Vulnerability of water availability in India due to climate change: a bottom-up probabilistic Budyko analysis

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Abstract

Quantifying the dependence of future water availability on changing climate is critical for water resources planning and management in water stressed countries like India. However, this remains a challenge as long-term streamflow data is scarce and there are significant uncertainties regarding future climate change. We present a bottom-up probabilistic Budyko framework that estimates the vulnerability of available water to changing climate using three hydro-climatic variables: long-term precipitation, potential evapotranspiration and actual evapotranspiration. We assimilate these variables within a probabilistic Budyko framework to derive estimates of water availability and associated uncertainty. We then explore a large range of possible future climates to identify critical climate thresholds and their spatial variation across India. Based on this exploratory analysis, we find that Southern India is most susceptible to changing climate with less than 10% decrease in precipitation causing a 25% decrease in water availability.

1. Introduction

With rapidly increasing population and urbanization, India is heading towards acute water scarcity resulting from an ever increasing gap between supply and demand of freshwater [*IDFC*, 2011]. Past efforts at quantifying the availability of freshwater resources across the country have relied mainly on estimating streamflow trends either through measurements or empirical estimation techniques [*CWC*, 2013]. Hydrologic models have also been employed to predict future water availability although this approach, too, relies on streamflow records [*Mondal and Mujumdar*, 2015; *Raje et al.*, 2014]. Despite an escalation in the spatial extent of water stressed regions across the country, streamflow data remains scarce hindering the growth and development of hydrologic modeling frameworks to provide management solutions [*Mujumdar*, 2015; *Rockstrom et al.*, 2009; *UNEP*, 2008]. In addition, there is significant uncertainty about trajectories of future water supply due to large uncertainties in projected precipitation changes over the region [*Mall et al.*, 2006; *Hijioka et al.*, 2014]. This necessitates the development of frameworks that can fare well in such a data limited setting and accommodate large uncertainties in future precipitation change.

One way to overcome the challenges posed by limited data and uncertain future precipitation change is to combine advances in Budyko curve based techniques with bottom-up approaches. The recently introduced probabilistic Budyko framework enables the estimation of water availability along with their associated uncertainty [*Greve et al.*, 2015]. The application of the bottom-up approach to this framework provides a way to explore changes in water availability independent of future projections of climate [*Weaver et al.*, 2013; *Singh et al.*, 2014; *Poff et al.*, 2015]. The term 'bottom-up' here refers to decision making approaches that use exploratory modeling analysis to assess a wide range of future climates and identify combinations that lead to vulnerable regimes in the indicator of interest (left panel in Fig. 1). Available data from climate models can also be assimilated in this approach *aposteriori*, i.e., after a large range of possibilities of future climate change have been explored.

In this study, we propose and test a bottom-up probabilistic Budyko framework to identify critical climate thresholds for water availability across India. It offers three basic advantages. First, it serves as a standalone baseline to compare estimates based on streamflow data and hydrologic modeling. Second, it provides uncertainty in estimates on freshwater availability that are either overlooked [*CWC*, 2013] or if accounted for, are mainly driven by uncertainties from the input climate [*Mondal and Mujumdar*, 2015]. A probabilistic framework enables the quantification of uncertainties from additional sources such as physical characteristics of the region. Third, the proposed framework is simple in design and computationally inexpensive, thus increasing the potential for aiding a wide range of decision makers by providing a first order estimation of likely changes in future water supply as well as their sensitivity to changing climate.

2. Methodolody

We follow a three-step procedure to estimate critical climate thresholds for changes in water availability across India (right panel in Fig. 1). In Step 1, we identify possible future climates expressed here as different combinations of precipitation and temperature (represented through potential evapotranspiration) change. In Step 2, we apply the probabilistic Budyko framework to obtain projections of evaporation ratio (AE/P) for each climate combination identified in Step 1. This allows us to estimate water availability and associated uncertainty in Step 3. Finally, we identify critical climate change thresholds that lead to a decrease in water availability below a selected level. We begin our methodological description with the probabilistic Budyko framework (Section 2.1). Following this, we describe the process of estimating the long-term water availability for a region for historical (validation) and assumed future (bottom-up approach) climates based on the relationship between water availability and variables of the Budyko curve (Section 2.2). Finally, we discuss the criteria behind the selection of possible climates and identification of critical climate thresholds to demonstrate the feasibility of the proposed approach (Section 2.3).

