The suitability of water scarcity indicators to the Indian context

Riddhi Singh[1,2], Rohini Kumar[3]

[1] Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai, India. Email: riddhi@civil.iitb.ac.in

[2] Interdisciplinary Programme in Climate Studies, Indian Institute of Technology Bombay, Mumbai, India

[3] UFZ-Helmholtz Centre for Environmental Research, Leipzig, Germany. Email: rohini.kumar@ufz.de

Abstract

Quantifying the spatiotemporal variation of water scarcity is critical for identifying strategies to support sustainable management of water resources and associated food-energy systems. To this end, several assessments have attempted to provide a global mapping of water scarcity with a number of underlying methodological choices. Scarcity metrics vary in their definitions and thresholds for scarce conditions to prevail. We review these methodologies in the context of the biophysical and socio-economic setting of India. We suggest four avenues for improving metric assessments to increase policy relevance: incorporation of surface water- groundwater interactions along with non-renewable groundwater resources, accounting for minimum environmental flows, consideration of deep uncertainties, and addressing underlying socio-economic disparities in metric assessment.

Keywords

Water scarcity, India, metrics, blue water, green water, population

1. Introduction

Water crisis continues to be a threat to India's sustainable development goals. Increasing population and water intensive lifestyles coupled with deeply uncertain future climate change are likely to create significant uncertainty regarding future water availability across India. As of 2017, the total renewable water resources per capita in India is estimated at 1080 m^3/year, which is lower than the global average of 5732 m^3/person/year (FAO , 2017). Several assessments identify India as a water scarcity hot-spot (Vörösmarty et al., 2000; Alcamo et al., 2000; Kummu et al., 2010; Schewe et al., 2014; Gosling and Arnell, 2016). A recent study estimated nearly 1 billion people living under water scarcity in India (Mekonnen and Hoekstra, 2016). Recent analyses considering the impact of changing climate and increasing population on India's future water availability also suggest increases in water scarcity as we transition from a 1.5°C warmer world to a 2.0°C warmer world (Singh and Kumar, 2019).

Despite a large number of studies that attempt to map the spatiotemporal extent of India's water scarcity, relatively few examples can be found of their use in policy making. We could identify a few issues that lead to this, beginning with the proliferation of available scarcity metrics (Hoekstra et al., 2012; Liu et al., 2017; Hanasaki et al. 2018; Vanham et al., 2018). Some focus on per capita water availability while others estimate the ratio of demand to supply of water (Liu et al., 2017). The definition of available water also varies across studies, along with the spatiotemporal resolution of underlying (observational or modeled) datasets used to arrive at estimates (Liu et al., 2017). Overall, this leads to large variations in the estimated population under risk of water scarcity. Second, scarcity assessments often assume critical thresholds of water scarcity metrics to identify vulnerable populations. While there is some evidence to show that commonly used thresholds (such as 1700 m^3/year for per capita water availability) are probably linked with the sufficiency of locally renewable water resources, there can be regional disparities in critical thresholds that need further investigation (Hanasaki et al. 2018). Third, most studies focus on certain future periods such as mid-century or end-of-century. The specific trajectory of socioeconomic development, tied closely to climate change signals, undertaken by a region is therefore not considered. This issue is crucial for India, where median projections for river runoff are greater for end-of-century than mid-century under different projected scenarios, indicating that regions are likely to undergo greater water scarcity in near future than far future (Singh and Kumar, 2019). Fourth, uncertainties due to climate and population change are included by identifying various scenarios of change (Haddeland et al., 2014; Schewe et al., 2014). However, further studies are needed to discern how such uncertainties should eventually guide policy making (see e.g., Poff et al., 2016). And finally, extremes such as droughts and floods are not generally considered, except a few very recent studies that show that when considering extremes, much more population can be at risk (Aadhar and Mishra, 2019; Kumar and Mishra, 2020).

In a recent analysis, Singh and Kumar (2019) assessed the relative importance of population and climate changes on determining future water availability across India. The analysis identified regional differences in dominant factors driving water scarcity, indicating that policy approaches may have to differ depending upon the main driver of scarcity. For example, in regions where physical water scarcity is likely the main driver behind classifying a region as water scarce, augmenting supplies and reducing demands would be required. On the other hand, in regions with plentiful water resources such as north-eastern India, the rapid urbanization is likely to drive water scarcity in the future. In such conditions, capacity building and focusing on infrastructure development would be the key to cope with water scarcity. While this analysis provided interesting insights, further studies that explore such connections between climate and demographic changes are needed to realistically model the time evolving nature of water scarcity in India.

The goal of this article is to understand the likely causes that stigmatize the quick adoption of existing scarcity quantification in decision making related to water resources. We discuss two main issues in this article: the issue of multiple metrics and the quantification of underlying uncertainty. Thereafter, we showcase the likely difference in perceptions of water scarcity that arise due to different (methodological) choices of water scarcity metrics. We conclude by discussing possible improvements in data collection or methodologies considering the requirement of planning agencies. Section 2 presents an overview of water scarcity metrics for global water scarcity assessments used in recent literature. This is followed by Section 3 that provides a summary of uncertainty quantification methods. Section 4 presents a comparative analysis of the metrics for India. Section 5 synthesizes these concepts in the context of India.

2. Water scarcity metrics: a review of global studies

Mapping the spatiotemporal variation of global water scarcity, in line with the 2030 Agenda for Sustainable Development target 6.4.2, has become fundamental to identify strategies for sustainable management of global water resources and associated water-food-energy nexus (D'Odorico et al., 2018). Several attempts have been made in the past three decades to assess the spatio-temporal variations of global water scarcity (Table 1). These assessments have led to an evolving picture of water scarcity and its relation to human water use. While our understanding of water scarcity grew, so did the methodological choices in quantifying this metric, resulting in a proliferation of indicators with different approaches to estimate water scarcity (Liu et al., 2017).

<Table 1 approximately here>

2.1 Methodological choices in quantification of water scarcity metrics

Methodological choices related to quantifying water available in a region range from using river discharge (blue water; including surface water and near-surface shallow groundwater storages), mined deeper groundwater (blue water), green water (soil moisture fed by direct precipitation), or a combination of these. Estimates of river discharge can be naturalized or impacted depending on whether human impacts are accounted for or not. Human impacts are diverse ranging from direct interventions like building of dams and reservoirs to groundwater abstractions for meeting water demands like humans drinking facilities or growing foods (irrigations) (Wiedmann and Lenzen, 2018; Felfelani et al., 2021). The latter has led to unsustainable depletion of groundwater across several regions throughout the Globe (Rodell et al., 2009; Wada et al., 2010; Gleeson et al., 2012; Famiglietti, 2014; Dalin et al., 2017; Greve et al., 2018; Rodell et al., 2018; Bierkens and Wada, 2019; de Graaf et al., 2019).

