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# The Impact of Climate Change Policy on the Risk of Water Stress in Southern and Eastern Asia

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—*Ronald G. Prinn and John M. Reilly,*  
*Joint Program Co-Directors*

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## LETTER

# The impact of climate change policy on the risk of water stress in southern and eastern Asia

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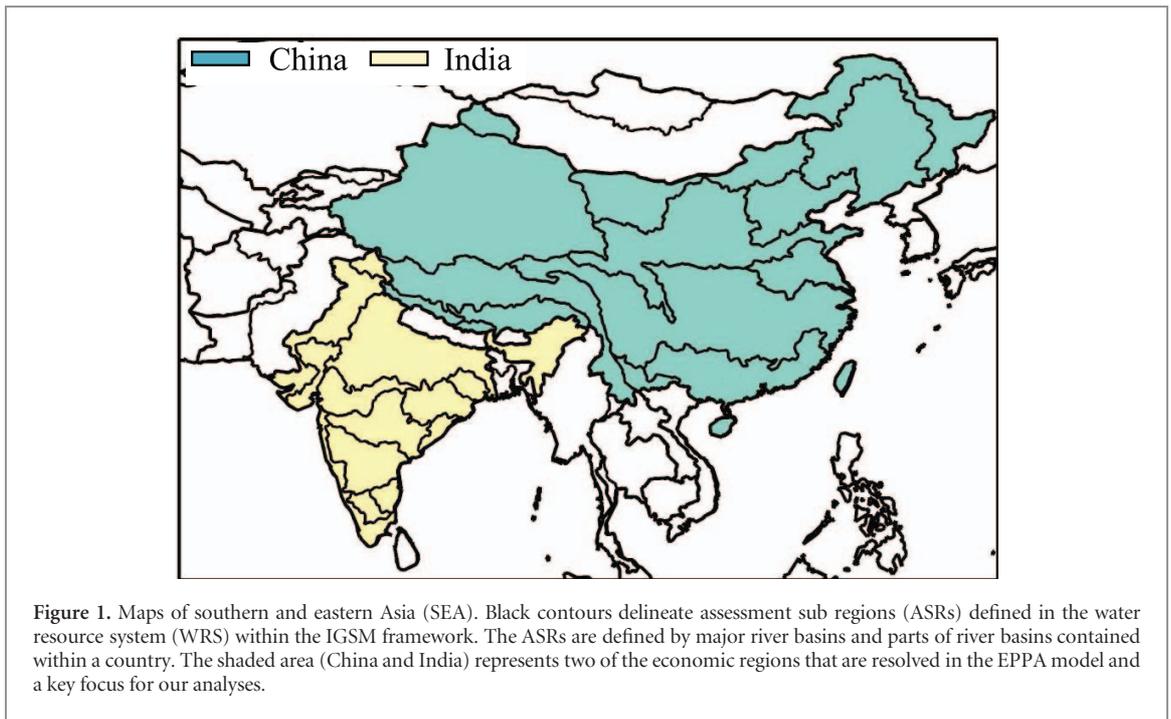
## Abstract

The adequacy of freshwater resources remains a critical challenge for a sustainable and growing society. We present a self-consistent risk-based assessment of water availability and use under future climate change and socioeconomic growth by midcentury across southern and eastern Asia (SEA). We employ large ensemble scenarios from an integrated modeling framework that are consistent across the spectrum of regional climate, population, and economic projections. We find socioeconomic growth contributes to an increase in water stress across the entire ensemble. However, climate change drives the ensemble central tendency toward an increase in water stress in China but a reduction in India, with a considerable spread across the ensemble. Nevertheless, the most deleterious unabated climate-change impact is a low probability but salient extreme increase in water stress over China and India. In these outcomes, annual withdrawals will routinely exceed water-storage capacity. A modest greenhouse gas mitigation pathway eliminates the likelihood of these extreme outcomes and also benefits hundreds of millions of people at risk to various levels of water stress increase. Over SEA we estimate an additional 200 million people under threat of facing at least heavily water-stressed conditions from climate change and socioeconomic growth, but the mitigation scenario reduces the additional population-under-threat by 30% (60 million). Nevertheless, there remains a 1-in-2 chance that 100 million people across SEA experience a 50% increase in water stress and a 1-in-10 chance they experience a doubling of water stress. Therefore, widespread adaptive measures may be required over the coming decades to meet these unavoidable risks in water shortfalls.