2.1. The Probabilistic Budyko Framework

The Budyko curve relates long-term values of three hydro-climatic variables in a basin: long-term precipitation (P), potential evapotranspiration (PE), and actual evapotranspiration (AE). It represents the relationship between aridity index, PE/P, and evaporation ratio, AE/P, for a control volume. The Budyko curve has primarily been employed for watershed scale analysis as AE/P is estimated using long term streamflow records,

$$\frac{AE}{P} = 1 - \frac{Q}{P} \tag{1}$$

where Q is the long-term streamflow, and other variables are defined before. However, if we use an independent estimate of AE, the curve can be developed for any spatial extent as water and energy balance must be satisfied in a control volume. Several global estimates of AE at various spatial and temporal resolution are now available enabling the development of Budyko frameworks in any spatial extent [*Wagner et al.*, 2009; *Mueller et al.*, 2011]. Since many decisions regarding water management in India are still political driven, we use political units (districts) instead of topographically defined watersheds to locate regions on the Budyko curve [*Shah and Koppen*, 2006]. Also, precipitation data was available at district level and could be directly used without losing much information in upscaling it to a watershed scale.

While originally proposed as a space-time invariant relationship [*Budyko*, 1958; *Pike*, 1964], it has now been shown that catchment and climatic characteristics do affect the position of a basin on the curve [*Donohue et al.*, 2007; *Potter et al.*, 2005; *Gentine et al.*, 2012; *Berghuijs and Hrachowitz*, 2014]. Thus, several parametric forms of the Budyko curve have been suggested but they remain deterministic in their formulations [*Fu*, 1981; *Zhang et al.*, 2004; *Wang and Tang*, 2014]. Our approximation of the Budyko curve is based on the analytical expression of *Fu* [1981] that relates PE/P to AE/P using a single parameter (ω):

$$\frac{AE}{P} = 1 + \frac{PE}{P} - \left(1 + \left(\frac{PE}{P}\right)^{\omega}\right)^{(1/\omega)}. \tag{2}$$

The long term mean climatic condition represented through PE/P is the primary controlling factor for the AE/P. The parameter ω integrates the secondary effects of climate variability and bio-geo-physical characteristics including as terrain, soils, vegetation, etc. [*Donohue et al.*, 2007; *Potter et al.*, 2005; *Gentine et al.*, 2012; *Berghuijs and Hrachowitz*, 2014]. Recently, *Greve et al.* [2015] have proposed a way to estimate the parametric uncertainty in the Budyko curve thus extending the deterministic formulation of the curve to a probabilistic one. Based on this approach, we calibrate the Fu's equation using historically available data sets to obtain optimal estimates of ω for each control volume (district). Not desired but inevitable, the calibrated ω accounts for errors in data sets and the socio-economic factors influencing water budgets in the control volume. The calibrated district level ω are then grouped together to (six) higher political units to obtain distinct regional distribution of ω over India.

We implement two key modifications that enable us to extend the framework by *Greve et al.* [2015] to a data scarce region like India. First, we do not assume any underlying functional form of the Budyko curve parameter (ω), instead directly use its empirical distribution. In this way, we do not lose any information provided by the data while keeping the assumptions on uncertainty bounds of projections to a minimal. Second, we apply this method to political units (districts) and derive regional distribution of ω across major regional divisions of India. Budyko curve based applications can potentially be applied to a wide range of spatial scales, conditional on appropriate calibration and validation of the curve's parameter [*Donohue et al.*, 2007]. We also note that the calibration process likely accounts for the socio-physiographic control on partitioning of incoming precipitation into evapotranspiration and surface/sub surface water.

2.2. Water Availability Estimation

The water budget in a control volume can be expressed as,

$$\frac{dS_t}{dt} = P_t + GW_{in,t} + Q_{in,t} - GW_{out,t} - Q_{out,t} - AE_t \quad (3)$$

,where, S is the hydrologically active storage, $GW_{in}(_{out})$ is the inflow (outflow) of ground water from the control volume, $Q_{in}(_{out})$ is the inflow (outflow) of surface water from the control volume at time t, and remaining variables are defined before. The water availability is given by,

$$WA_t = GW_{out,t} + Q_{out,t} - GW_{in,t} - Q_{in,t} \tag{4}$$

,where, WA_t represents the water availability at time period t represented by net outflow of surface and ground water from a given control volume. For sufficiently long time scales such as decades, the net change in hydrologically active storage in a basin can be assumed to be zero. This leads to the following simplified representation for water availability,

$$WA_t = P_t - AE_t. \tag{5}$$

As we intend to obtain projections of water availability for a given climatic condition, we assimilate these hydro-climatic variables within the probabilistic Budyko framework (Section 2.1). This approach requires estimates of P, PE, and AE to estimate water availability for a given control volume.