Blue water is not the only available water to humans. A significant portion of incoming precipitation may be used for evapotranspiration by food crops either directly from precipitation as soil moisture or interception supplemented by irrigation with surface or shallow ground water sources. This green water over agricultural lands is eventually embedded in food (Kampman et al., 2008; Dalin et al., 2017). Thus, inter-regional trade of water can also alter the water availability in a region. Food grain export out of a region indicates loss of available water resources (as virtual water) and vice-versa. Green water stress can emerge in agriculture areas where less water is available due to historically low rainfalls, when high proportion of precipitation is lost as blue water, or irrigation facilities are poorly developed. Thus, considerations of water quality (grey water), interactions between blue-green water sources, and virtual water trade impacts water available in a region (Siebert and Doll, 2010; Dalin et al., 2017; van Vliet et al., 2017; Vanham et al., 2018).

Scarcity metrics have similar methodological choices regarding their definitions and thresholds for scarce conditions to prevail. Scarcity can be due to the tension between available water and water requirements for various uses in a region including human and environmental needs (Vanham et al., 2018). In this interpretation, it is quantified by combining information on available water and consumption or withdrawal patterns. Alternatively, scarcity can be also quantified using water shortage indicators that estimate water available per person, sometimes after discounting for environmental needs. Typically, minimum environmental flows (MEFs) requirements are not explicitly considered in the quantification of water scarcity metrics. When the metric value falls below a selected threshold, it indicates a possibility of conflicts between human and environmental needs. Some analyses, however, assume MEF requirements and deducted the same from natural runoff prior to calculation of water availability. For example, Mekonnen and Hoekstra (2016) allocate 80% of natural runoff as MEFs, leaving only 20% of runoff for human use which is considered as blue water available.

The choice of spatio-temporal dimensions also affects the perception of scarcity. Assessments range from grid scale to basin scale, and from daily to decadal scales. The most common approach is to conduct a grid level analysis for long-term water availability, from which results can be aggregated to coarser spatial resolution. Mekonnen and Hoekstra (2016) has shown that the temporal resolution of analysis can significantly alter the estimates of population living under water stressed conditions. Similarly, coarser spatial resolution may mask the underlying spatial disparities in water availability.

Finally, the social dimensions of water availability are rarely explored in model driven studies. Often modelling studies provide an estimate of physical water scarcity but the prevailing socio-political context truly determines the availability of water at the scale of households (Wolters, 2014; Lund, 2015). For example, while the coastal city of Mumbai (India) falls in a region of plentiful water resources, a high percentage of slum population have limited access to clean drinking water (Satapathy, 2014). This indicates that gross level analysis needs to be complemented by associated socio-economic analysis that quantifies level of access. Similar challenges for basin wide planning of water resources have been highlighted by Akhter (2017).

2.2 Role of uncertainties in future climatic and socio-economic conditions

The seminal study by Vorosmarty et al. (2000) provides one of the first global maps of water scarcity, focusing on likely impacts of long-term climate and population changes. Since then, incorporating changing socio-economic and climate conditions has been a part of water scarcity assessments. Recent studies include many possible socio-economic change pathways so that potential uncertainties in exposed population living under water scarcity can be highlighted. However, climate change projections (especially for precipitation) remain highly uncertain (Knutti and Sedláček, 2013). Similarly, evolution of the coupled human-natural system places limitations on our ability to project prevailing socio-economic conditions decades into the future. The challenge is that many natural and human systems can exhibit threshold-based behaviour, transitioning to new stable regimes within a short period of time (Singh et al., 2018).

Such uncertainties regarding the system when experts cannot agree on the system model or its characterizing parameterizations are termed as deep uncertainties (Brown et al., 2012). Planning under deep uncertainties requires a paradigm shift in modelling philosophy. Instead of focusing on likely changes in a variable of interest, the safe limits of operation of a policy need to be explored. There is a growing body of literature in this area addressing the issue of deep uncertainties in management of ecological and hydrological systems (Singh et al., 2015; Poff et al., 2016). However, these studies are generally carried out for specific study regions. It may be prudent to explore the utility of these approaches in estimating the safe operating climates and socio-economic conditions from the perspective of water security at varying spatial scales. This approach is likely to shift the focus from projection specific insights to system level insights.

3. Comparative analysis for India

We quantify a commonly used water scarcity metric, water available per person, using various water availability definitions. Although we test a limited number of possibilities, our goal here is to highlight the critical role of these (methodological) choices in estimates of the number of people exposed to water scarce conditions across India. Water availability is quantified using a probabilistic Budyko framework (insert Box 1). We consider different combinations of blue water, green water, in addition to accounting for inter-regional trade of water and minimum environmental flow requirements. The six definitions of water availability that emerge from these are: (i) blue water only, (ii) blue water after accounting for minimum environmental flows, (iii) green water, (iv) green water after accounting for virtual water embedded in food products, (v) sum of blue--green water resources estimated from (i) and (iii), and (vi) sum of blue-green water resources estimated from (ii) and (iv), thus including considerations of minimum environmental flows and virtual water trade.

<Figure 1 approximately here>

The resulting estimates of per capita water availability across India for 1983-2000 using the six definitions present interesting patterns (Fig. 1a-f). When only blue water is considered, as in many previous analyses (Vorosmarty et al., 2000; Alcamo et al., 2000; Arnell et al., 2004, 2014; Schewe et al., 2014; Kummu et al., 2016), large parts of the Indo-Gangetic plains and southern India emerge as extremely water scarce (per capita water availability < 500 m^3/year). On further accounting for instream environmental requirements, regions under extreme water scarcity increases from 16% to 31% and the number of people under extreme water scarcity increase from 209 to 397 million (Fig. 1b). Instream environmental requirements combined with more conservative stress thresholds increase the number of people under water stress from 481 million to 615 million for a threshold of 1000 m^3/year/person. Overall, if only blue water is considered, water scarcity hotspots emerge in an alarmingly large part of northern and southern India. Note that the employed framework estimates blue after accounting for the evapotranspiration losses from agricultural and non-agricultural land, thus the blue water estimates include human abstractions and cannot be considered as naturalized values.

