. When quantifying the impact of climate change to strategic flood management studies in

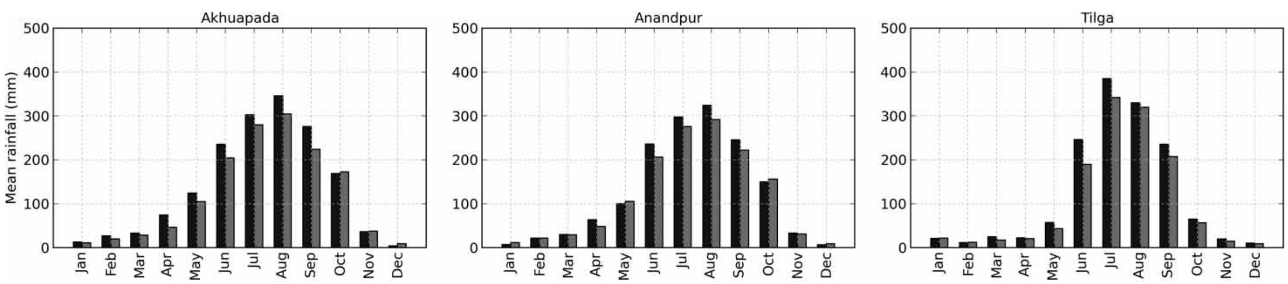

Figure 3 | Monthly mean precipitation for the period 1990–2007 as observed in the APHRODITE dataset (grey) and by CWC (black).

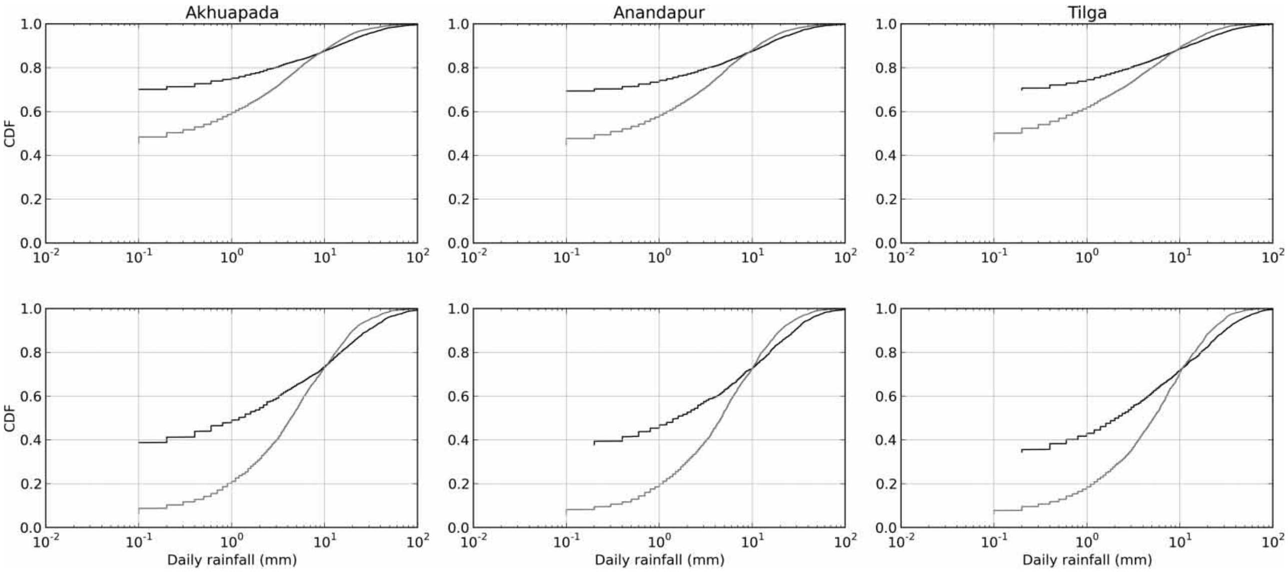

Figure 4 | CDF curves of daily rainfall for the period 1990–2007 as observed in the APHRODITE dataset (grey) and by CWC (black) for the entire year (top) and monsoon season (bottom).

practice, the rainfall deviations between APHRODITE and gauge extremes should be considered as they will influence the projected changes in rainfall extremes.

Comparison of APHRODITE and GCM baseline data

The SW monsoon, lasting from June to September, is the most important feature of the Indian climate. Its onset and withdrawal dates are highly variable. Over the period 2000–2012, the actual onset date over the Kerala coast varied from 23 May to 8 June (Puranik *et al.* 2013). As per the IMD, the normal monsoon onset date for the Brahmani-Baitarani river basin is 10 June. However, during 2005–2012, the actual onset dates varied from 6 to 26 June (Indian Meteorological Department). As a consequence, total rainfall in the month of June varies significantly in the Brahmani-Baitarani river basin. The baseline simulations of the three GCMs show a fair comparison with the observed rainfall on annual basis (see Figure 5). However, for the monsoon season, the baseline simulations show an underestimation of average seasonal rainfall. Rainfall amount in June is underestimated by both HadGEM2-ES and MIROC-ESM (11% and 19%, respectively, of observed), and June underestimations are especially large for the deltaic region where the GCM cells cover both land and sea.