2.3. The bottom-up approach

When uncertainties regarding future climate trajectories increase to such an extent that even the direction of change in affected variables (such as water availability) becomes unclear, bottom-up approaches become pertinent [*Weaver et al.*, 2013]. They reverse the traditional forward propagation approaches that generally force a hydrologic model using available climate change projections to obtain future changes in water availability (Fig. 1). In contrast, bottom-up approaches begin with the identification of vulnerable ranges of water availability and then find the regions in the climate space that are likely to cause this vulnerability [*Singh et al.*, 2014].

We apply the bottom-up approach by identifying a large number of possible climates for India that encompass the projected changes in precipitation and temperature for the South Asia region. We sample 100 equally spaced values each climate variable, thus resulting in 10,000 possible climate combinations of P and PE, each of which is represented by its aridity index (PE/P). We then obtain the distribution of water availability under each climate based on the probabilistic Budyko framework (see Section 2.1). The vulnerability of available water resources to changing climates is calculated based on relative change from historical estimates:

$$VI = \frac{\Delta WA}{WA} \times 100 \tag{6}$$

,where, VI is the vulnerability index, WA is the long-term historical water availability defined in equation (5), and ΔWA is the change in long-term water availability. The estimation for vulnerability index across a range of climates allows us to identify a critical climate threshold for a chosen level of vulnerability. Furthermore, this approach can help us to locate hot spots, or, regions that are highly vulnerable to changing climate across India.

3. Study area and data sources

We perform the analysis using all India data set spanning over more than 600 political units (districts) each of which is assumed to be an independent control volume. The districts areas range from 10-80420 km^2 and 94% districts have an area greater than 1000 km^2. We obtain the district wise monthly precipitation data from 1901-2000 from the Indian Meteorological Department, Pune (India). Daily maximum and minimum temperature estimates are available from the same source at a spatial resolution of $(1 \times 1)^\circ$ for the period 1951-2000. Due to limited data availability, we used the temperature-based [*Hargreaves and Samani*, 1985] method to estimate gridded fields of potential evapotranspiration.

Another essential element in establishing the Budyko curve is the long term estimates of actual evapotranspiration (AE). There are several AE products available in the literature each having their own potential and limitations [*Mueller et al.*, 2011]. Here we use the remote sensing based monthly AE product derived by *Zhang et al.* [2009] that was validated using eddy-covariance tower flux data sets. The spatial resolution of 0.073° ($\approx$ 8 km) and the global availability of this AE products for a relatively long time period (1983-2006) makes it ideal for its application in this study. We note that the same product has been also used in a recent study by *Xu et al.* [2013] for validating simulated AE of the Budyko framework. Finally, both PE and AE estimates are estimated for each district using area-averaging.

A common overlapping period of eighteen years, 1983-2000, across all three variables (i.e., P, PE, and AE) is selected for further analysis. Districts that do not have at least 10 years of overlapping data for all three variables are removed from further analysis. We also remove districts that violate the physical constrain of the atmospheric water supply (AE $<$P) and demand (AE $<$ PE) laws (i.e., points lying outside the energy or water limit lines). Thus, we construct the Budyko curve using data from 520 districts out of a total 636 districts over India.

4. Results and Discussion

4.1. Validation of the probabilistic Budyko framework

The value of Fu's parameter ω that minimized the root mean squared error between observed and simulated AE/P is estimated for each district (Fig. 2a). We find a substantial scatter in the values of ω, which span over a broad range of 1.1 to 21.9 with 1.4, 1.7 and 3.6 being the 5%, 50% and 95% quantiles, respectively. The district level optimal values of ω are then grouped to higher spatial units based on pre-defined regions. The districts are combined to form states (higher political units) which are further combined to form six larger political regions within India based on location (southern, central, northeastern, northwestern, northern states excluding Himalaya dominated regions, and Himalaya dominated regions). In this manner, the regional distribution of ω is obtained (Fig. 2b-g). The regional distribution of ω is used to predict AE/P for each district and obtain the associated uncertainty estimates.