On considering green water as a proxy for water availability, we find low per capita water availability in the Indo-Gangetic plains, southern coastal districts, and parts of mid-western India (Fig. 1b,e). Also note the change in patterns of water scarcity hotspots, particularly the emergence of mid-western districts as water stressed ($<$ 1000 m^3/person/year). Farmers in these districts have historically witnessed significant crises (Mishra, 2006) but considering blue water alone does not highlight them as highly water stressed regions. The population under low green water availability (< 500 m^3/year) in Northern India increases from 28 to 99 million after accounting for the virtual water trade across India (Fig. 1e). Thus, surprisingly, the trade of virtual water trade may increase green water stress in some areas. This may happen as regions become centers of agricultural production and export water embedded in products at the cost of local green water stress.

We demonstrate that the choice of water scarcity thresholds and methodological definitions can have large uncertainty in perception of water scarcity and the resulting exposed population across India (Fig. 1g). Overall, anywhere between 46 million to 778 million people across India may be classified as under water stress based on choice of definitions and stress thresholds. Both sources of uncertainties, i.e., choice of definitions and thresholds, impart similar uncertainties to the output estimates of people under stress. On an average, across definitions of water availability, the number of people across India under water stress are 191, 434, and 636 million for thresholds of 500, 1000, and 1700 m^3/year/person, respectively. On the other hand, across different stress thresholds, the mean number of people under water stress are 447, 492, 194, 597, 504, 288 for definitions (i) to (vi), respectively. To put these numbers into perspective of projected climate scenarios, we also estimated the uncertainty in per capita water availability using projections of future climate and population and found that the uncertainties due to future changes in climate-alone are smaller than those arising out of varying definitions of water availability (Box insert 2).

Box insert 1

A Probabilistic Budyo framework to estimate water scarcity metrics

We estimate long--term water availability using only observed long--term climate (precipitation and temperature) data and satellite based actual evapotranspiration using the Budyko function (Singh and Kumar, 2015). The function relates a climate indicator, the aridity index (ratio of long--term potential evapotranspiration to long--term precipitation) to a water availability indicator, the evaporation ratio (ratio of long--term actual evapotranspiration to long--term precipitation). We employ a form of the Budyko curve with a firm physical basis (Fu, 1981):

$$\frac{AET}{P} = 1 + \frac{PET}{P} - \left(1 + \left(\frac{PET}{P}\right)^{\omega}\right)^{1/\omega},$$

where, AET is the long--term actual evapotranspiration, P is the long--term precipitation, PET is the long--term potential evapotranspiration estimated from temperature data (Hargreaves and Samani, 1985), and ω is a parameter inferred using historical data. A probabilistic approach groups ω inferred from smaller regions to obtain uncertainty ranges for larger regions (Greve et al., 2015). Regions are defined based on earlier virtual water analysis (Kampman, 2008). Blue water is estimated as the difference between long--term precipitation and actual evapotranspiration, assuming changes in storage over multi-decadal time scales are zero. For green water (AET_AG) estimation, we overlay satellite-based AET data with the land use map of India extracted from the Global Land Cover dataset for the year 2000 (Bartholome and Belward, 2005). AET estimates from cropland areas are considered as green water embedded in crops. The analysis was carried out at district level, which are fine scale political divisions in India. An earlier analysis quantified inter-regional trade of virtual water embedded in crops by dividing India into four main zones and estimating the water transferred between these zones by employing data on water budget and crop imports/exports (See Supplementary Material for more details).

To estimate per capita water availability, 2001 census of India's district wise population data is used. Remote sensing based monthly AET product with a spatial resolution of 0.073°(~8 Km) available from 1983--2006 is used (Zhang et al., 2009). Monthly precipitation data from 1901-2000 for each district is obtained from the Indian Meteorological Department, Pune (India). Daily maximum and minimum temperature data at a spatial resolution of (1x1)° for the period 1951-2000 is available from the same source. An overlapping period of 1983-2000 was used to derive the long--term estimates of climatic variables. Districts with less than ten years of overlapping data or in violation of the physical constrains of atmospheric water supply (AET<=P) and demand (AET<=PET) were removed from the analysis. We use a least-squares fit to obtain ω.

Box Insert 2

Uncertainties shape the perception of water scarcity

<Figure 2 approximately here>

4. Enhancing scarcity metrics for policy relevance

Due to its complex socio-economic setting and large variability in physio-climatic characteristics, the driving forces behind water scarcity are complex and evolving in India. Considerable resources are being allocated to prepare water budgets at a fine spatial resolution. Examples of advances include the launch of a national level information portal for water resources information (WRIS, https://indiawris.gov.in/wris/), and the continuation of National Hydrology Project (http://mowr.gov.in/schemes-projects-programmes/schemes/national-hydrology-project). Concurrently, efforts to understand and mitigate the impact of climate change are also underway (https://cckpindia.nic.in/). Similarly, groundwater departments exist at central and state level to monitor and manage groundwater resources (http://cgwb.gov.in/gwresource.html). An integrated assessment of water scarcity would require synthesis of information across these resources. While the commonly available water scarcity metrics provide useful information, their adoption by policy makers may be strengthened by further improving in the following aspects:

1. Integrating surface and groundwater estimates: According to recent reports and published research, nearly 23% of administrative units in India have already exhausted their groundwater resources as pumping exceeds natural recharge rates (CGWB, 2019; Rodell et al., 2009, 2018; Wada et al., 2010; Graaf et al., 2019). In these regions, non-renewable groundwater resources are being pumped to supply

irrigation water (Dalin et al., 2017). However, a majority of regions are still classified as ‘safe’ in terms of groundwater resource development (CGWB, 2019). Thus, avenues for conjunctive use of surface water and groundwater resources exist and may ease the pressure on surface sources. However, this is challenging given the heterogeneity of the aquifer systems in India that result in varied stream-aquifer interactions, as well as responses to pumping. Few studies have proposed ways manage the regional aquifer systems underlying the Gangetic plains (Foster and van Steenbergen, 2011; Khan et al., 2014). Estimating water scarcity by considering these aspects would provide a better picture for policy makers, but would require inclusion of recent advancements in global scale surface-groundwater modeling to regional assessments (Wada et al. 2014).

