Future climate and runoff projections across South Asia from CMIP5 global climate models and hydrological modelling

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\textbf{A B S T R A C T}

\textbf{Study region:} The South Asia.

\textbf{Study focus:} This paper presents future climate and runoff projections for the South Asia region under the RCP8.5 scenario with climate change informed by 42 CMIP5 GCMs. Runoff is projected for 0.5° grids using hydrological models with future climate inputs obtained by empirically scaling the historical climate series.

\textbf{New hydrological insights:} The modelling results indicate that future runoff will increase throughout most of the region except in the far north-east and far north-west. The median projection shows increases in mean annual runoff of 20–30\% in the Indian sub-continent for 2046–2075 relative to 1976–2005. The change in runoff is driven mainly by the change in precipitation, moderated (in wetter futures) or intensified (in drier futures) by higher temperature and potential evaporation. The paper also investigates the uncertainties of the projection due to scaling methods and selection of GCMs. The difference in runoff projections from different scaling methods is small relative to the large uncertainty in precipitation projections from the GCMs. Sub-selecting only the “better” performing GCMs shows marginal difference in the uncertainty range of projected runoff. For the broad scale projections presented here, it is best to use projections informed by all the GCMs to provide an indication of the full uncertainty range.

\section{1. Introduction}

Water security in South Asia will be under increasing stress owing to socio-economic growth and global climate change. It is forecasted that the population in South Asia will be more than 2.3 billion by 2050 \cite{UnitedNations2015}. The growth of population and expanding economies will result in an increase in water demand. Meanwhile, there is strong evidence that many parts of South Asia are experiencing long-term warming trends that will continue into the future \cite{Hijioka2014}. The changes in climate will have significant impacts on water availability. Moreover, the warmer future climate will increase evapotranspiration and hence increase demand for water in irrigated agriculture, urban centres and water-dependent ecosystems. Exacerbated by climate change, it is estimated that water scarcity could cost up to 6\% GDP loss in South Asia by 2050 \cite{WorldBank2016}.

As water impacts practically all sectors (people, agriculture, industries and ecosystems), there have been considerable research efforts on predicting or projecting water availability under future climate conditions \cite{Devkota2015,Gupta2004,Immerzeel2010,Immerzeel2012,Nepal2015} to inform the development of effective adaptation options. For South Asia, most studies of hydrological response to climate change only investigate limited regions...
and climate scenarios. For example, Akhtar et al. (2008) simulated the hydrological response to climate change for three river basins (Astore, Gilgit and Hunza) in the upper Indus using two downscaling approaches driven by the HadAM3P GCM. One of the downscaling approaches was a form of statistical downscaling using the ‘delta change’ approach and another was dynamical downscaling using the PRECIS regional climate model at 25 km resolution. Lutz et al. (2014) assessed potential changes of water availability for the large basins in northern South Asia, with increased runoff projected for 2050 for the upper Ganges, Brahmaputra, Salween and Mekong primarily due to projected precipitation increases and for the Indus due to accelerated glacier melt in the upper basin.

The hydrological response to climate change is generally predicted using downscaled future climate projections to drive a hydrological model (Chiew et al., 2009a; Teng et al., 2012a). One of the key challenges in factoring climate change into water resources management lies in the uncertainty in the projections (Jiménez Cisneros et al., 2014; Lopez et al., 2009). The sources of the projection uncertainties could be from the GCMs, the downscaling approaches, or the hydrological models (Chen et al., 2011; Teng et al., 2012b; Vetter et al., 2016). The performance of GCMs over the South Asia region have been investigated by quite a few researchers (e.g., Chaturvedi et al., 2012; Freychet et al., 2015; Jourdain et al., 2013; Ogata et al., 2014; Palazzi et al., 2015; Saha et al., 2014). For example, Saha et al. (2014) found that the majority of the CMIP5 GCMs fail to simulate the post-1950 decreasing trend of Indian summer monsoon rainfall, as they did not capture the weakening monsoon associated with the warming of southern Indian Ocean and strengthening of cyclonic formation in the tropical western Pacific Ocean. Some studies have suggested placing more weight on or using only projections from the better performing GCMs As noted by Palazzi et al. (2015), however, it is challenging in selecting better performing GCMs for the region as none of GCMs can reproduce all the salient features (e.g. seasonal and annual rainfall amounts, distribution and trend, or the large scale atmospheric-oceanic drivers of rainfall in the region). Like the GCMs, the latest dynamic downscaling runs in the CORDEX regional climate model experiments also do not capture the observed monsoon precipitation trends or the correct magnitude of observed warming (Ghimire et al., 2015; Mishra et al., 2014). In any case, the uncertainty in climate projections (from GCMs and from downscaling approaches) must be adequately represented within the specific context and objectives of any hydrological modelling and integrated water resources management study.

This paper aims to present future climate (precipitation, temperature and potential evaporation) and runoff projections across South Asia, and the associated uncertainties and robustness of the projections from different considerations or treatments of climate change projections and hydrological modelling. The future runoff is projected using hydrological models with future climate inputs informed by 42 GCMs reported in the Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC AR5) (IPCC, 2013). The paper investigates (i) the sensitivity of runoff to changes in the climate variables, (ii) the projected runoff change resulting from different hydrological modelling approaches, (iii) the projected runoff change using different empirical downscaling approaches, (iv) the uncertainties of runoff projection within and across the GCMs, and (v) whether using a sub-set of the ‘better’ performing GCMs can reduce the uncertainties in the projection. The structure of the paper is as follows – Section 2 outlines the data and methods used; Section 3 presents and discusses the projected changes in the climate variables across South Asia; Section 4 presents the climate change impacts on runoff and water supply security, and also discusses results and implications from different modelling considerations; Section 5 presents the summary and conclusions.