After obtaining the regional distribution of ω, we cross-validate the efficiency of the distributions at three scales: i) all-India level, ii) regional level, and iii) district level. To validate the distribution of ω at a given scale, we estimate the observed area averaged values of long term AE/P for the control volume and compare it against the projected values based on ω distributions. The full set of ω is used to project the distribution of AE/P for all-India scale, while regionally grouped ω values are used for obtaining AE/P projections each of the six regions and at district level. We considered the spatial distribution of ω and the decision making context of the water resources problems in the study region to determine the regional grouping of ω. As the spatial distribution of ω is fairly uniform, uncertainty bounds resulting from proximity based groupings (eg. nearest neighbors) will be relatively small (Fig. S1). Note that *Greve et al.* [2015] use the full distribution of ω across all catchments for projecting of AE/P for each catchment. Here, we chose groupings midway between a full distribution and nearest neighbors approach. Finally, as we analyze water budget for political divisions (districts), we upscale the ω distributions to larger political regions.

The bias in the median projected values of AE/P at regional scales range from 2.5% to 17.5% of the observed values (Table 1). The bias in median projections is largest for southern India but remains less than 10% for the remaining regions with sufficient data. The area averaged estimates for northeastern India and northern India dominated by Himalayan mountainous regions are not calculated due to lack of sufficient data (when more than 33% of constituting districts have missing data). The simulated AE/P at district level also shows satisfactory performance with observed values falling within 5% and 95% percentiles bounds of projected AE/P for 89% of the districts. Significant regional variations are observed in the water partitioning behavior of districts across India (Fig. 3). For the same value of PE/P, regions in northwestern India tend to have lower AE/P than those in northern India. The central India region tends to have relatively narrow uncertainty bounds when compared with the rest of India.

4.2. Identifying critical climate thresholds

We estimate the vulnerability of future water availability to changing climate across a wide range of possible climates (10,000) at different spatial resolutions ranging from all India level to regional and district levels. According to the latest IPCC report, the 5%-95% range of precipitation and temperature changes for the South Asia region is between -25% to 50% and 0°C to 6°C, respectively [*Stocker et al.*, 2013]. We vary the precipitation and potential evapotranspiration (a proxy for temperature changes) from -50% to 80% and 0% to 20%, of their historical estimates, respectively.

This exploratory analysis allows us to estimate the median and inter-quartile range of the vulnerability indices at all India scale, which are shown as filled colored and grey contours in Figure 4a, respectively. The inter-quartile range reflects the uncertainty in the estimates of vulnerability index due to uncertain ω values of the Budyko curve. The downscaled projections of precipitation and potential evapotranspiration for five CMIP-5 models under two extreme representative concentration pathways (RCP2.6 and RCP8.5) are also shown in the figure (Tables S1-S2). These CMIP-5 models form a part of the recently coordinated global scale effort of the Impact Model Intercomparison Project (ISI-MIP) that provides a rough estimate of likely climate change over the study region [*Hempel et al.*, 2013; *Warszawski et al.*, 2014]. The contours for mean value of vulnerability indices reveal that precipitation change has a much stronger control on water availability than temperature change. The contours also reveal that regions undergoing drying trends have lower uncertainty ranges and vice-versa at the scale of all India, reflected in the lower values of the inter-quartile range as compared to that observed in regions undergoing wetting trends. Similar patterns of climatic controls and uncertainties were found in a previous analysis using the Budyko curve within a hydrologic modeling framework for the United States by *Singh et al.* [2011].

We now extend this analysis to identify critical climate thresholds for a selected level of vulnerability. As an example, we evaluate changes in precipitation that will lead to a 25% reduction in water availability with a fixed level of change in potential evapotranspiration

(10%). Other scenarios can easily be tested with the proposed framework. The critical precipitation threshold is identified for each district based on the regional ω distributions (Fig. 4b). Results indicate that southern India is the most vulnerable to decreasing precipitation, where less than 10% decrease in precipitation leads to a -25% decrease in water availability. The remaining parts of India show moderate vulnerability, with 10% to 20% decrease in precipitation required to cross the selected vulnerability threshold. The spatial patterns showing the highest vulnerability for southern India are also found for other tested threshold criteria (see Fig. S3-S5). Therefore, a key finding of this analysis is that Southern India is most vulnerable to changing precipitation with smallest changes in precipitation leading to high vulnerability of water availability to changing climate.