Several scarcity metrics consider shallow groundwater which interacts with river discharge. New perspectives are needed to ascertain whether a combined metric that considers both renewable and non-renewable water resources are needed to gain a clearer picture of water scarcity in such regions. The main issue is that inclusion of non-renewable groundwater in water availability estimates would present a false picture of water sufficiency. In principle, such resources should be omitted from availability calculations and included only in water use estimates with a greater penalty when compared to renewable sources. However, no clear guideline has emerged from literature on this critical issue. In addition, such resources are also hard to quantify. For example, the unique setting of hard rock aquifers in Southern India necessitates development of local models and integration with existing surface water estimates.

2. Explicit consideration of MEFs: Satisfying human needs often comes into direct conflict with maintenance of aquatic ecosystems. This is particularly relevant for India where freshwater resources are already over committed (Soni et al. 2014). Future water scarcity assessments can become more policy relevant if they explicitly account for impact on MEFs. It would be useful to explore different approaches for MEF estimation (Paster et al. 2014) and evaluate the impact of choices around MEFs on resultant scarcity estimates. A few studies provide global assessments of MEFs or their impacts on water and food availability (Paster et al., 2014, 2019; Gerten et al. 2013). Gerten et al. (2013), for example, showed that considering aquatic ecosystem needs resulted in lower boundaries for planetary freshwater consumption for humans. More recently, Paster et al. (2019) in their study on extensively agriculture-dominated areas have shown that maintenance of MEFs would require substantial reduction in irrigated areas with a concurrent increase in rain-fed regions to meet global food requirements. These studies provide a way forward to include MEFs in water scarcity assessments, though the uncertainty in these estimates warrant further investigations.

3. Expanding observational networks and improving uncertainty estimation methods: Almost all the global studies reviewed used a grid with spatial resolution of 0.5°x0.5° or used large river basins for computation of water scarcity indicators (Table 1). At this resolution, river routing processes may not be adequately represented and could introduce errors in runoff computations. A more critical issue is that gridded runoff estimates are generally based on water balance models and their parametrization is often based on observed runoff data. The density of runoff gages varies considerably; in poorly gauged and ungauged parts of the globe the simplification of extrapolating model parametrizations from gauged to ungauged locations results in high degree of

uncertainties in runoff simulations. Ruhi et al. (2018) show that gage density across the globe has in fact declined in the last decade. Finally, many future estimates of water scarcity ultimately rest on our ability to project the impact of climate change on water availability. This procedure is itself fraught with uncertainties arising from different sources including climate model parametrizations and specification of emission scenarios as well as the choice of downscaling and bias correction approaches. Singh and Biswal (2019) provide a comprehensive review of available approaches and challenges. Overall, these issues point towards the need for expansion of existing runoff gage networks in India and elsewhere as well as the need for better characterization of uncertainty in contemporary and future runoff simulations. Focused approaches like prioritizing regions with sensitive ecosystems may help balance economic considerations with prediction accuracy (Ruhi et al., 2018).

4. Consideration of deep uncertainties: often, estimates of water scarcity are employed for long-term water resources planning. For example, large scale public investments such as inter-basin water transfers require an understanding of time evolution of water scarcity in participating basins. Deep uncertainties regarding the nature of coupled human-natural systems implies that policy makers would need a paradigm shift away from scenario specific information. Instead, the robustness of various policy options should be tested against a large number of possible future scenarios (Lempert et al., 2008; Singh et al., 2015; Poff et al., 2016). Although robustness has gained traction in long-term policy analysis in regional water resources management, national to global scale analyses still heavily rely on scenario specific projections. Greve et al. (2018) provide an assessment of uncertainty in global water scarcity estimate and indicate the need for robust decision making in regions that are likely to witness large

uncertainties in future estimates of the metric. This promising analysis illustrates the essential need to quantify uncertainties in metric values. Our quantitative analysis indicates a similarly high uncertainty in assessment of population under water stress across India. In regions where water scarcity is hard to quantify either due to disparities emerging from methodological choices or due to deeply uncertain futures, decision makers should resort to robust decision-making frameworks to design management strategies in lieu of cost-benefit analyses (Lempert et al., 2010; Poff et al., 2016).

5. Translating water scarcity metrics for a diverse socio-economic group: the water scarcity metrics aggregated at any spatial resolution (city or state or national) would always fail to capture the reality that some individuals or communities are inherently more exposed to water risks due to their socio-economic disposition. Only a philosophical transformation in the understanding of water scarcity would address this issue. Scarcity metrics need to undergo a bottom-up transformation: water scarcity for whom? The possibility to provide a distribution of water scarcity for a spatial unit, instead of a single deterministic estimate needs to be explored. Some regions are likely to show a great variance in water scarcity exposure due to underlying socio-economic gaps. Such regions are likely to need much different policy structures than those where a fairly uniform sharing of scarcity risk is envisioned.

5. Concluding remarks

Our analysis highlights the value of uncertainty communication and presents various interpretations of water scarcity indicators that are crucial for the 2030 Sustainable

Development target 6.4.2 of water scarcity. Despite not considering other dimensions of water scarcity such as water quality, temporal variability of water availability, climate uncertainties, demographic changes, etc.; we still find a very large uncertainty in estimated number of people under water stress in India, varying somewhere between 5% to 74% of the country's population. The large uncertainties in estimates of the number of people exposed to water scarcity indicates that analyses of water stress should aim to present each of these multiple dimensions of water scarcity to provide policy relevant information. In addition, we suggest three important ways in which scarcity metrics can be tailored to provide decision relevant information:

1. Consideration of surface water -groundwater interactions and MEFs: Water scarcity metrics should explicitly consider the contribution of surface water and groundwater resources to blue water assessment. They also need to account for ecosystem water needs by adjusting blue water estimates based on MEFs.
2. Accounting for deep uncertainties in metric assessment: Long-term planning is fraught with deep uncertainties regarding the future trajectories of the coupled human-natural systems. Thus, scarcity metrics and associated quantifications of people under stress need to be re-designed to suggest whether the estimates are robust against the various underlying choices in metric assessment.
3. Physical water scarcity vs. socio-economic water scarcity: Metrics need to consider the underlying heterogeneities in access to water resources, especially in countries with large economic disparities. These assessments would require active collaboration of social scientists with water resource managers to provide novel and reliable metric definitions.

Author contributions

Riddhi Singh: Conceptualization, Methodology, Formal Analysis, Visualization, Writing – Original Draft.