2. Data and methods

In this study, the South Asia region refers to the domain between 5.25–38.00 °N and 65.25–93.75 °E. To facilitate presentation and discussion of results, nine sub-regions based on the freshwater ecoregion map of Abell et al. (2008) are used. The nine sub-regions, as shown in Fig. 1, are North-West region (NW), part of the Tibetan Plateau (TP), Indus River Basin (IND), Ganges-Brahmaputra River Basin (GA), part of the Arakan Coast (AC), Narmad-Tapti River Basin (NT), Deccan Plateau (DP), Ghats Coast (GH), and Sri Lanka Island (SL).

2.1. Baseline observations and CMIP5 database

The baseline period of 1976–2005 is used for this study (‘baseline’, ‘present’ and ‘historical’) are used interchangeably throughout the paper, they all refer to the period 1976–2005. The daily gridded climate data of precipitation, temperature, wind speed, air pressure and radiation are obtained from the Princeton Global Forcing (PGF) dataset with spatial resolution of 0.5° × 0.5° (Sheffield et al., 2006). Fig. 1 shows the annual mean of precipitation, temperature, potential evaporation and aridity index for the baseline period across the South Asia region. The precipitation and temperature comes directly from the PGF dataset. Potential evaporation is estimated from the PGF climate variables using Morton’s formulation of wet environment (or equilibrium or areal potential) evaporation (Morton, 1983; Chiew and McMahon, 1991). Aridity index is defined as mean annual potential evaporation divided by mean annual precipitation.

The future climate scenarios are derived from the CMIP5 database (http://cmip-pcmdi.llnl.gov/cmip5/), which archives transient climate experiments from more than 20 climate modelling groups around the world. All the ensemble runs of 42 CMIP5 GCMs with both historical and future outputs available on 15 March 2013 (the same date as that adopted by IPCC AR5) are used here. The results presented in this study are for a future period over 2046–2075 relative to the baseline period (1976–2005) for RCP8.5 (high representative greenhouse gas concentration pathway corresponding to radiative forcing of 8.5 W/m² by 2100 relative to pre-industrial value, see Moss et al., 2010; Taylor et al., 2012). It is worth noting that the discussions and results presented throughout this paper are applicable for any future global warming pathway or scenario, but the projected changes would be smaller for lower RCPs (like RCP4.5, RCP2.6 and RCP6.0).
2.2. Empirical downscaling of GCM climate variables

Downscaling is the process of translating (or modelling) the coarse resolution outputs from GCMs to catchment scale climate that is required for impact-adaptation-vulnerability studies and hydrological modelling. There are three types of downscaling approaches (Fowler et al., 2007; Chen et al., 2011; Ekström et al., 2015): (1) Empirical downscaling, or change-factor method, which applies the change informed by GCMs (for a future period relative to a baseline period) to perturb the baseline observations to reflect a future climate, (2) Statistical downscaling, which develops a statistical relationship between GCM atmospheric variables and observed climate variables, and then use this relationship to derive future climate variables from future GCM variables; and (3) Dynamical downscaling, where regional climate models (RCMs) are used (Kumar et al., 2013) to model the physical atmospheric and land surface processes at smaller spatial scale informed or constrained by a larger scale GCM.

Many downscaling comparisons have been conducted (Chen et al., 2011; Fowler et al., 2007) and generally conclude that no
single downscaling method is better, and this is largely because, like GCMs, different downscaling methods are tailored for different applications. Chiew et al. (2010) found that results from empirical downscaling typically lie within the range of other regionally available statistical and dynamical downscaling methods. Frost et al. (2011) recommends using empirical downscaling methods for regional water resource planning applications, due principally to the method’s robustness.

This study therefore uses empirical scaling to scale the baseline climate observations, informed by GCM outputs for a future period relative to the baseline period, to reflect a future climate (Zheng et al., 2015). For the empirical downscaling here, the scaling factor for precipitation and potential evaporation is estimated as,

\[ SF = \frac{X_f}{X_h} \]

where \( X_f \) and \( X_h \) are the GCM simulation for the future (2046–2075) and baseline (1976–2005) periods respectively. Once derived, the scaling factor is then used to scale the baseline climate observations (1976–2005) to produce a future climate time series. As the GCMs spatial resolutions are different to the observations, and different GCMs have different spatial resolutions, the scaling factors derived for each of the GCMs are resampled to match with the 0.5° x 0.5° grid in Princeton dataset.

In Eq. (1), if \( X_f \) and \( X_h \) are annual means, then the scaling approach is defined as ‘annual scaling’, where all the daily values of precipitation (or potential evaporation) in the 30-year baseline period (1976–2005) are scaled by this single annual scaling factor to provide a 30-year future (2046–2075) daily precipitation (or potential evaporation) series. Most of the results presented here, describing runoff sensitivity to climate inputs (Section 4.1) and comparing different modelling approaches (Section 4.2) are for ‘annual scaling’.