5. Conclusions

The proposed framework in its current form has a few limitations which can form the thrust of potential future investigations. First, the estimates of vulnerability depend upon the AE data product used. A comparison of various available AE products within the probabilistic framework for India would be useful. Second, understanding controls on ω values across regions will shed light on the underlying socio-hydrologic dynamics. The parameter, ω, essentially represents the balance of available water and energy within a control volume. When applied to political units, it should represent the complex hydro-climatic as well as socio-economic setting of the region. Finally, the ranges of water availability obtained here may be used to constraint hydrologic model response, thus complementing the constraints derived from streamflow [*Yadav et al.*, 2007].

It is also worth mentioning that the vulnerability index used in the present study only considers the natural water supply (through P) and demand (through AE), and does not consider any elements of human activities such as changes in water demand, water quality requirements, artificial storages in reservoirs and dams, etc. Considering these additional elements for the estimation of vulnerability requires a holistic approach which is beyond the scope of present study. Another avenue for further analysis is the impact of the choice of grouping of ω on the vulnerability levels. Alternative groupings such as those based on nearest neighbor approach, or more sophisticated techniques exploiting the spatial correlation of ω values can be explored. Despite these limitations, we show the benefits of the probabilistic Budyko framework that can be very useful in data scarce regions to provide a first order estimate of the spatial variability of vulnerability of a region to changing climate.

The current framework opens up a range of possibilities to assess decision relevant vulnerabilities in data scarce regions. It enables the assessment of the spatial distribution of water availability in a data scarce and water stressed region like India in the presence of large uncertainties in future climate. Our exploratory analysis combining the probabilistic Budyko framework with the bottom-up approach shows that Southern India is a highly vulnerable region in terms of sensitivity to changing climate. We also find significant variation of both vulnerability and associated uncertainty across major regions of India indicating the need for diverse approaches to manage water across India.

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Table 1. Cross-validation of the Fu's parameter (ω) over the selected regions of India.

Region	PE/P	Obs. (AE/P)	Pred. (AE/P)			% Error_{50}
			5%	50%	95%	
All India	1.06	0.50	0.35	0.53	0.81	6.0
Southern India	1.15	0.57	0.43	0.67	0.85	17.5
Central India	0.99	0.40	0.34	0.41	0.51	2.5
North-western India	2.04	0.55	0.30	0.58	0.76	5.5
Northern India (Gangetic plains)	0.99	0.51	0.39	0.55	0.81	7.8