Monthly rainfall amounts of HadGEM2-ES are almost all below APHRODITE values; this corresponds with findings of Menon *et al.* (2013) that HadGEM2-ES is 'too dry' compared to long-year observations. Their conclusion that MIROC-ESM is 'quite wet' does not hold throughout the year for the baseline period for the Brahmani-Baitarani river basin. MIROC-ESM underestimates rainfall in February–May in the delta region and during the monsoon in the mountainous region. GFDL-CM3 overestimates rainfall during the monsoon season in the deltaic region but overall performs best.

Impact of downscaling method on future GCM projections

We made a modification to the LS method for the month of June as the underestimation of monsoon rainfall in June by HadGEM2-ES and MIROC-ESM would result in extreme large correction factors, unrealistic rainfall amounts (up to 900 mm/day) and, consequently, an unrealistic large increase in heavy rain events. We decided to apply the July multiplier also for June. In June the monsoon season (JJAS) starts and, especially for the second half of the month, meteorological conditions in June are comparable to the next month – July. By doing this, the GCM total monsoon rainfall amount of MIROC-ESM and HadGEM2-ES

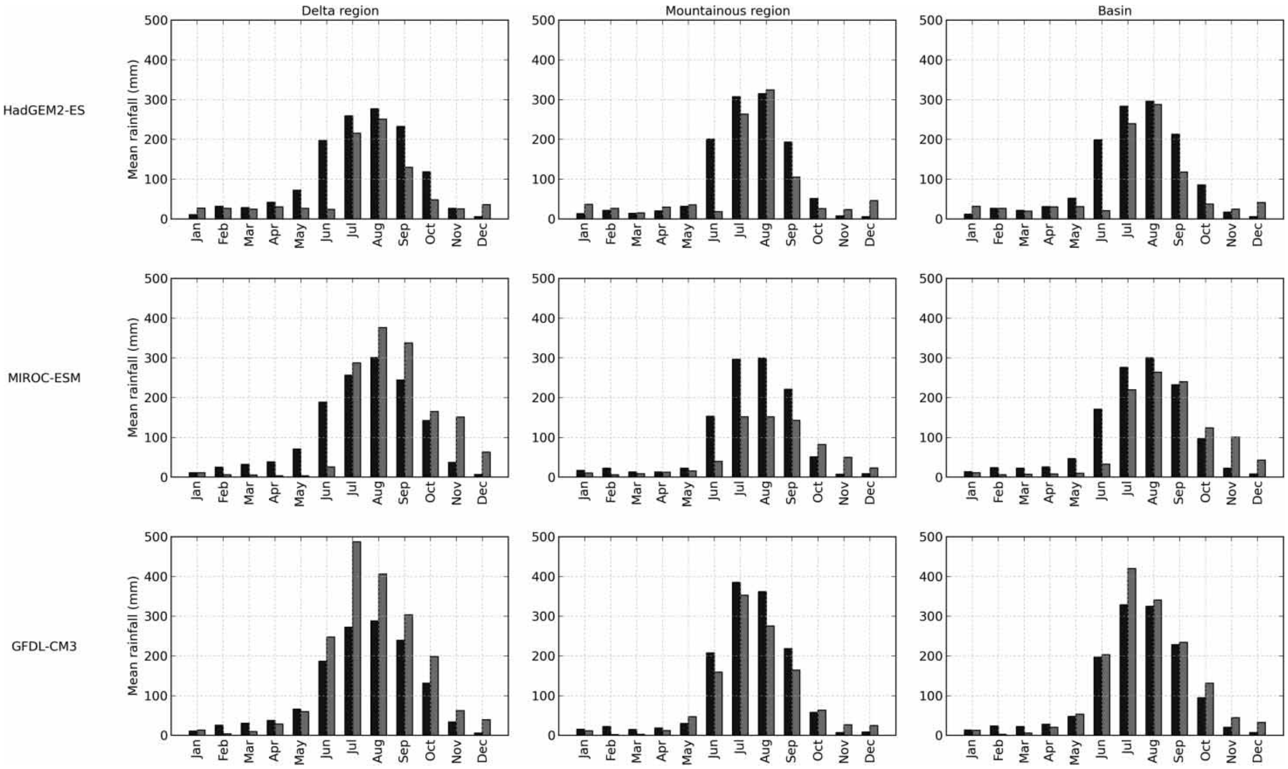

Figure 5 | Monthly mean rainfall for the period 1961–1990 as observed (black) and simulated by the three GCMs (grey).

became closer to the APHRODITE dataset. Only for GFDL-CM3, does total monsoon rainfall become slightly lower than that of APHRODITE values. By applying the multiplier of July in June, the annual mean baseline rainfall amounts will be somewhat different between the LS and DC methods. Although the underestimation of rainfall by MIROC-ESM for the winter season in the delta region leads to high multipliers as well, we decided not to apply a tailored correction here as it would only be applicable for one of the GCMs.