The study here (in Section 4.3) also explores the difference in runoff projection where the climate variables in the different seasons are scaled by factors estimated separately for the different seasons (‘seasonal scaling’), and where daily precipitation amounts or percentiles are scaled differently (‘daily scaling’). In the seasonal scaling, the original seasonal scaling factors are firstly estimated for each of the four seasons (Dec-Jan-Feb, Mar-Apr-May, Jun-Jul-Aug, Sep-Oct-Nov) informed by the GCM outputs. These factors are then rescaled such that the eventual future climate series has the same change to that from “annual scaling” approach at the mean annual level. The rescaled seasonal scaling factors are estimated as,

\[ SF'_i = SF \times \frac{S_i X_h}{\sum_i S_i X_h} \]

where \( SF \), \( SF'_i \), \( S_i \), and \( X_{h,i} \) are the original and rescaled seasonal scaling factors for season \( i \) respectively, \( SF_a \) is the annual scaling factor, and \( X_{h,i} \) is the observed baseline mean for season \( i \).

The ‘daily scaling’ is carried out only for precipitation, mainly to reflect potentially different climate change impact signal in the higher daily precipitation intensity. Here, for each season, 53 daily scaling factors are calculated representing the changes in the highest 50 daily precipitation values (as reflected by the GCM), and changes in the average of the 51–100th daily precipitation values, 101–200th daily precipitation values, and 200th onward daily precipitation values. Similar to the rescaling of seasonal factors, the original daily scaling factors derived from the GCMs are rescaled for each season to ensure the seasonal change is the same when the corresponding rescaled seasonal scaling factor is used.

The ‘annual scaling’ therefore uses a single factor to scale all the baseline daily precipitation (or potential evaporation) to reflect a future climate. The ‘seasonal scaling’ uses four different factors to scale the precipitation (or potential evaporation) in the different seasons. The ‘daily scaling’ scales the daily precipitation in accordance with 53 x 4 scaling factors. The rescaling procedure mentioned above ensures that the change in mean annual precipitation (or potential evapotranspiration) in the ‘annual scaling’, ‘seasonal scaling’, and ‘daily scaling’ are the same, as reflected by the GCM at the mean annual scale, and allows results from the different empirical scaling methods to be directly compared. The intention here is not to find the best method, but to explore potential uncertainties owing to different empirical scaling treatments to obtain the future climate series.

Different to precipitation and potential evaporation, the scaling factor of temperature is defined as the absolute change of temperature and is expressed as,

\[ SF = T_{f} - T_{h} \]

where \( T_f \) and \( T_h \) are the GCM simulated annual/seasonal mean daily temperature for the future and baseline periods respectively. Both annual and seasonal scaling factors of temperature are derived herein.

In the above empirical scaling methods, the future daily climate sequence is the same as the baseline climate sequence, scaled by different factors. The annual, seasonal and daily empirical scaling are applied to precipitation. For temperature and potential evaporation, only the annual and seasonal scaling are applied.

To explore climate change impact on water supply reliability (in Section 2.4 and Section 4.4), the potential change in future climate sequence is also considered. Here, a quantile mapping bias correction approach is used, where the GCM daily precipitation value at a given percentile/rank in the baseline period is matched to the observed daily precipitation value (at the Princeton 0.5° grid) at the same percentile/rank, and this relationship is then used to translate the future GCM daily precipitation series to an 0.5° grid future daily precipitation series. This quantile mapping bias correction is processed as,

\[ X'_{fut} = F_{obs}^{-1} [F_{his} (X_{fut})] \]

where \( F_{obs} \) is the cumulative distribution function of the historical observation, \( F_{his} \) is the cumulative distribution function of the historical GCM simulation, \( X_{fut} \) is the future daily GCM precipitation value and \( X'_{fut} \) is the future 0.5° grid precipitation value. The cumulative distribution function is considered separately for each of the four seasons, and only precipitation amounts greater than
0.01 mm are considered. Like in the empirical scaling methods, the future precipitation series here is rescaled such that the change in seasonal means are the same as those in the empirical seasonal scaling and the change in the annual mean is the same as that in the empirical annual scaling. It should be noted that the distribution of daily precipitation simulated by GCMs can be very different to the distribution of observed daily precipitation (daily precipitation is smaller in GCMs, and there are more rain days in GCMs), and the quantile mapping bias correction can introduce large errors and artificially corrupt future GCM projected trends and characteristics (Hay and Clark, 2003; Maraun, 2013; Piani et al., 2010).

2.3. Modelling climate change impact on runoff

The climate change impact on runoff presented and discussed in various parts of Section 4 come from three sources: (1) Direct simulations from the GCMs, (2) Budyko relationship estimates for the future relative to the baseline (using annual means with scaling factors of precipitation and potential evaporation), and (3) H08 hydrological modelling for the future relative to the baseline (using daily climate inputs with scaling factors of precipitation and temperature). The similarities and differences in the runoff projections from the different sources and methods are explored.