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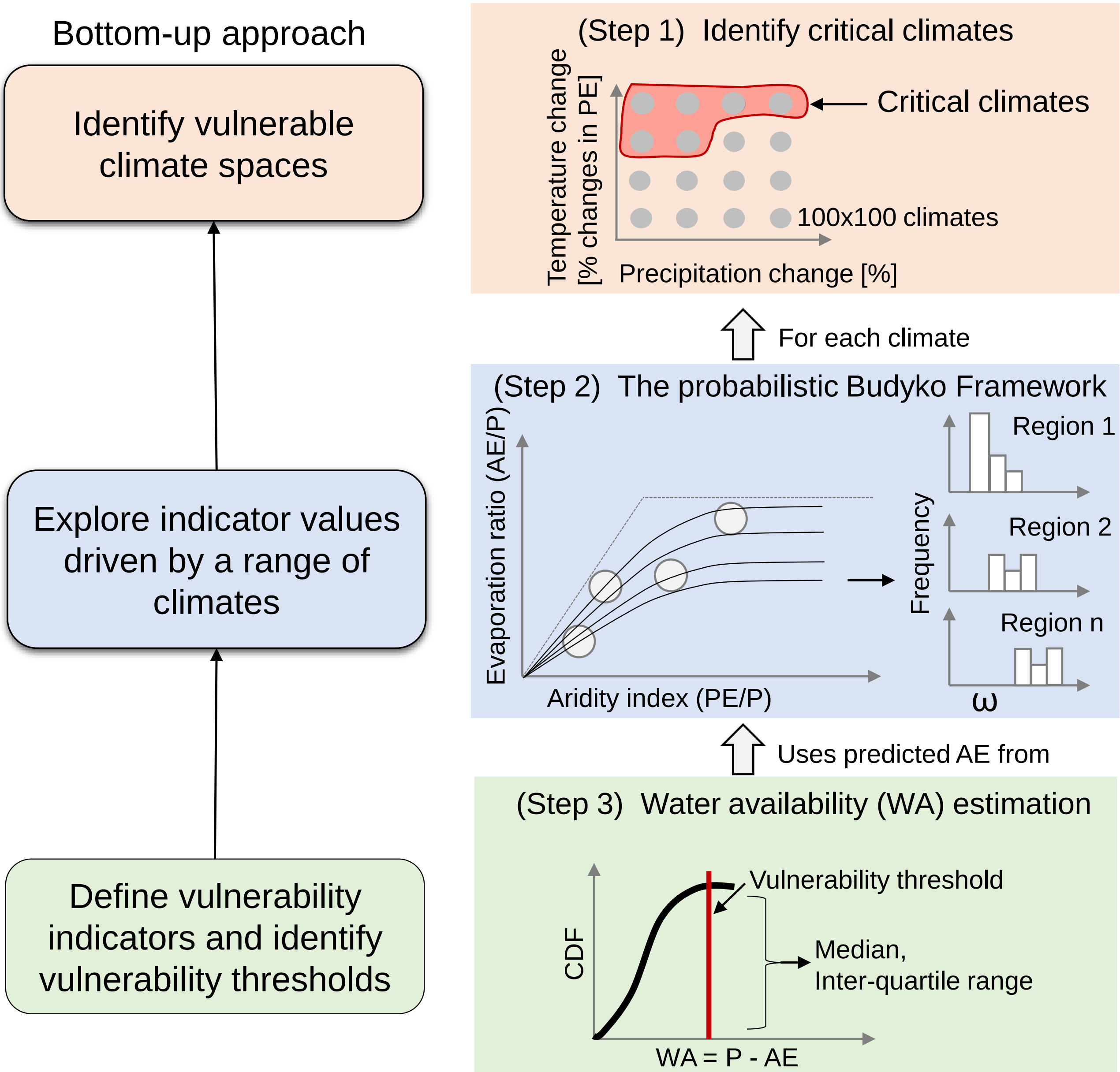

Figure 1. (Left panel) Overview of the bottom-up approach. (Right panel) Application of the bottom-up approach to assess critical climate thresholds for India. (a) Selecting a wide range of possible climates for exploration (b) The probabilistic Budyko framework employed to obtain regional distribution of ω (c) Derivation of water availability statistics based on output from (b).