Mean seasonal rainfall

Figure 6 presents the mean seasonal rainfall for baseline and future climate. Nine panels are used to summarize our findings, showing for each GCM individually, changes for the delta region (left), the mountainous region (middle) and for the basin as a whole (right). Towards the end of the century, monsoon rainfall is projected to increase throughout the basin, with the delta region in MIROC-ESM as the only exception. For the shorter time horizon, the signal is more variable; according to GFDL-CM3, monsoon rainfall will first decrease, whereas the other regions project increases except for the delta region in MIROC-ESM. Both HadGEM2-ES and GFDL-CM3 also project increases for the pre-monsoon season. Increases are, in general, larger for the DC method; the multipliers of the LS method may reduce the change signal. In general, all changes in mean monsoon rainfall derived with HadGEM2-ES and MIROC-ESM are significant ($\rho = 0.05$ level). GFDL-CM3 shows this significance only for the changes at the end of the century (2085). For the mountainous region, changes in pre-monsoon mean rainfall are also significant at $\rho = 0.05$ level for the long-term climate projection.

The projection obtained here are in line with the study of Guhathakurta *et al.* (2011), Lal *et al.* (2000), May (2004) and Menon *et al.* (2013), who also reported increases for monsoon rainfall in east and north-east India. We also made a brief comparison with projected changes derived using the CWC dataset as reference and found similar changes.

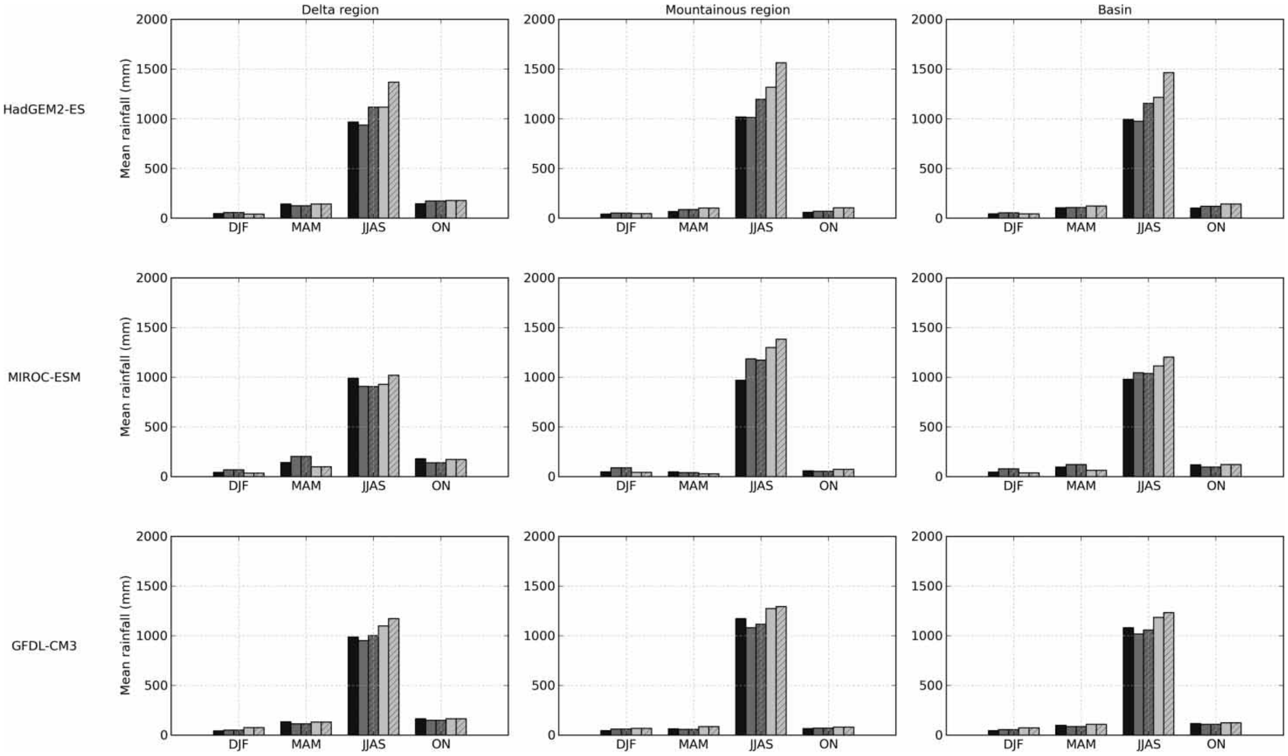

Figure 6 | Mean seasonal rainfall. Observations (black), 2045 short-term climate projection (dark grey: LS, dashed dark grey: DC), and 2085 long-term climate projection (light grey: LS, dashed light grey: DC).

Number of wet days

The projected change in the number of wet days (WD – Figure 7) highly depends on the correction method used and the direction of the bias in the GCM data. For the DC method, the impact of climate change is given by the difference between the future GCM and the APHRODITE data to which the DC method was applied. For the LS method there is a mismatch in the number of WD for the GCM data for the baseline period and the APHRODITE data. The impact of climate change can thus only be derived when comparing future GCM data with the bias-correction baseline when using the LS method.