The Budyko relationship (Budyko, 1974) is the most widely used equation to describe basin or regional scale long-term energy and water balance (Oudin et al., 2008; Sivapalan et al., 2003; Teng et al., 2012b; Zhang et al., 2004). The Budyko relationship is commonly presented as,

$$\frac{E}{P} = \left[ \phi \tanh\left(\frac{1}{\phi}\right)(1-\exp(-\phi)) \right]^{1/2}, \quad \phi = \frac{PET}{P}$$

(5)

where E is the mean annual actual evapotranspiration, P is the mean annual precipitation, PET is the mean annual potential evapotranspiration and φ is the aridity index. Over a long enough time period (several years), the mean annual runoff (Q), can be estimated from the above equation as the difference between mean annual precipitation and mean annual actual evaporation (Q = P - E). This simple Budyko relationship is remarkably robust for estimating large-scale energy and water balance and has been used in literally thousands of studies, including adaptations to account for landscape features (particularly vegetation) and for local conditions, and to represent sub-annual and inter-annual time scales. In this study, the simple basic Budyko relationship above is used to directly estimate the baseline (1976–2005) and future (2046–2075) mean annual runoffs from mean annual values of precipitation and potential evaporation.

The H08 model used here is one of the main global hydrological models used in regional and global water modelling studies (Hanasaki et al., 2008; Haddeland et al., 2011; Warszawski et al., 2014; Zhang et al., 2016). The runoff simulation scheme in H08 is based on the bucket model concept (Manabe, 1969) but modified by using a “leaky bucket” formulation in which subsurface runoff occurs continually as a function of soil moisture. The algorithm used in H08 for PET estimation is the mass-transfer method (Dalton, 1802; Penman, 1948), which relates PET to vapour pressure deficit and wind speed. The H08 runs on a daily time step and consists of six main modules (land surface hydrology, river routing, crop growth, reservoir operation, environmental flow, and anthropogenic water withdrawal). This study uses only the land surface hydrology module, which conceptualises each grid or catchment as inter-connected stores with equations describing the hydrological processes (including snowmelt processes) and movement of water between stores. The daily climate inputs needed to run the model are precipitation, temperature, solar radiation, humidity, and wind speed. The suggested or default parameters of H08 (Hanasaki et al., 2008) are used for the modelling here without further calibration against local data. Global hydrological models like H08 has limitation in simulating reliably the actual runoff values at a particular location, but they can reasonably simulate the runoff variability over annual and longer time scales and the trend in runoff, as well as relative changes in runoff resulting from changes in the climate inputs (Haddeland et al., 2011; Zhang et al., 2016).

Unlike the simple Budyko relationship, the H08 hydrological model runs on a daily time step and dynamically models the different hydrological fluxes and stores. The H08 model is therefore likely to better represent the hydrology of the region (compared to the Budyko relationship) as well as take into account changes in the climate inputs at the sub-annual scale. The H08 modelling here, at 0.5° grid resolution, therefore provides a consistent and broad-scale estimation of the climate change impact on runoff across the South Asia region, but cannot replace the need for more detailed and intensive modelling efforts (like parameter calibration and model validation) to fully inform specific management, planning or adaptation in local catchments or basins.

2.4. Modelling climate change impact on water supply security

The climate change impact on water availability will be reflected not only in the average streamflow volume but also in other river flow characteristics. The seasonality in river flow is likely to increase with wet seasons becoming wetter and dry seasons becoming drier (Ashfaq et al., 2009; Sivakumar and Stefanški, 2011). This enhanced hydrologic variability will change the reliability of water supply, thus compounding water management and climate adaptation challenges.

To investigate the impact of climate change on water supply security, a storage analysis (McMahon and Adeloye, 2005; McMahon et al., 2007) is carried out, where the dynamic monthly water balance of a hypothetical reservoir storage is modelled as,

$$S_{t+1} = S_t + Q_t - D_t, \quad 0 \leq S \leq S_{\text{max}}$$

(6)

where $S_{t+1}$ and $S_t$ are the reservoir storages in month $t$ and $t+1$ respectively, $Q_t$ is the runoff (or inflow into the storage) in month $t$, and $D_t$ is water demand or withdrawal in month $t$. For the hypothetical modelling here, the storage capacity ($S_{\text{max}}$) is set equal to the mean annual runoff and the monthly water demand (assumed to also include evaporation from the reservoir) is set to 0.9 times the
mean monthly runoff. To express the storage modelling results, a reservoir or storage reliability is defined here as 100% minus the percentage time (or months) that the demand cannot be adequately met (i.e. when \(S_{t+1}\) is negative and has to be set to zero).

3. Projected climate change across South Asia from CMIP5

The plots in Fig. 2–4 show the range of projected changes in the daily average temperature, potential evaporation and precipitation respectively across South Asia, presented for each of the four seasons and annual values. The plots show the median value, 25–75th percentile range and 10–90th percentile range from the 42 CMIP5 GCMs for RCP8.5. The range of temperature projections in
Fig. 2 (and to a large extent precipitation projections in Fig. 4) are consistent with those in the IPCC AR5 atlas of global and regional climate projections (IPCC, 2013). However, the projections here are presented at higher temporal and spatial resolutions and come from a much larger and complete set of CMIP5 GCMs, to adequately reflect the range of uncertainty in hydrological modelling to inform impact-vulnerability-adaptation assessments of water resources and related sectors across South Asia.