Rohini Kumar: Conceptualization, Methodology, Writing – Reviewing and Editing.

Funding Source

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

References

Aadhar, S., Mishra, V., 2019. A substantial rise in the area and population affected by dryness in South Asia under 1.5° C, 2.0° C and 2.5° C warmer worlds. Environmental Research Letters. 14(11), 114021. https://doi.org/10.1088/1748-9326/ab4862.

Akhter, M., 2017. The political ecology of the water scarcity/security nexus in the Indus Basin: decentering per capita water supply, in: Addel, Z., Wirsing, R. G. (Eds.), Imagining Industan: Overcoming Water Insecurity in the Indus Basin. Springer International Publishing, Switzerland, pp. 21-33. Doi: 10.1007/978-3-319-32845-4.

Alcamo, J., Henrichs, T., Rosch, T., 2000. World water in 2025 - Global modelling and scenario analysis for the World Commission on Water for the 21st Century. Report A0002, Centre for Environmental System Research, University of Kassel, Germany. url: http://www.usf.uni-kassel.de/usf/archiv/dokumente/kwws/kwws.2.pdf.

Arnell, N.W., Lloyd-Hughes, B., 2014. The global-scale impacts of climate change on water resources and flooding under new climate and socio-economic scenarios. Climatic Change. 122(1-2), 127-140. https://doi.org/10.1007/s10584-013-0948-4.

Arnell, N.W., 2004. Climate change and global water resources: SRES emissions and socio-economic scenarios. Global environmental change. 14(1), 31-52. https://doi.org/10.1016/j.gloenvcha.2003.10.006.

Bartholome, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. International Journal of Remote Sensing. 26(9), 1959-1977. https://doi.org/10.1080/01431160412331291297.

Bierkens, M.F., Wada, Y., 2019. Non-renewable groundwater use and groundwater depletion: a review. Environmental Research Letters. 14(6), 063002. https://doi.org/10.1088/1748-9326/ab1a5f.

Brown, C., Ghile, Y., Laverty, M., Li, K., 2012. Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. Water Resources Research, 48(9). https://doi.org/10.1029/2011WR011212.

Central Ground Water Board, 2019. Dynamic Ground Water Resources of India, 2017. Ministry of Jal Shakti, Government of India. Online report: http://cgwb.gov.in/GW-Assessment/GWRA-2017-National-Compilation.pdf

Dalin, C., Wada, Y., Kastner, T., Puma, M.J., 2017. Groundwater depletion embedded in international food trade. Nature. 543(7647), 700-704. https://doi.org/10.1038/nature21403.

de Graaf, I.E., Gleeson, T., van Beek, L.R., Sutanudjaja, E.H., Bierkens, M.F., 2019. Environmental flow limits to global groundwater pumping. Nature. 574(7776), pp.90-94. https://doi.org/10.1038/s41586-019-1594-4.

D'Odorico, P., Davis, K.F., Rosa, L., Carr, J.A., Chiarelli, D., Dell'Angelo, J., Gephart, J., MacDonald, G.K., Seekell, D.A., Suweis, S., Rulli, M.C., 2018. The global food-energy-water nexus. Reviews of Geophysics. 56(3), 456-531. https://doi.org/10.1029/2017RG000591.

Famiglietti, J.S., 2014. The global groundwater crisis. Nature Climate Change. 4(11), 945-948. https://doi.org/10.1038/nclimate2425.

Food and Agriculture Organization (FAO), 2017. AQUASAT Database. AQUASAT Website accessed on 14.07.2021. http://www.fao.org/aquastat/statistics/query/index.html

Foster, S., van Steenbergen, F., 2011. Conjunctive groundwater use: a 'lost opportunity'for water management in the developing world?. Hydrogeology Journal, 19(5), pp.959-962.

Fu, B. On the calculation of the evaporation from land surface (in chinese). Sci. Atmos. Sin. 5, 23–31 (1981).

Gerten, D., Heinke, J., Hoff, H., Biemans, H., Fader, M., Waha, K., 2011. Global water availability and requirements for future food production. Journal of Hydrometeorology. 12(5), 885-899. https://doi.org/10.1175/2011JHM1328.1.

Gerten, D., Hoff, H., Rockström, J., Jägermeyr, J., Kummu, M., Pastor, A.V., 2013. Towards a revised planetary boundary for consumptive freshwater use: role of environmental flow requirements. Current Opinion in Environmental Sustainability, 5(6), pp.551-558.

Gleeson, T., Wada, Y., Bierkens, M.F., Van Beek, L.P., 2012. Water balance of global aquifers revealed by groundwater footprint. Nature. 488(7410), 197-200. https://doi.org/10.1038/nature11295.

Gosling, S. N., Arnell, N. W., 2016. A global assessment of the impact of climate change on water scarcity. Climatic Change. 134(3), 371-385. https://doi.org/10.1007/s10584-013-0853-x.

Greve, P., Gudmundsson, L., Orlowsky, B., Seneviratne, S. I., 2015. Introducing a probabilistic bBudyko framework. Geophysical Research Letters. 42, 2261–2269. https://doi.org/10.1002/2015GL063449.

Haddeland, I., Heinke, J., Biemans, H., Eisner, S., Flörke, M., Hanasaki, N., Konzmann, M., Ludwig, F., Masaki, Y., Schewe, J., Stacke, T., 2014. Global water resources affected by human interventions and climate change. Proceedings of the National Academy of Sciences. 111(9), 3251-3256. https://doi.org/10.1073/pnas.1222475110.

Hargreaves, G., Samani, Z., 1985. Reference crop evapotranspiration from temperature. Transaction of ASAE. 1, 96–99.

Hoekstra, A.Y., Mekonnen, M.M., Chapagain, A.K., Mathews, R.E., Richter, B.D., 2012. Global monthly water scarcity: blue water footprints versus blue water availability. PloS one, 7(2), p.e32688.

Ritchie, H., 2017. Water Use and Stress. Published online at OurWorldInData. https://ourworldindata.org/water-use-stress (accessed 31st December 2020).

Kampman, D., Hoekstra, A., Krol, M., 2008. The water footprint of India. Value of Water Research Report Series 32, 1–152.

Khan, M.R., Voss, C.I., Yu, W., Michael, H.A., 2014. Water resources management in the Ganges Basin: a comparison of three strategies for conjunctive use of groundwater and surface water. Water Resources Management, 28(5), pp.1235-1250.