Changes in this index cannot be captured well by the DC method. With the DC method the observed day-to-day variability remains unchanged in the future time-series and intensities are only scaled with monthly average correction factors (Teutschbein & Seibert 2013; Camici *et al.* 2014). Changes are therefore directly related to the seasonal mean rainfall and only slightly differ due to the definition of the rainfall amount for a wet day. To project changes in the WD, while applying LS as correction method, the number of WD has already been captured well by the GCMs for the future time period. Both HadGEM2-ES and MIROC-ESM show a distinct increase in WD in both regions and for both short- and long-term projections. While the 'too dry' and 'too wet' GCMs (Menon *et al.* 2013) show a clear trend, the trend in the 'representative' GCM (GFDL-CM3) is minimal from a small decrease for the short-term projections to a small increase in WD in the long-term projections. From the mixed signals presented in Figure 8, no clear conclusions on the potential direction of change in the WD during the monsoon season can be drawn; on average, there is an indication for an increase. This increase was also found by Chatuverdi *et al.* (2012). The changes in WD during monsoon due to climate change are significant ($\rho = 0.05$ level) for HadGEM2-ES and MIROC-ESM, except for the DC method in the delta region in the latter GCM. GFDL-CM3 shows a more diverse pattern with only significant changes of WD in the monsoon period for the long-term climate projection (2085).

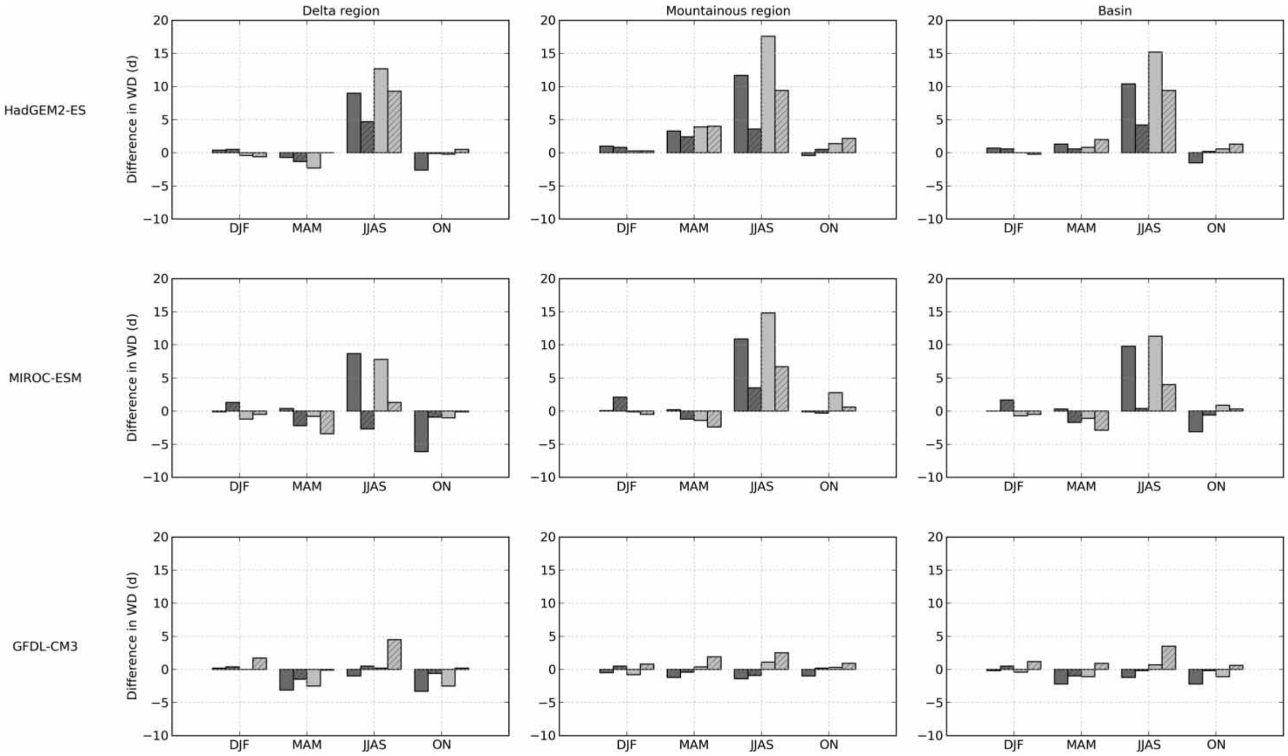

Figure 7 | Difference in number of WD: 2045 short-term climate projection (dark grey: LS, dashed dark grey: DC) and 2085 long-term climate projection (light grey: LS, dashed light grey: DC).