As shown in Fig. 2, there is reasonable agreement between the GCMs in the temperature projections. For example, all the GCMs project increases in temperature, compared to precipitation where projection can range from large increases to large decreases (Fig. 4). Averaged across the South Asia region, the median projection for RCP8.5 is an increase in daily average temperature of 2.9 °C by 2046–2075 relative to the baseline period (1976–2005), with a 25–75th percentile range of 2.6 to 3.5 °C and 10–90th percentile range of 2.3 to 4.0 °C. The projected increase in daily minimum temperature is slightly higher and the projected increase in daily...
maximum temperature is slightly lower than the projected increase in daily average temperature (not presented here). Seasonally, the projected temperature increase is slightly higher in winter (DJF) than in summer (JJA). Spatially, the projected temperature increase is noticeably higher in the north (high altitude regions) than in the south, which is consistent with that found by Mountain Research Initiative EDW Working Group, (2015).

There is also general agreement in the potential evaporation projections (Fig. 3), where the potential evaporation for each GCM grid is estimated from the solar radiation, maximum and minimum temperatures, and actual vapour pressure data using Morton’s wet environment (or equilibrium or areal potential) evaporation formulation (Morton, 1983). These projected increases in potential evaporation are driven mainly by the increase in temperature. Most GCMs also show a slight increase in vapour pressure deficit (which will also increase potential evaporation), but there is little change and agreement between GCMs in the direction of change of
other variables (solar radiation and wind speed) that influence potential evaporation. Averaged across the South Asia region, the median projection for RCP8.5 is an increase in mean annual potential evaporation of 6.2% by 2046–2075 relative to baseline, with a 25–75th percentile range of 4.8 to 7.6% and 10–90th percentile range of 3.4 to 8.8%. At the extreme percentile, some of the projections show a decrease in potential evaporation in summer due to higher relative humidity, and possible decrease in solar radiation. Seasonally, the projected percentage increase in potential evaporation is considerably greater in winter (DJF) than in summer (JJA).

Spatially, the projected percentage increase in potential evaporation tends to be greater in the north-west.

There is much greater uncertainty in the precipitation projections, with large variations between GCMs, and in the different seasons and regions (Fig. 4). Nevertheless, a higher proportion of GCMs project an increase in precipitation, particularly in the north-east and much more so in the monsoon summer (Jun-Jul-Aug) than in winter (Dec-Jan-Feb). The higher monsoon precipitation under a warmer climate is also consistent with those reported in climate processes and climate modelling studies briefly described in the Introduction above. Averaged across the southern half of the South Asia region (latitude below 25°N), the median projection for RCP8.5 is a change in annual precipitation of +11% (with a large 10–90th percentile range of -2% to +41%) by 2046–2075 relative to the 1976–2005 baseline, and averaged across the northern half of the region (latitude above 25°N), the median projection for RCP8.5 is a change in precipitation of +7% (with a 10–90th percentile range of -9% to +35%). The projections also suggest possible intensification in the high extreme precipitation (i.e. the highest 0.1 percentile daily precipitation) particularly in the southern parts (not shown here).

4. Climate change impact on water across South Asia

4.1. Climate elasticity of runoff across South Asia

The plots in Fig. 5 show the climate elasticity of runoff, which is a useful concept that describes the sensitivity of runoff to changes in precipitation, potential evaporation and temperature, as simulated by the Budyko relationship and the H08 hydrological model. The climate elasticity of runoff is defined as the percentage change in runoff for a one percent change in precipitation or potential evaporation, or a one degree change in temperature (Schaake, 1990; Sankarasubramanian and Vogel, 2001; Chiew et al., 2006; Chiew, 2006).

To estimate the climate elasticity of runoff, the climate data of the baseline period is perturbed from -10% to +10% for precipitation and potential evaporation (with gradations of 1%) and from -2.0°C to +2.0°C for temperature (with gradations of 0.1°C).
The perturbed climate data is then used as inputs into the Budyko relationship and H08 hydrological model, and the modelled runoff for the perturbed climate is compared with the modelled runoff for the baseline climate to estimate the climate elasticity of runoff. The mean of the estimated elasticity basing on all the perturbations are then presented in Fig. 5. As discussed earlier, potential evaporation for the Budyko relationship is estimated here using Morton’s areal potential evaporation formulation, whilst the H08 model estimates potential evaporation directly using the algorithms in the model.

The H08 modelling results in Fig. 5 indicate that the precipitation elasticity of runoff generally range from about 1.5 or 2.0 (i.e. a 10% change in precipitation is amplified as a 15–20% change in runoff) in the wetter regions in the west coast, east coast and north-east to greater than 2.0 (i.e. a 10% change in precipitation is amplified as a 20% change in runoff) in the drier regions in the north-west and inland south. As expected, both the H08 hydrological model and the Budyko relationship show the similar spatial trends in the precipitation elasticity of runoff (Fig. 5). However the runoff sensitivity to changes in precipitation is higher in the Budyko relationship, with precipitation elasticity of runoff of 2.2 for regions with aridity index ($\phi = \text{PET}/\text{P}$) of 1 and 3.0 for aridity index of 2. It is worth mentioning that the Budyko relationship is developed and parameterised from global energy and water datasets and will give the same results for regions with the same aridity index. For cold regions like the North-West and the Tibetan Plateau, the Budyko relationship may not lend itself to extrapolation into the future where higher temperatures will affect snow, glacier and permafrost processes. In contrast, the H08 model simulates the hydrological dynamics and fluxes and storages at a daily time scale, and therefore reflect in more detail the hydroclimatology of the region, for the baseline climate data here and the hydrology as conceptualised and parameterised in H08.