Knutti, R., Sedláček, J., 2013. Robustness and uncertainties in the new CMIP5 climate model projections. Nature Climate Change. 3(4), pp.369-373. https://doi.org/10.1038/nclimate1716.

Kumar, R., Mishra, V., 2020. Increase in population exposure due to dry and wet extremes in India under a warming climate. Earth's Future. 8(12), e2020EF001731. https://doi.org/10.1029/2020EF001731.

Kummu, M., Guillaume, J.H., de Moel, H., Eisner, S., Flörke, M., Porkka, M., Siebert, S., Veldkamp, T.I., Ward, P.J., 2016. The world’s road to water scarcity: shortage and stress in the 20th century and pathways towards sustainability. Scientific reports. 6, 38495. https://doi.org/10.1038/srep38495.

Kummu, M., Ward, P.J., de Moel, H., Varis, O., 2010. Is physical water scarcity a new phenomenon? Global assessment of water shortage over the last two millennia. Environmental Research Letters. 5(3), 034006. https://doi.org/10.1088/1748-9326/5/3/034006.

Lempert, R.J., Popper, S.W., Bankes, S.C., 2010. Robust decision making: coping with uncertainty. The Futurist, 44(1), p.47.

Lempert, R. J., Bryant, B. P., Bankes, S. C., 2008. Comparing algorithms for scenario discovery. RAND, Santa Monica, CA.

Liu, J., Yang, H., Gosling, S.N., Kummu, M., Flörke, M., Pfister, S., Hanasaki, N., Wada, Y., Zhang, X., Zheng, C., Alcamo, J., 2017. Water scarcity assessments in the past, present, and future. Earth's Future. 5(6), pp.545-559. https://doi.org/10.1002/2016EF000518.

Lund, J.R., 2015. Integrating social and physical sciences in water management. Water Resources Research. 51(8), 5905-5918. https://doi.org/10.1002/2015WR017125.

Mekonnen, M. M., Hoekstra, A. Y. 2016. Four billion people facing severe water scarcity. Science Advances. 2, e1500323. https://doi.org/10.1126/sciadv.1500323.

Mishra, S., 2006. Farmers' suicides in Maharashtra. Economic and Political Weekly. 41(16), 1538–1545.

Pastor, A.V., Ludwig, F., Biemans, H., Hoff, H., Kabat, P., 2014. Accounting for environmental flow requirements in global water assessments. Hydrology and earth system sciences, 18(12), pp.5041-5059.

Pastor, A.V., Palazzo, A., Havlik, P., Biemans, H., Wada, Y., Obersteiner, M., Kabat, P., Ludwig, F., 2019. The global nexus of food–trade–water sustaining environmental flows by 2050. Nature Sustainability, 2(6), pp.499-507.

Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2016. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nature Climate Change. 6(1), pp.25-34. https://doi.org/10.1038/nclimate2765.

Rockström, J., Falkenmark, M., Karlberg, L., Hoff, H., Rost, S., Gerten, D., 2009. Future water availability for global food production: the potential of green water for increasing resilience to global change. Water Resources Research. 45(7), W00A12. https://doi.org/10.1029/2007WR006767.

Rodell, M., Famiglietti, J.S., Wiese, D.N., Reager, J.T., Beaudoing, H.K., Landerer, F.W., Lo, M.H., 2018. Emerging trends in global freshwater availability. Nature. 557, 651-659. https://doi.org/10.1038/s41586-018-0123-1.

Rodell, M., Velicogna, I., Famiglietti, J. S., 2009. Satellite-based estimates of groundwater depletion in India. Nature. 460, 999–1002. https://doi.org/10.1038/nature08238.

Ruhi, A., Messager, M.L., Olden, J.D., 2018. Tracking the pulse of the Earth's fresh waters. Nature Sustainability, 1(4), pp.198-203.

Satapathy, B.K., 2014. Safe drinking water in slums: from water coverage to water quality. Economic and Political Weekly. 49(24), 50-55.

Schewe, J., Heinke, J., Gerten, D., Haddeland, I., Arnell, N.W., Clark, D.B., Dankers, R., Eisner, S., Fekete, B.M., Colón-González, F.J., Gosling, S.N., 2014. Multimodel assessment of water scarcity under climate change. Proceedings of the National Academy of Sciences.111(9), 3245-3250. https://doi.org/10.1073/pnas.1222460110.

Siebert, S., Döll, P., 2010. Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation. Journal of Hydrology. 384(3-4), 198-217. https://doi.org/10.1016/j.jhydrol.2009.07.031.

Singh, R., Biswal, B., 2019. Assessing the Impact of Climate Change on Water Resources: The Challenge Posed by a Multitude of Options. In Hydrology in a Changing World (pp. 185-204). Springer, Cham.

Singh, R., Kumar, R., 2015. Vulnerability of water availability in india due to climate change: A bottom-up probabilistic Budyko analysis. Geophysical Research Letters. 42, 9799–9807. https://doi.org/10.1002/2015GL066363.

Singh, R., Kumar, R., 2019. Climate versus demographic controls on water availability across India at 1.5° C, 2.0° C and 3.0° C global warming levels. Global and Planetary Change. 177, 1-9. https://doi.org/10.1016/j.gloplacha.2019.03.006.

Singh, R., Quinn, J.D., Reed, P.M., Keller, K., 2018. Skill (or lack thereof) of data-model fusion techniques to provide an early warning signal for an approaching tipping point. PloS one. 13(2), e0191768. https://doi.org/10.1371/journal.pone.0191768.

Singh, R., Reed, P.M., Keller, K., 2015. Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. Ecology and Society. 20(3), 12. http://dx.doi.org/10.5751/ES-07687-200312.

Soni, V., Shekhar, S., Singh, D., 2014. Environmental flow for the Yamuna river in Delhi as an example of monsoon rivers in India. Current Science, pp.558-564.

van Vliet, M. T., Florke, M., Wada, Y., 2017. Quality matters for water scarcity. Nature Geoscience. 10, 800-802. https://doi.org/10.1038/ngeo3047.

Vanham, D., Hoekstra, A.Y., Wada, Y., Bouraoui, F., De Roo, A., Mekonnen, M.M., Van De Bund, W.J., Batelaan, O., Pavelic, P., Bastiaanssen, W.G., Kummu, M., 2018. Physical water scarcity metrics for monitoring progress towards SDG target 6.4: An evaluation of indicator 6.4. 2 "Level of water stress". Science of the total Environment. 613, 218-232. https://doi.org/10.1016/j.scitotenv.2017.09.056.

Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global water resources: vulnerability from climate change and population growth. Science. 289(5477), 284-288. https://doi.org/10.1126/science.289.5477.284.

Wada, Y., Van Beek, L.P., Van Kempen, C.M., Reckman, J.W., Vasak, S., Bierkens, M.F., 2010. Global depletion of groundwater resources. Geophysical Research Letters. 37(20), L20402. https://doi.org/10.1029/2010GL044571.

Wada, Y., Wisser, D., Bierkens, M.F., 2014. Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. Earth System Dynamics, 5(1), pp.15-40.

Wolters, E.A., 2014. Attitude–behavior consistency in household water consumption. The Social Science Journal. 51(3), 455-463. https://doi.org/10.1016/j.soscij.2013.10.003.

Zhang, K., Kimball, J.S., Mu, Q., Jones, L.A., Goetz, S.J., Running, S.W., 2009. Satellite based analysis of northern ET trends and associated changes in the regional water balance from 1983 to 2005. Journal of Hydrology. 379(1-2), 92-110. https://doi.org/10.1016/j.jhydrol.2009.09.047.

Table 1. Selected studies on global water scarcity highlighting key methodological choices, arranged in chronological order. Q: mean annual surface and subsurface (shallow aquifer) runoff accumulated as river discharge, AET: actual evapotranspiration from agricultural areas, MEF: minimum environmental flows

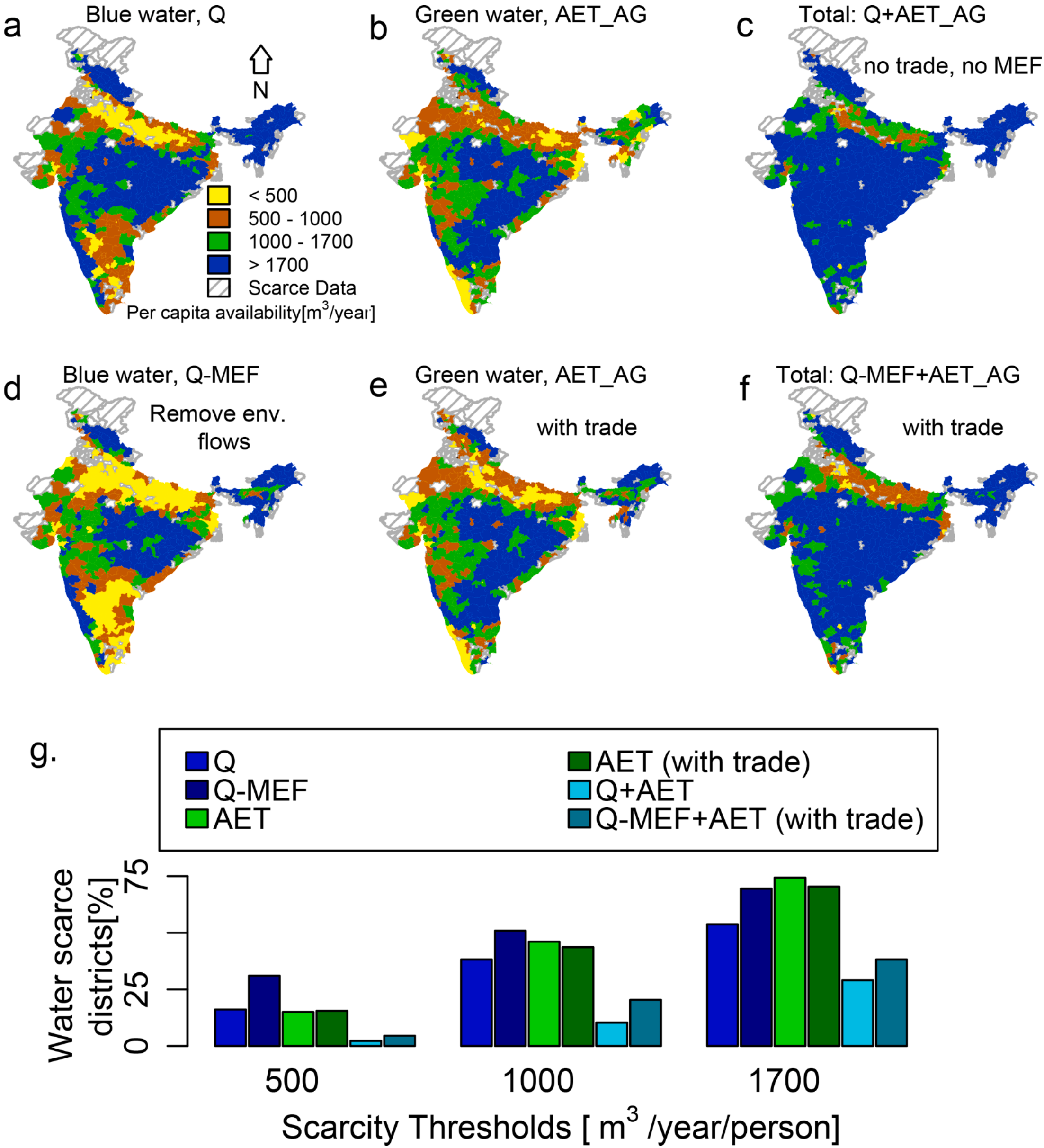
SNo.	Reference	Water availability	Scarcity metric	Spatio-temporal variation	Threshold
1	Vorosmarty et al., 2000	Q (natural)	Demand/Q	30’x30’ grid/ Annual	20% and 40%
2	Alcamo et al., 2000	Q (natural)	Withdrawal/Q	Large river basins/ annual	40%
3	Arnell, 2000	Q (natural)	Q per capita	0.5°x0.5° grid/ Daily	1000
4	Rockstrom et al. 2009	Q +AET	Q + AET per capita	0.5°x0.5° grid/ Daily	-
5	Gerten et al., 2011	Q (natural) + AET	Q + AET per capita	0.5°x0.5° grid/Daily1000	-
6	Arnell and Lloyd-Hughes, 2014	Q (natural)	Q per capita	0.5°x0.5° grid/30-year average	1000
7	Haddeland et al., 2014	Q (impacted)	Consumption/Q	0.5°x0.5° grid/Annual	-
8	Schewe et al., 2014	Q (natural)	Q per capita	0.5°x0.5° grid/31-year	500, 1000