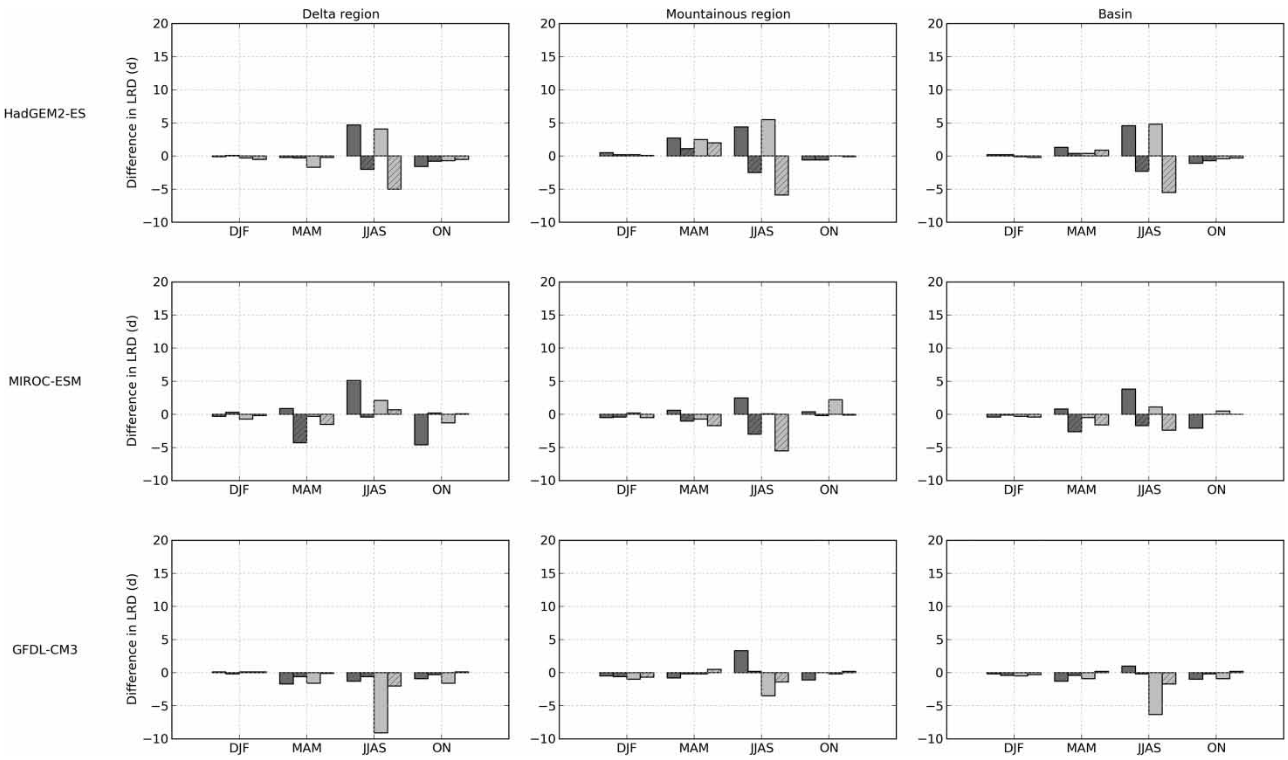

Figure 8 | Difference in number of LRD: 2045 short-term climate projection (dark grey: LS, dashed dark grey: DC) and 2085 long-term climate projection (light grey: LS, dashed light grey: DC).

For the LS method, we conclude that for a reliable projection of change in WD, the WD in the GCM baseline period should be close to observed, otherwise the correction method and bias from observations will disturb the change signal too much. For GFDL-CM3, we have seen that the number of WD during the baseline period is 103, which already nearly corresponds to the entire monsoon season which explains the small increase found for this GCM. With the DC method, the WD only increase based on the monthly linear increase in total precipitation.

Light, moderate and heavy rains

The impact of climate change on these indices is computed similar to the WD indices. As expected, the projected changes obtained with the DC method are directly related to the change in mean seasonal rainfall with decreases in LRD (Figure 8) and increases in both MRD and HRD (Figures 9 and 10). Overall, rainy days will become wetter with the exception being the delta region in MIROC-ESM, that partially includes the sea. The increase in MRD and HRD is particularly visible during the long-term climate projection (2085). The general increase in HRD is confirmed by the results of the LS method applied to HadGEM2-ES and MIROC-ESM for the mountainous region. Notable are the minimal changes in HRD obtained from GFDL-CM3. This change in day-to-day variability is a direct result of changes in rain intensity and frequency in the GCM itself. Overall, there is a strong indication for the impact of climate change during monsoon on LRD, MRD and HRD in both regions at $\rho = 0.05$ significance level.

Return periods

Both HadGEM2-ES and MIROC-ESM project decreases in return periods for extreme rainfall amounts for both the delta and mountainous regions (see Figure 11). In general, changes derived after applying the DC method are more modest as a result of the unchanged day-to-day variability – changes will most likely be within the present day climate