## 1. Introduction

Water is essential for socioeconomic development and maintaining healthy ecosystems. Yet two-thirds of the global population (4.0 billion people) live under conditions of severe water scarcity at least 1 month of the year and half a billion people in the world face severe water scarcity year around (Mekonnen and Hoekstra 2016). Asia is a global hot spot for water insecurity. It remains home to 60% of the global population and half of the world's poorest people (Asian Development Bank 2016), yet the availability of freshwater is less than half the global annual average of 6380 m<sup>3</sup> per

inhabitant (Chellaney 2012). In the face of rapidly rising populations, the fastest-growing economies, expanding irrigation and water-intensive industries, and escalated household consumption, per capita water availability in Asia has been declining over the decades by 1.6% per year (Chellaney 2012). Climate change may further exacerbate water scarcity via altering the hydrological cycle (Oki and Kanae 2006), such as changing rainfall patterns, increasing climate variability and the occurrence of extreme weather events (Prudhomme *et al* 2014), as well as reducing the availability of supply (glaciers/snow and rivers, etc.) (Immerzeel *et al* 2010, Siegfried *et al* 2011).



It is estimated that up to 3.4 billion out of predicted 5.2 billion population in Asia could be living in water-stressed areas by 2050 (International Institute for Applied Systems Analysis 2016).

Understanding future risks to freshwater resources is vital to ensuring sustainable growth. Yet the future adequacy of freshwater resources is difficult to assess, owing to a complex and rapidly changing geography of water supply and consumption as a result of multifaceted interplay among human society, terrestrial hydrological cycle and climate change (Arnell 2004, Alcamo *et al* 2007, Haddeland *et al* 2014, Hagemann *et al* 2013). Given the considerable uncertainty inherent in changing hydro-climatic and socioeconomic conditions, there is an increasing call for risk-based approaches to water resource planning and management (Kundzewicz *et al* 2008, Döll *et al* 2015, Hall and Borgomeo 2013, Turner *et al* 2016). Many studies used single (Arnell 2004, Alcamo *et al* 2007, Arnell *et al* 2011, Gosling and Arnell 2016, Vörösmarty *et al* 2000, Kiguchi *et al* 2015) or several global hydrological models (Haddeland *et al* 2014, Hagemann *et al* 2013, Schewe *et al* 2014) forced with multiple climate projections from general circulation models (GCMs), in combination with different emissions scenarios or pathways, to examine the vulnerability of global water resources from climate change and/or direct human impacts. These studies fall short of providing quantitative insights on ‘risk’ or the probability of different intensities (particularly associated with extremes and variability) because (1) a few selected GCMs may not adequately represent the full range of possible outcomes; (2) the multi-model ensemble-mean and range is typically employed to characterize the occurrence of a future state. A few studies applied risk-based extrapolations of limited GCM samples in

the assessment and evaluation of water scarcity (Hall and Borgomeo 2013, Turner *et al* 2016, Borgomeo *et al* 2014, Veldkamp *et al* 2016), but mostly targeted probabilistic hydroclimate (water availability) uncertainties solely. We conduct a self-consistent risk-based assessment of water availability and use as well as water resource adequacy in response to climate change and socioeconomic growth by midcentury, focusing particularly on the impact of climate change policy on such risk. The assessment is achieved by employing a large ensemble of scenarios that are consistent across the probability distributions of population, economic growth, regional hydroclimate changes, and emissions. Such consistency in socioeconomic and environmental factors is lacking in previous studies, but highly relevant for assessing climate impacts and climate-policy benefits (discussed later). We focus on large watersheds or assessment subregions (ASRs) in southern and eastern Asia (SEA), which previous studies indicated as likely hotspots of severe water stress in the coming decades (Arnell 2004, Alcamo *et al* 2007, Haddeland *et al* 2014, Arnell *et al* 2011, Gosling and Arnell 2016, Schlosser *et al* 2014). In particular, we highlight China and India—the world’s two most populous countries and among the fastest growing major economies (figure 1).