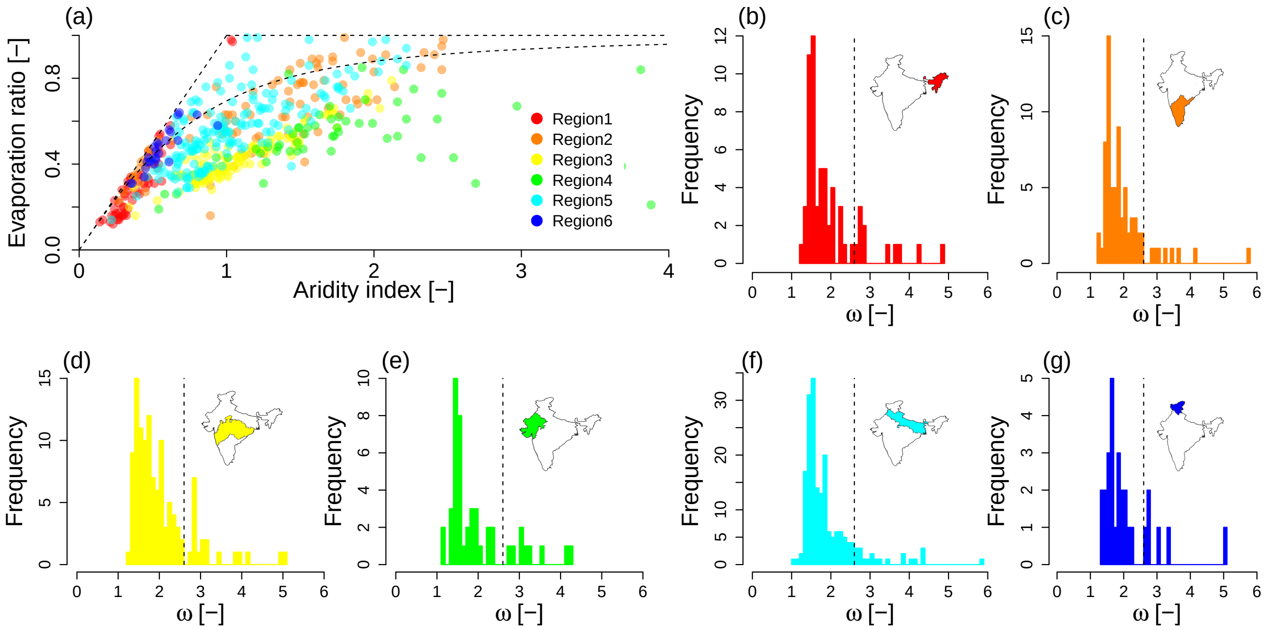

Figure 2. (a) Location of districts across India on the Budyko plot with aridity index (PE/P) on the x-axis and evaporation ratio (AE/P) on the y-axis. Dashed curve shows the value of ω set at 2.6. (b-g) Histograms showing the distribution of ω values calibrated to individual districts for each of the six regions. The maps in each histogram subplot show the location of the region. Vertical dashed lines in histogram plots represent the default ω value at 2.6