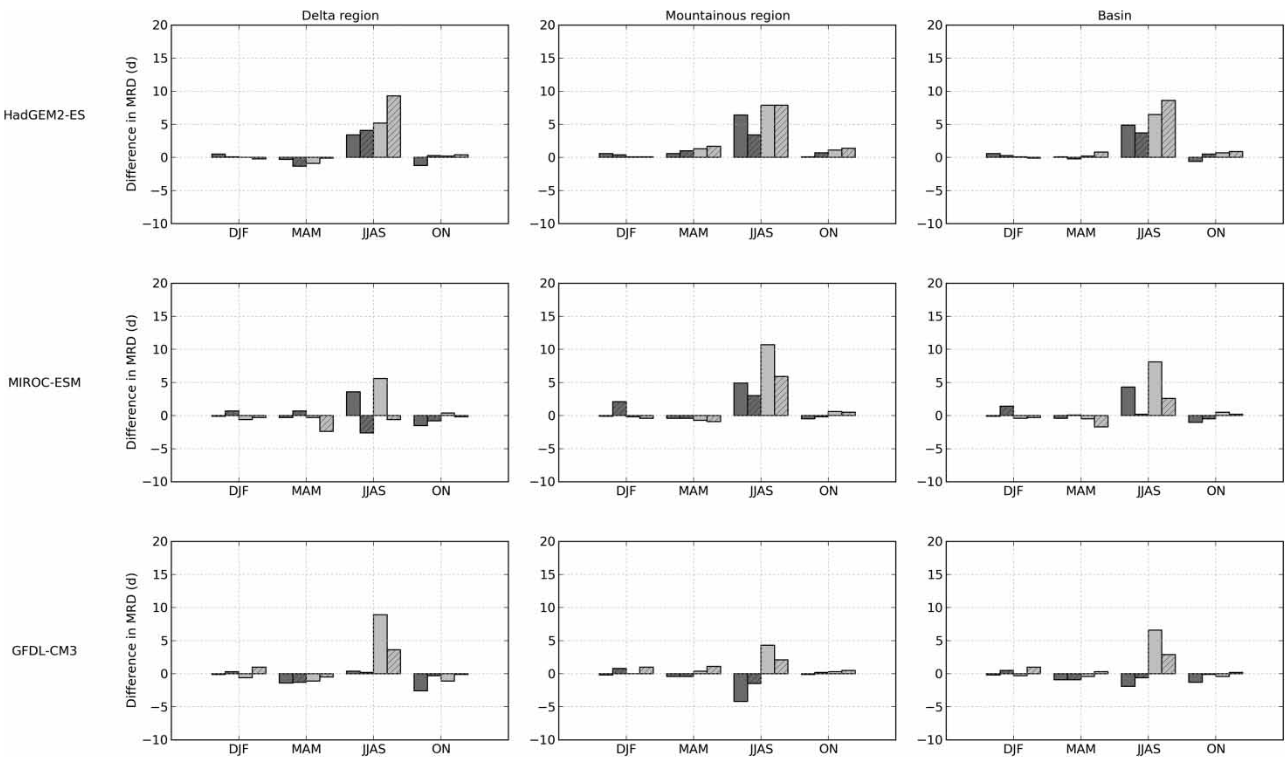

Figure 9 | Difference in number of MRD: 2045 short-term climate projection (dark grey: LS, dashed dark grey: DC) and 2085 long-term climate projection (light grey: LS, dashed light grey: DC).