## 2. Models and simulations

For any given ASR, runoff, inflow of upstream ASRs, and pumped groundwater (limited by recharge rate) constitute available water supply, hereafter referred to as ‘water supply’. Water withdrawal includes irrigation as well as domestic and industrial sectors. Withdrawal can be greater than supply because of returned and

reused water within a ASR and river basin. A ‘local’ water stress index (WSI) is determined at every ASR as the ratio of annual water withdrawal to water supply. Values between 0.3–0.6 and 0.6–1.0 indicate moderately and heavily stressed conditions, respectively, whereas those greater than 1.0 and 2.0 reflect conditions of overly and extreme water exploitation, respectively (Smakhtin *et al* 2004). All the metrics are aggregated (summed) to the national scale for the assessment, except that the WSI of each ASR is weighted by its population. Such weighting is necessary to avoid masking regional water stress when aggregating water rich and water scarce ASRs. We track water resources out to midcentury under two different climate trajectories: an unconstrained emissions (UE) and a modest climate-mitigation target (L2S). In the L2S scenario (Webster *et al* 2012), human emissions are limited to the extent that there is a 20% probability that climate warming would not exceed 2°C and nearly 90% chance it would not exceed 3°C at the end of the century. In this study, we focus on the impact of greenhouse gas mitigation and thus do not consider long-term adaptive responses (subject of a subsequent paper).

We employ a water resource system (WRS) embedded within the Massachusetts Institute of Technology Integrated Global System Model (IGSM) framework (Strzepek *et al* 2013, supplementary figure S1 available at [stacks.iop.org/ERL/13/064039/mmedia](https://stacks.iop.org/ERL/13/064039/mmedia)). IGSM consists of a human system model (the Emissions Prediction and Policy Analysis or ‘EPPA’, Paltsev *et al* 2004) and an earth system model which includes a two-dimensional (zonally averaged) atmospheric model with interactive chemistry coupled to an anomaly-diffusing ocean model and a land system model (Sokolov *et al* 2018). It is designed to provide the flexibility and computational efficiency for probabilistic uncertainty analyses. We perform a large ensemble of 50 year (2001–2050) simulations at  $2 \times 2.5^\circ$ —consistent across a range of climate policies, climate parameters, population growth, and emissions of all greenhouse gases, aerosol, and pollutants (Fant *et al* 2016). Most previous model-based studies, however, have been driven with exogenous climate forcing that is disconnected from consistent socioeconomic pathways, thus lacking the interactions between natural processes and human activities. These inconsistencies occur mainly because the developers and the users of these socioeconomic scenarios (i.e. the four Representative Concentration Pathways (RCPs) adopted by IPCC for its Fifth Assessment Report) come from different research groups and disciplinary communities. For example, even with a common land-use scenario implemented, the different Earth system models can have different interpretations of land-use classes, making the resulting differences in the carbon cycle and land-use forcing difficult to interpret. Further, each of the four RCP scenarios was produced by a different group and their projections of future air pollutant emissions are not consistent

with one another, which can contaminate the analysis of the climate-policy benefits. Our employed integrated framework includes a detailed representation of economic activities to track inter-sectoral and inter-regional links as well as a detailed representation of various physical, chemical, and biological components of the Earth system that are impacted by human activity. Such framework ensures consistent treatment of interactions among population growth, economic development, energy and land system changes and physical climate responses, which can provide improved assessments of climate impacts across multiple sectors (Monier *et al* 2018).

For each greenhouse gas control policy scenario, we produce 400 member ensemble of IGSM zonal projections with different values of climate parameters (effective climate sensitivity, ocean heat uptake rate, and net aerosol forcing) and economic parameters (labor and energy productivity growth, population, resource availability, technology costs, pollution emissions and substitution elasticities) as described in Webster *et al* (2012). This ensemble projections are then expanded with the pattern-scaling (Schlosser *et al* 2012) based on 17 climate models in the Coupled Model Intercomparison Project Phases 3 (CMIP3) (Meehl *et al* 2007) (supplementary figure S2) to develop a 6800 member ensemble of two-dimensional (longitude-latitude) climate change projections. The use of climate change projections from the entirety of the CMIP3 climate model collection is justified by the fact that projections of water scarcity are strongly influenced by the particular regional patterns of change these models produce under any given climate scenario (Arnell *et al* 2011, Gosling and Arnell 2016). Then, for the sake of computational efficiency, a Gaussian quadrature procedure (Arndt *et al* 2015) is employed to produce a subset (539 and 630 members for UE and L2S, respectively) and corresponding weight for each ensemble member. The procedure ensures that the resulting reduced ensembles reproduce the distributional features of a set of highly relevant water-resource metrics (i.e. population, GDP, and hydro-climate changes) given by the full 6800 member ensemble (supplementary figure S3).