Both the H08 hydrological model and Budyko relationship also show the similar spatial trends in the potential evaporation elasticity of runoff (Fig. 5). The runoff sensitivity to potential evaporation is slightly greater in the H08 model (particularly in the western arid regions) with 1% increase in potential evaporation resulting in 2–5% decrease in runoff, compared to the Budyko relationship indicating a 2–3% decrease in runoff for a 1% increase in potential evaporation. Because of the complementarity in the runoff sensitivity to precipitation and runoff sensitivity to potential evaporation (as can be seen in the Budyko relationship, see also Arora, 2002; Dooge et al., 1999; Zheng et al., 2009), the regions with high (positive) precipitation elasticity of runoff also have high (negative) potential evaporation elasticity of runoff.

The sensitivity of runoff to higher future temperature reflects clearly the increase in potential evaporation from the increase in temperature causing the decrease in runoff. The spatial trends in the temperature elasticity of runoff and potential evaporation elasticity of runoff are therefore the same. In most regions across SA, the H08 hydrological model indicates that a 1 °C increase in temperature will result in about 5% increase in potential evaporation, which in turn leads to a 5–10% decrease in runoff. The elasticity is close to the Clausius-Clapeyron rate, which means an increase in the water holding capacity of air (the saturation water vapour pressure) of approximately 7% per degree Celsius rise in temperature (Held and Soden, 2006).

4.2. Modeled climate change impact on mean annual runoff across South Asia

The plots in Fig. 6 show the percentage change in mean annual runoff for the RCP8.5 scenario for 2046–2075 relative to the baseline (1976–2005), modelled by the H08 hydrological model, Budyko relationship and global climate models (GCMs). The future runoff for H08 and Budyko are modelled using ‘future 2046–2075’ precipitation, potential evaporation and temperature (daily series for H08 and annual values for Budyko) obtained by scaling the baseline climate using empirical annual scaling factors derived from the 42 GCMs. The plots in Fig. 6 present the median as well as the 10th and 90th percentile of annual runoff change across the South Asia. The percentiles of H08 and Budyko come from the 42 future climate projections informed by the 42 GCMs, while the percentiles of the GCM modelled runoffs come from only 17 models where runoff outputs are readily available. Nevertheless, the percentiles of H08 and Budyko estimated from the same subset of 17 GCM show relatively minor differences compared to those estimated from all the 42 GCMs.

The median projections from the H08 hydrological modelling indicate that runoff will be greater in the future across most of South Asia except in the North-West (where projections show a 12% decline in mean annual runoff in 2046–2075 relative to 1976–2005 baseline). Elsewhere, the median H08 modelling projections indicate increases in mean annual runoff of about 10% in Indus region (IND), Tibetan Plateau region (TP) and Arakan Coast region (AC), about 15% in Ganges-Brahmaputra region (GA), Deccan Plateau region (DP) and Ghats Coast region (GH), and a bit more than 20% in Narmad-Tapti region (NT) and Sri Lanka (SL). There is large uncertainty in the projections, with the 10th percentile and 90th percentile estimates of percentage change in future mean annual runoff differing by more than 50% in most regions and more than 100% in some regions. Nevertheless, there is good agreement in the direction of projected change in future precipitation (Fig. 4) and future runoff (Fig. 6) over the south, central and north-east of the South Asia region, with practically all the modelling results projecting an increase in future runoff in the regions. In contrast, in the north-east, there is considerable disagreement between the GCMs in the direction of change in future precipitation and therefore future runoff.

It is comforting to see much similarity in the projected change in future runoff from the H08, Budyko and GCM modelling, in the spatial trends and the direction of change, and to a lesser extent also the modelled values. This gives some confidence in the broad scale direction and range of plausible future projections in the climate and runoff. However, despite the similarities and consistency in the projections from the different modelling approaches, there are several key exceptions. First, the median projection from H08 indicate runoff increase in the Indus region, but the median projection from Budyko show little change and the median GCM projection indicate runoff decrease. Second, the future runoff projections from the GCMs, and to a lesser extent the Budyko relationship, are wetter in the south compared to the projections from H08 modelling (slightly wetter in the median projection and considerably wetter in the 90th percentile projection). The higher projected absolute runoff change by the Budyko relationship
compared to the H08 hydrological model (in all regions, drier in the north-west and wetter and elsewhere) occurs because of the higher precipitation elasticity of runoff in the Budyko equation as discussed in Section 4.1. Third, the range and therefore uncertainty in the projections from the GCMs is higher than in the H08 modelling. This is most likely because of the different land surface hydrology conceptualisation and parameterisation in the GCMs compared to the single H08 parameterisation modelling the change in runoff resulting from the change in the climate inputs.

The uncertainty in the future runoff projection mainly comes from the uncertainty in the future precipitation projection. This is illustrated in Fig. 7, which shows the range of percentage change in future runoff modelled by H08 from projected changes in precipitation alone (the baseline temperature and potential evaporation series is used for these simulations) and from projected increases in temperature and potential evaporation alone (the baseline precipitation series is used for these simulations). The results in Fig. 7 indicate that the small range (or differences) in the projected increase in temperature and potential evaporation from the 42 GCMs translates to a relatively small range in the projected decrease in the modelled future runoff. In contrast, the large range in the projected change in precipitation (with GCMs disagreeing in the direction of change, particularly in the north-west) translates to a large range in the modelled change in future runoff.