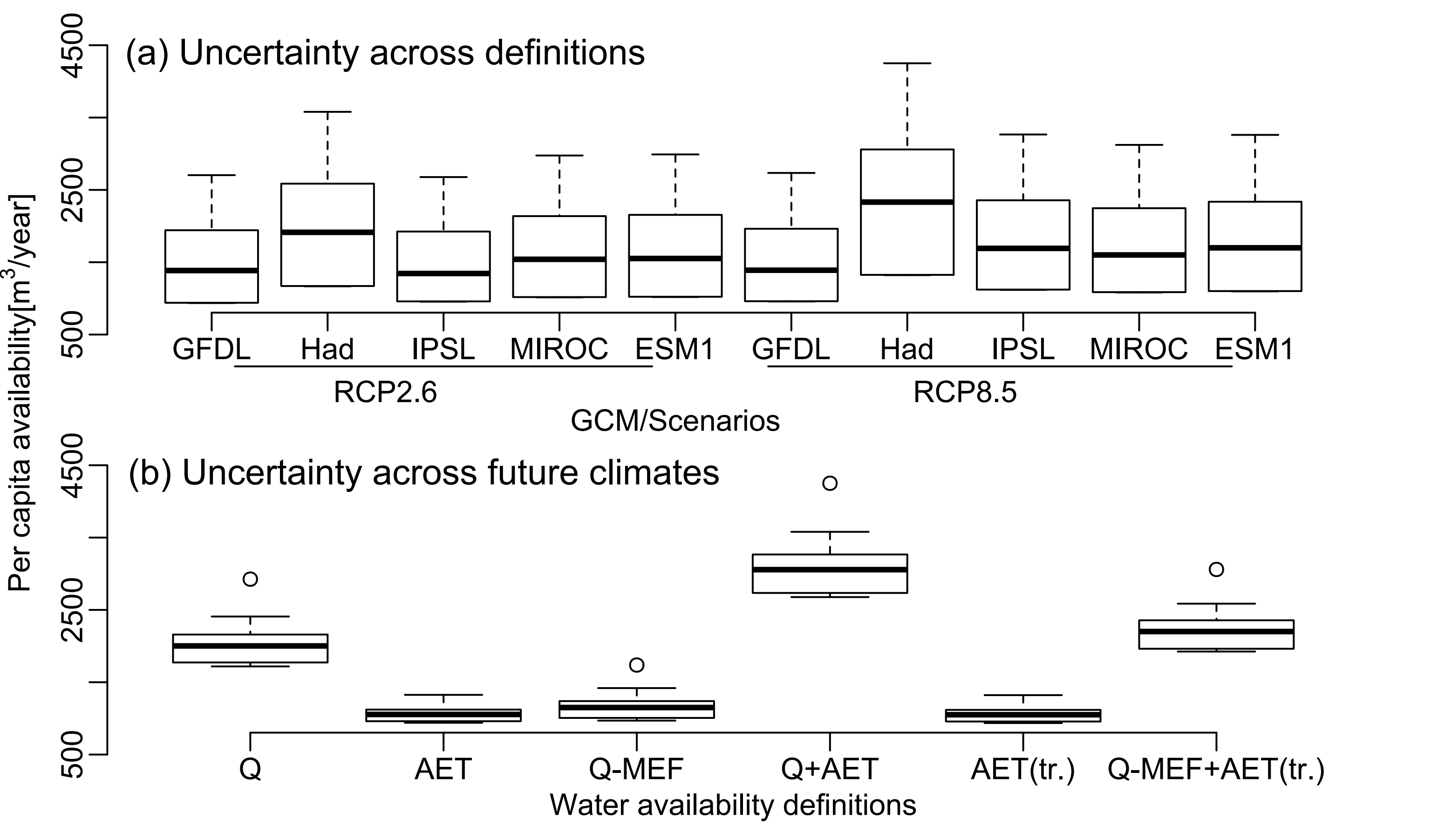
				average	
9	Kummu et al. 2016	Q (natural)	Multiple metrics	Sub-national/ decadal	Multiple thresholds
10	Mekonnen and Hoekstra, 2016	Q (impacted)	Withdrawal/Q	30’x30’ grid/monthly	MEF

Figure Captions

Figure 1. (a-f) Long term (1983-2000 average) per capita water availability across India at a spatial resolution of fine political units using various definitions of water availability. Q refers to mean annual runoff including shallow groundwater; AET_AG is the evapotranspiration from agricultural areas; MEF refers to minimum environmental flows. Case (e) accounts for impact of virtual water trade on net AET_AG. (g) Percentage of districts under water scarcity as a function of choice of water availability definition and threshold of scarcity.

Figure 2. Uncertainty in future water availability due to (a) multiple definitions of water availability, and (b) due to future projections of climate from different global climate models (GCMs) and representative concentration pathways (RCPs). Panel (a) shows the range of uncertainty in projected per capita water availability across six different definitions of water availability for each GCM-RCP combination. Panel (b) shows the range of per capita water availability across GCM-RCPs for each definition of water availability. All values are aggregated across India. The ranges are shown as boxplots, which show median values by solid black horizontal lines. The box boundaries show the 25th and 75th percentile of the data. The whiskers extend to data values that are up to 1.5 times the interquartile range from either ends of the box. Any data points outside these ranges are shown by empty circles and classified as outliers. See Supplementary Text S2 for details on GCMs and RCPs.


a
Blue water, Q
N
< 500
500 - 1000
1000 - 1700
> 1700
Scarce Data
Per capita availability[m3/year]
b
Green water, AET_AG
c
Total: Q+AET_AG
no trade, no MEF
d
Blue water, Q-MEF
Remove env. flows
e
Green water, AET_AG
with trade
f
Total: Q-MEF+AET_AG
with trade
g.
Q
Q-MEF
AET
AET (with trade)
Q+AET
Q-MEF+AET (with trade)
Water scarce districts[%]
0
25
75
500
1000
1700
Scarcity Thresholds [m3 /year/person]


(a) Uncertainty across definitions
Per capita availability[m3/year]
4500
2500
500
GFDL
Had
IPSL
MIROC
ESM1
GFDL
Had
IPSL
MIROC
ESM1
RCP2.6
RCP8.5
GCM/Scenarios
(b) Uncertainty across future climates
4500
2500
500
Q
AET
Q-MEF
Q+AET
AET(tr.)
Q-MEF+AET(tr.)
Water availability definitions