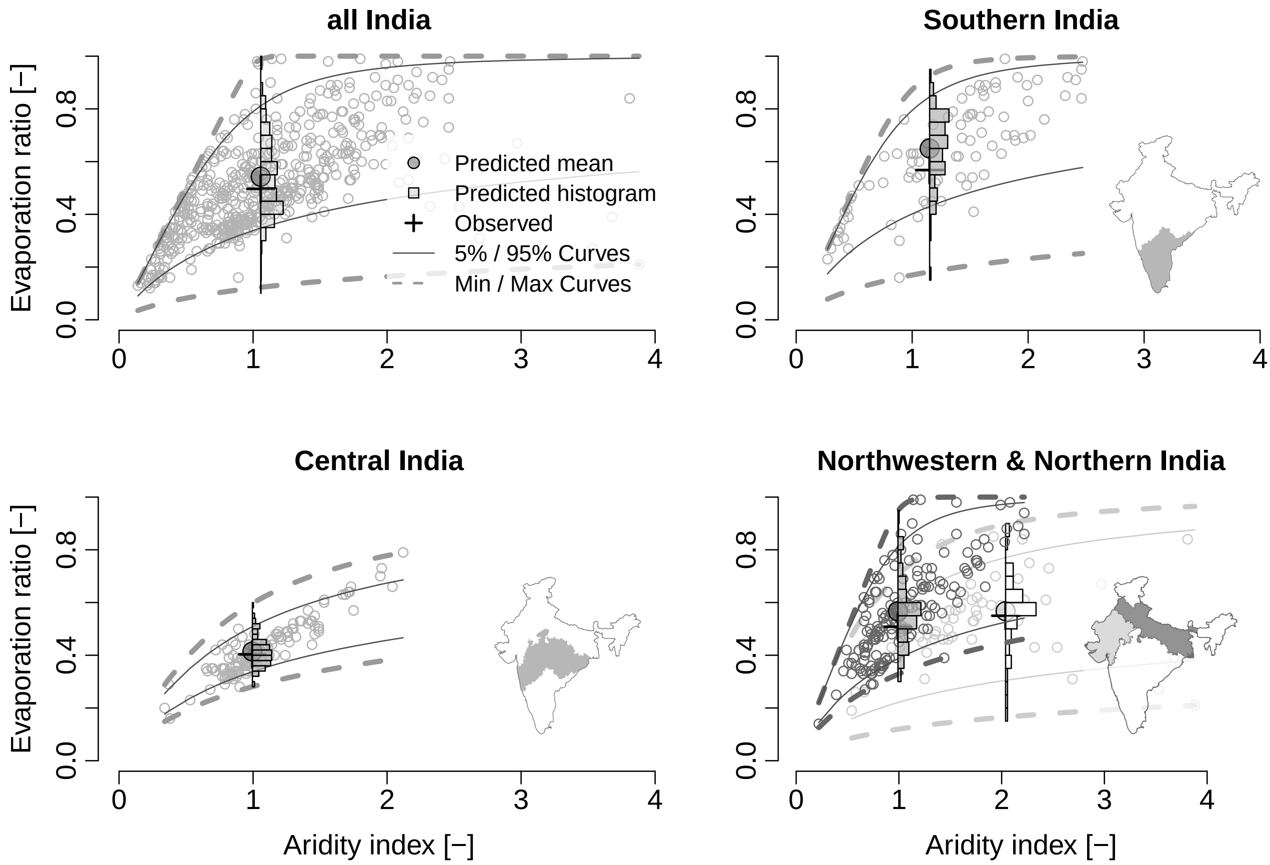

Figure 3. Validation of calibrated ω values for (a) all India (b) southern India (c) central India, (d) north and northwestern India. The histogram shows the distribution of projected AE/P values for the area averaged PE/P for the region. The mean values of projected AE/P are shown by grey filled black bordered circle. Dashed (solid grey) lines represent the envelop of minimum-maximum (5%-95%) projections for AE/P across the full range of dryness. White circles with grey border show the observed locations of a district. The maps in each subplot show the location of the region. Details on the histograms of the projected AE/P values for each region are provided in Figure S2.

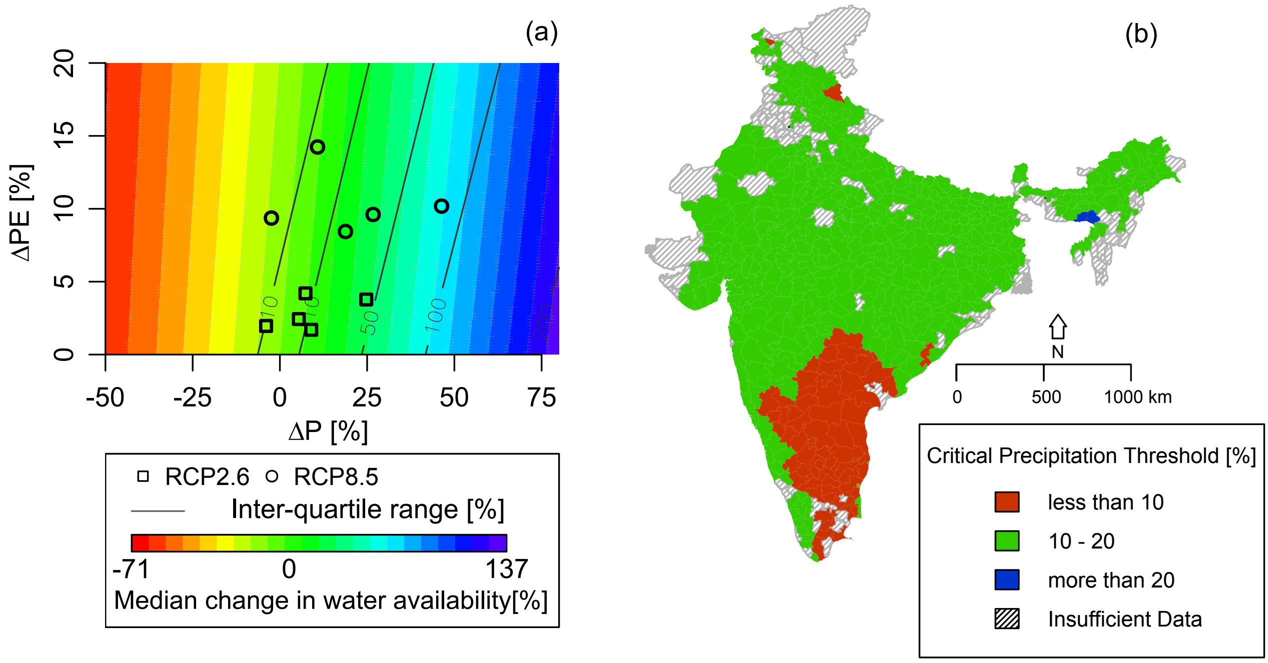

Figure 4. (a) Vulnerability of water resources at all India level estimated as a function of precipitation (ΔP) and potential evapotranspiration change (ΔPE). The colored and grey contours represent median and inter-quartile range of vulnerability indices respectively. The projected changes in all India P and PE between 1981-2000 and 2081-2099 from five contemporary CMIP-5 models and under two extreme representative concentration pathways (RCP2.6 and RCP8.5) are also overlain. (b) Spatial variation of critical precipitation threshold resulting in a 25% decrease in median water availability across India