The modelled change in mean annual runoff is driven by the projected change in the climate variables (Section 3) and the runoff sensitivity to the climate variables (Section 4.1). However, the modelled change in future runoff is not a direct sum of the change due
to precipitation change alone and due to temperature and potential evaporation change alone. This is partly because of the non-linearity in the hydrological response to the different climate variables, and partly because of the different possible combinations of changes in the climate variables in the GCMs (for example, the median projected change in future runoff does not necessarily come from the median projected changes in all the different climate variables). In general, the H08 modelling results indicate that the future change in runoff by 2046–2075 across most of South Asia is driven mainly by the change in precipitation, and moderated (where a runoff increase is projected) or amplified (where a runoff decrease is projected) by the change in temperature and/or potential evaporation.

4.3. Runoff projections from different empirical scaling treatments to obtain future climate change inputs

The plots in Fig. 8 show the H08 modelled changes in future runoff using future climate inputs derived using ‘annual scaling’, ‘seasonal scaling’ and ‘daily scaling’ respectively. The results indicate that the future runoff projections from the seasonal scaling is wetter than those from the annual scaling, where the median projection from the seasonal scaling show 2–4% greater increase in future mean annual runoff. This is because the seasonal scaling method reflects the proportionally higher projection of precipitation increase in the summer monsoon (Jun-Jul-Aug), when higher runoff occurs, compared to winter (see Fig. 4). The seasonal scaling treatment therefore enhances the summer monsoon runoff and subsequently the annual runoff compared to the annual scaling treatment. Similarly, since daily scaling reflects the proportionally higher increases in the high daily precipitation amounts (that generate high runoff) projected by the GCMs (particularly in the south), the future runoff projections from daily scaling is wetter than those from the seasonal scaling, except in the far north. The increases in future mean annual runoff modelled with future precipitation inputs from the daily scaling, for the median projection, are 3–10% greater (more in the south) than in the seasonal scaling.

As also shown in Fig. 8, the 10th percentile, median and 90th percentile of the projection for each scaling method indicate the uncertainty in the future runoff projections resulting from the uncertainty or range in the future precipitation projected by GCMs. The uncertainty of runoff projections owing to empirical scaling treatments are relatively smaller than that due to the range in the future precipitation projections. However, the difference of runoff projection from the three empirical scaling treatments can be significant and may need to be accounted for in detailed modelling studies to inform planning and adaptation, particularly when the projected changes at the seasonal and daily scale are supported by multiple lines of evidence from climate science and climate modelling, and where simulations of river flow characteristics other than just the long-term averages are required.
Fig. 8. Modelled percentage change in mean annual runoff (median, 10th and 90th percentiles) for RCP8.5 for 2046–2075 relative to present/baseline (1976–2005) from the H08 hydrological model, with annual scaling, seasonal scaling and daily scaling treatments to obtain future climate inputs informed by climate projections from the 42 GCMs.

Table 1
Modelled percentage change in reservoir storage reliability (median, 10th and 90th percentiles) for RCP8.5 for 2046–2075 relative to historical/baseline (1976–2005) with future climate inputs derived using annual scaling, seasonal scaling, daily scaling and bias corrected quantile mapping (informed by 42 CMIP5 GCMs).

<table>
<thead>
<tr>
<th>Grid</th>
<th>Brahmani-Baitarni grid (21.25°N, 85.75°E)</th>
<th>Koshi grid (27.25°N, 86.25°E)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scaling method</td>
<td>Annual scaling</td>
<td>Seasonal scaling</td>
</tr>
<tr>
<td>Percentage change in storage reliability</td>
<td>10th percentile</td>
<td>−7.7</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>90th percentile</td>
<td>2.3</td>
</tr>
</tbody>
</table>
4.4. Modelling climate change impact on future water supply security

Table 1 shows the storage reliability for the two grid cells where the Brahmani-Baitarani and Koshi basins are located (see Fig. 1). The storage analysis is discussed in Section 2.4. The runoff or inflow inputs for the storage analysis come from the H08 modelling with the baseline period (1976–2005) and the projected runoff of the future derived from the annual scaling, seasonal scaling, daily scaling and bias correction methods.

Table 1 shows that the storage reliability from the modelling with baseline climate data (1976–2005) is 95% for the Brahmani-Baitarani grid and 91% for the Koshi grid. The results from the three empirical scaling treatments to obtain the future climate inputs are very similar (little change in Brahmani-Baitarani, and very small increase in storage reliability in Koshi). Accounting for the different changes in the climate inputs through the year (in seasonal scaling and daily scaling) therefore made little difference to the projection of future water supply security in these two grids compared to applying a uniform/constant percentage change through the year (annual scaling), although the results could be quite different elsewhere.

However, the results from the bias correction using quantile mapping are considerably different to those from the three empirical scaling methods. This is because the quantile mapping takes into account changes in the sequencing in the future climate series as well as the inter-annual and multi-year variability characteristics reflected by the GCMs. This highlights the importance of considering key climate drivers other than long-term averages that significantly influence the hydrologic metrics important for decision making and planning (the storage or water supply security in this particular example). Nevertheless, as discussed earlier (end of Section 2.2), simulations using bias corrected GCM (or even dynamically downscaled regional climate model) outputs must be interpreted cautiously because of the often large bias corrections required for GCM and RCM precipitation. This limitation and uncertainty is also reflected in the much larger range of results from the bias corrected quantile mapping compared to the empirical scaling methods (Table 1).