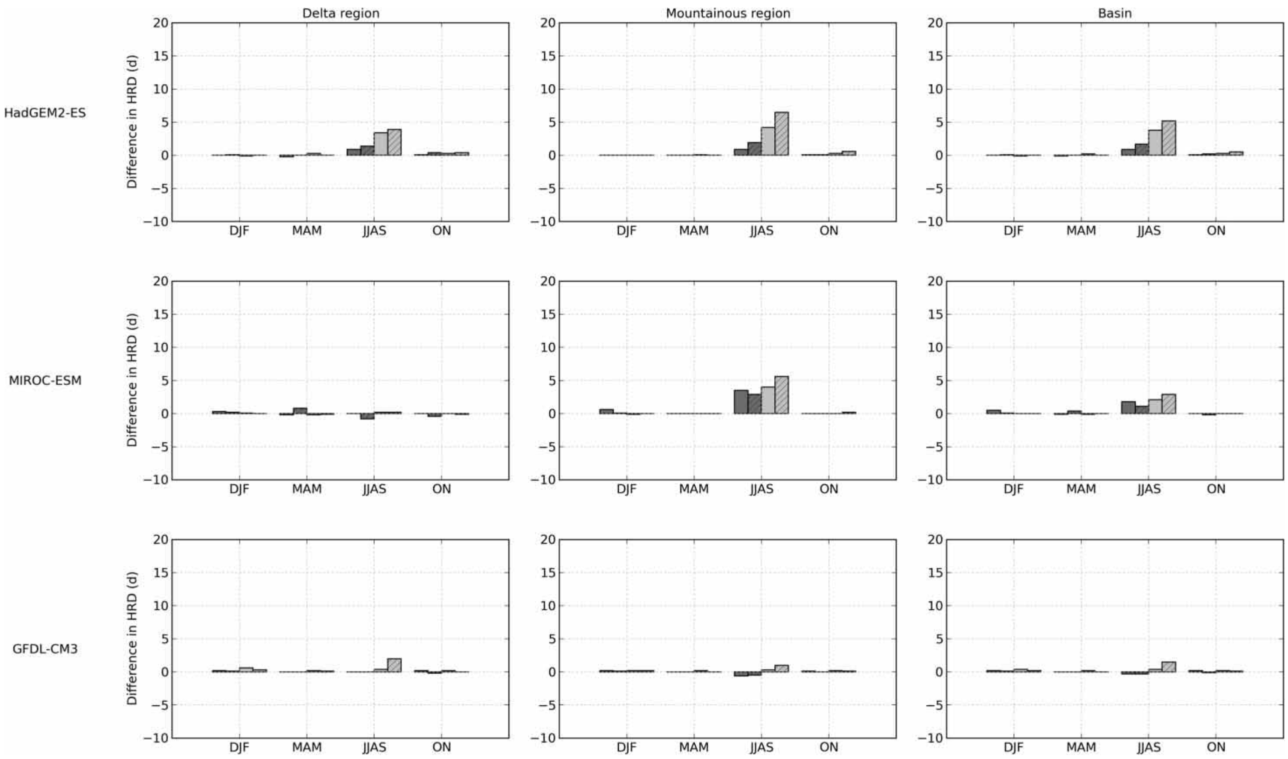

Figure 10 | Difference in number of HRD: 2045 short-term climate projection (dark grey: LS, dashed dark grey: DC) and 2085 long-term climate projection (light grey: LS, dashed light grey: DC).

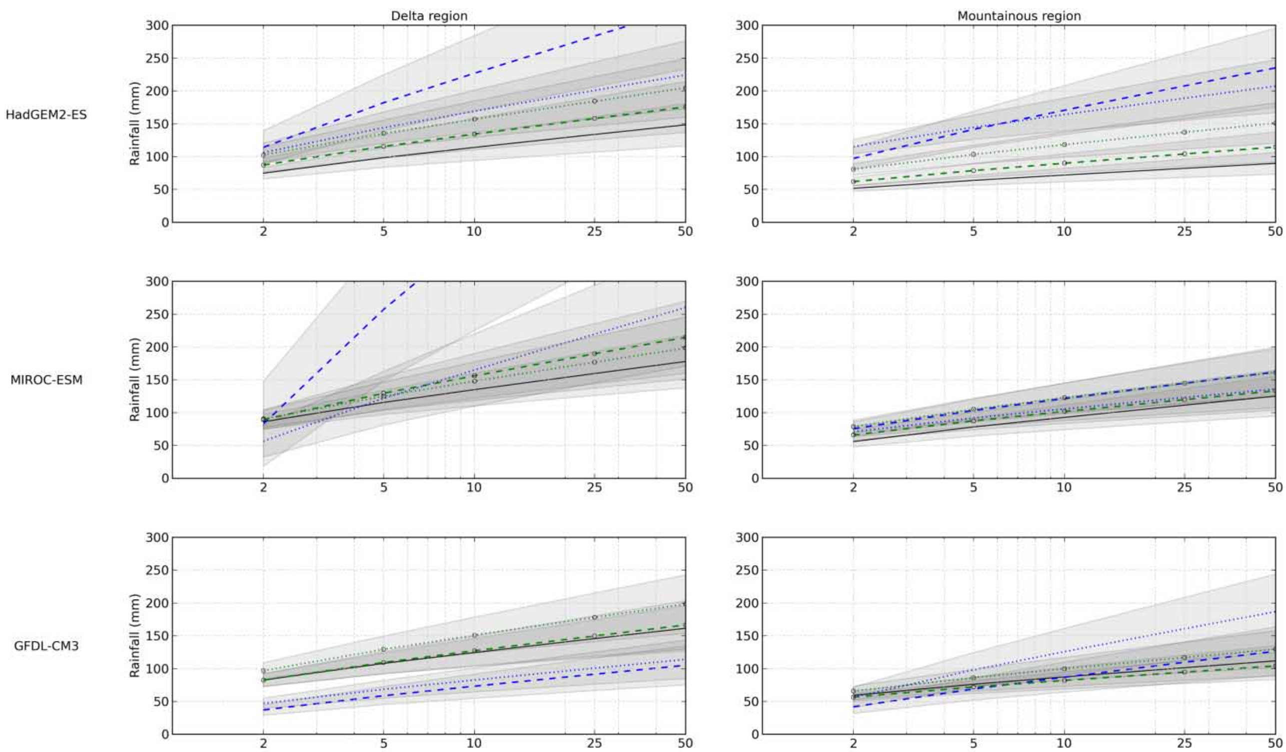

Figure 11 | Return periods based on annual maximum. Observations (black), 2045 short-term climate projection (dashed: LS, dashed with circle: DC) and 2085 long-term climate projection (dotted: LS, dotted with circle: DC). The reference Gumbel distribution is based on the APHRODITE dataset that has also been used for the bias-correction of the GCM data.

variability. Unfortunately, we find unrealistic high rainfall extremes for MIROC-ESM due to the high February–May multipliers that correct for the underestimation of winter and pre-monsoon rainfall in the delta region. The possible increases in return periods for the delta region, obtained after applying the LS method to GFDL-CM3, are inconsistent with all other projections and likely the result of correction multipliers below one that also decrease the extremes. The overall reduction in return times of annual extremes of daily rainfall for the late 21st century, which we find here, was also found by Ramesh & Goswami (2014).

With the DC method, changes in monthly mean precipitation amounts are projected on all daily rainfall amounts, whereas we know that precipitation extremes are likely to increase more (e.g., Goswami *et al.* 2006). As a result, the DC method results in lower future precipitation extremes than the LS method (see Figure 11).