4.5. Uncertainty in runoff projections from uncertainty in GCM precipitation projections

Fig. 9 shows the changes in future mean annual runoff modelled by the H08 hydrological model for the Brahmani-Baitarani and Koshi grid cells (2046–2075 relative to 1976–2005) informed by projected future climate from all ensemble runs for all 42 CMIP5 GCMs.

![Fig. 9. Changes in future mean annual runoff modelled by the H08 hydrological model for the Brahmani-Baitarani and Koshi grid cells (2046–2075 relative to 1976–2005) informed by projected future climate from all ensemble runs for all 42 CMIP5 GCMs.](image-url)
GCMs for RCP8.5. The first column (G00) shows results from the first run of each of the 42 GCMs, which was used for the presentation and discussion in the preceding sections. The other columns (G01 to G42) show the modelled changes in future runo护身符 using climate projections from all the available ensemble runs for each of the 42 GCMs. The plots show again the large range in runo护身符 projections resulting from the uncertainty in future projections of precipitation (G00), as well as show that the uncertainty in the projections within many GCMs can be as large as the differences in projections between GCMs.

The differences in the modelled future change in runo护身符 using future precipitation projections from all 42 GCMs versus using projections from only the ‘better’ GCMs are also investigated, with the results shown in Fig. 10. Here, the GCM performance is evaluated by comparing the ranked annual precipitation simulated by the GCM versus the Princeton 0.5° grid ‘observed’ precipitation (30 values over 1975–2006). The root mean square error is calculated with a lower value indicating better agreement between the GCM and observed annual precipitation distributions and therefore a better GCM ability in reproducing the baseline precipitation.

The modelling results from using the best five, best 10, best 15, best 20 and all 42 GCMs are presented in Fig. 10. Overall, there are no clear trends or conclusions from the results, although the ‘better’ GCMs tend to project slightly wetter futures (particularly daily scaling for Brahmani-Baitarani). The uncertainty or range in the projections are also similar for the different sub-selections of GCMs (except the best five GCMs for Koshi). To put this into context, there have been many studies on GCM sub-selection with most studies indicating little correlation between future precipitation projections and GCM ‘performance’ (Arnell, 2011; Brekke et al., 2008; Chiew et al., 2009b; Palazzi et al., 2015). Many studies favour the use of projections from all GCMs to represent the full range of uncertainty (Chiew et al., 2009b; Palazzi et al., 2015), although some studies sub-select GCMs to either remove the clearly poorly performing GCMs or to consider only GCMs with different or independent representation of the physical processes (Stainforth et al., 2005, 2007; Evans et al., 2011).

It is also difficult to adequately assess and determine which are the better performing GCMs (e.g. assessment against simulation of different precipitation and climate characteristics, assessment for the location of interest or regionally or globally, assessment against the large scale drivers/indices of local/regional precipitation and the relationship between them). Based on the limited consideration and assessment here, and for the broad scale projections presented here, it is probably best to use projections from all the available
GCMs to provide an indication of the full range of uncertainty.

5. Summary and conclusion

The paper presents future climate and runoff projections, estimated using a consistent method, across South Asia. The future runoff is modelled using the Budyko relationship and H08 global hydrological model, with future climate inputs informed by projections from the 42 CMIP5 GCMs. The modelling results indicate that future runoff will increase throughout most of the region (Indian sub-continent) except in the far north-east (southern part of the Tibetan Plateau) and the arid far north-west region. The median projection shows increases in mean annual runoff of 20–30% in the Indian sub-continent for 2046–2075 relative to 1976–2005 for RCP8.5 greenhouse gas concentration pathway. However, there is considerable uncertainty in the projections, with a 10th and 90th percentile range of more than 50%.

The uncertainty in the future runoff projections comes mainly from the uncertainty in the future precipitation projections, both within and between GCMs. Practically all the 42 GCMs project a wetter future throughout the Indian sub-continent (particularly in the south), but there is little agreement between GCMs in the direction of precipitation change in the far north-east and far north-west of the South Asia region. The percentage change in precipitation is generally amplified as a 1.5–2.0% (for wet areas) to > 2% (for dry areas) change in runoff. The change in runoff by 2046–2075 is driven mainly by the change in precipitation, moderated (where runoff increase is projected) or intensified (where runoff decrease is projected) by higher temperature and potential evaporation. The different hydrological modelling approaches (H08 hydrological model, Budyko relationship, runoff outputs from GCMs) show similar results, providing confidence in the broad scale runoff projections presented here.

The differences in modelled future runoffs using future climate inputs derived from different empirical scaling methods can be significant, but are relatively smaller than the uncertainty resulting from the large range in future precipitation projections. The choice of scaling method to reflect changes in future precipitation (and climate) characteristics that drive runoff can therefore be important in hydrological modelling studies to inform planning and adaptation, particularly where simulations of river flow characteristics other than just the long-term averages are needed. However, the methods used (including downscaling), particularly where significant modelling effort is required, must account for uncertainty from the range of GCMs and supported by scientific understanding of atmospheric-oceanic circulation processes in a warmer world.

There is little difference in the projections from using only the ‘better’ performing GCMs versus using all 42 GCMs in the modelling here. Therefore, for the broad scale projections presented here, it is best to use projections from all the GCMs to provide an indication of the full range of uncertainty.

Conflict of interest

None.

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