The return period analysis and the large uncertainty one finds for precipitation extremes when applying these simple bias-correction methods once more illustrate the importance of focusing on relative changes. The precipitation amounts for a 100-year return period of a 1-day rainfall event for the period 1990–2013 are 378 mm, 328 mm and 229 mm for Akhuapada, Anandpur and Tilga rainfall gauge, respectively, whereas the APHRODITE data and the baseline rainfall for the LS method applied to all GCMs and regions show intensities of 100–200 mm for the same return period. Therefore, translating absolute future climate results of extreme rainfall events based on the APHRODITE dataset to rainfall intensities, recognizable for local authorities familiar with the rainfall gauges, remains a challenge.

DISCUSSION

For this assessment, the APHRODITE dataset was the best openly available historical reference dataset as it provides continuous daily time-series for the full baseline period of the GCM simulations and performs relatively well for India (Rana *et al.* 2014). However, our comparison with gauge observations showed large biases which are most likely as a result of spatial smoothening introduced by the interpolation to the grid. The biases in extreme rainfall amounts in the APHRODITE dataset will have influenced the analysis of future changes in extremes. In addition, with a more reliable reference meteorological dataset that better matches the CDF of gauge data, an advanced correction method could have been employed, in which, realistic changes in extremes can be introduced and the day-to-day variability can be corrected towards observations.

Instead, we applied two relatively simple GCM correction methods. Both methods, we know, have disadvantages for use in climate impact analysis. The DC method only provided reliable information on changes in seasonal means, as it leaves the day-to-day variability unchanged and changes in extremes are linearly scaled with changes in the mean (Teutschbein & Seibert 2013; Camici *et al.* 2014). With the LS method we could obtain information on changes in rainfall frequency and intensity; however, as only monthly mean correction multipliers were applied, the day-to-day variability of corrected GCM baseline simulations remained different from the observed time-series. In addition, the monthly mean correction also influenced the values of the extremes, i.e., within an, on average, too wet month the extremes are linearly reduced with the same correction multiplier. Consequently, only relative changes in extremes could reliably be estimated from the baseline and future corrected GCM simulations.

We introduced an additional correction to the LS method by applying the multiplier for July to the data of June; this is to avoid the occurrence of extreme high rainfall amounts in the corrected data for June by compensating for the variable monsoon onset date. In future work, the selection of GCMs could be extended with more criteria, focusing not only on annual rainfall amounts, but also on the onset and amount of monsoon rainfall, thereby the need to apply such tailored corrections can be avoided.

From the above, we can conclude that the performed analysis is not based upon the latest state-of-the-art techniques as, for example, presented in Teutschbein & Seibert (2012), Christensen *et al.* (2008), Fowler *et al.* (2007), and many others. However, this study illustrates the restrictions one is faced with when working in less data-rich areas or in the case that available datasets are not open for use in all applications. As discussed, the quality in combination with the time-coverage of the historical observations did neither allow for statistical downscaling based upon predictor–predictant relationships nor for more advanced quantile mapping techniques. In addition, dynamically downscaled RCM data was not at hand. The simpler techniques that were applied did not allow for an analysis of all statistical quantities of interest. This demonstrates the gap between science and practice that still needs to be bridged in the area of local climate impact analysis (Dosio *et al.* 2012; Ehret *et al.* 2012).

This study focused on changes in rainfall only, but could be extended with impact analysis for water resources and flood risk management. As discussed above, the changes in daily rainfall and extreme events cannot be considered reliable, yet the seasonal and monthly changes provide information for (1) flood risk assessments for larger river basins where severe floods mainly occur as multiple day events due to the result of medium/long-term (weeks to months) rainfall conditions upstream and for (2) water resources management, groundwater recharge and soil moisture conditions of relevance to agricultural production. For the latter applications, the baseline change assessment should be extended to all seasons.

CONCLUSIONS

The following conclusions are drawn from the study:

- SW monsoon rainfall is, in general, projected to increase over the Brahmani-Baitarani river basin, especially in the mountainous regions. The number of WD is likely to increase in the monsoon season; changes are largest and most pronounced towards the end of the century. The number of days with heavy rain is also likely to increase.
- Although the annual rainfall cycle is captured well by all three GCMs, biases from observed data exist, with, as most important, the too late onset of the monsoon in HADGEM2-ES and MIROC-ESM and the underestimation of winter rainfall by MIROC-ESM in the delta region.
- The DC and LS correction methods disturb the projected changes in extremes. The LS method is preferred when analysing extremes and change in number of WD, as the DC method leaves the day-to-day variability unchanged. However, with the LS method, the analysis should be restricted to the relative changes between corrected baseline and future GCM time-series.
- The historical observation dataset APHRODITE underestimates the number of 'heavy rain' events when compared to observed data of CWC rain gauge stations. This affects the reliability of future climate change projections for precipitation. If openly available, the IMD dataset could have resulted in better projections.
- For proper correction and downscaling of GCM data, more advanced techniques exist. However, these techniques require high quality reference meteorological datasets and/or computing resources which were not available to this study. Assessment of the impact of these limitations to the actual climate change analysis will provide insight into the applicable bias-correction methods and can improve the interpretation of the results.

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