We employ three sets of meteorological forcings: (1) a global, 50 year (1951–2000), 3 hourly,  $1^\circ$  dataset (Sheffield *et al* 2006), hereafter referred to as ‘contemporary climate’; (2) detrended contemporary climate and then added to its year-2000 mean to emulate a 50 year (2001–2050) climate without any change, hereafter referred to as ‘baseline climate’; and 3) future climate is obtained with a delta method (Ramirez-Villegas and Jarvis 2010) by adding the IGSM downscaled climate anomalies from 2001–2050 (with respect to 1981–2000 climatology) to the baseline climate so that the inter-annual variability of baseline climate is maintained. The runoff is simulated from the Community Land Model (CLM) (Oleson *et al* 2004) forced by both the baseline and future climate from

2001–2050, with the initial condition at 2001 from the CLM simulation of 1951–2000 forced by contemporary climate. The bias in runoff is corrected with the International Food Policy Research Institute (IFPRI) Modeled Natural Flow (MNF) data set (Zhu *et al* 2018) using an established maintenance of variance extension procedure (Strzepek *et al* 2013) such that the monthly statistical properties of MNF (mean, standard deviation, and temporal variation) are preserved at each ASR. Domestic and industrial water requirements are determined by 400 member ensemble projections of population growth rate and gross domestic product (GDP) for each economic region in the EPPA. The uncertainty in population growth is taken from World Population Prospects: the 2006 Revision (UN 2007) as described in Webster *et al* (2008). Future population at each ASR is obtained by multiplying the population at 2000 from IPFRI (Rosegrant *et al* 2008) by the growth rate, both mapped to each ASR within the corresponding EPPA region. Irrigation requirements mainly respond to the climate (precipitation and temperature) and is calculated for a variety of crops with a crop water deficit module (CliCrop) (Fant *et al* 2012) of the WRS. Evidence demonstrated that percentage of agricultural irrigated land has remain fairly stable through the recent decade in China and India (World Bank Data Catalog 2015) even though food production has steadily increased (Zhang 2011, Deshpande 2017). This indicates that rising food demands in these countries are being met by technical progress in agriculture and intensification of existing irrigated land. Given the uncertainty in irrigation expansion (World Commission on Dams (WCOD) 2000) and to isolate the impact of mitigation from that of adaptive technologies (i.e. field and main delivery efficiencies), we set the irrigated area and irrigation efficiency at each ASR based on current estimates from IFPRI (Rosegrant *et al* 2008). The water system management of the WRS optimizes the routing of water supply across all of the ASRs, which sets priority for domestic and industrial uses followed by the agriculture sector.

For each policy scenario, we formulate three impact scenarios to quantify the separate and combined contributions of climate change and socioeconomic growth to water stress by 2050. The ‘growth’ (‘G’) scenario, where the domestic and industrial water requirements serve as key drivers of water conditions, applies projected GDP and population but holds climate at the baseline condition. The same distribution of future population projection is employed for both UE and L2S scenarios, which is consistent with our previous treatment of uncertainty in global change assessments (Webster *et al* 2012). The ‘climate’ (‘C’) scenario, where irrigation requirement and runoff serve as the main drivers of water stress, varies climate but fixes the population and GDP at year 2000 levels. The ‘climate and growth’ (‘CG’) scenario imposes both climate change and socioeconomic growth to assess

their combined effects on water stress. We gauge the changes in water supply, water requirements, and water stress from these scenarios against a baseline scenario. The baseline scenario represents 50 year (2001–2050) runoff and irrigation requirement produced with baseline climate but keeps domestic and industrial water requirements constant at year 2000 values. We further assess the expected variance of baseline water stress that results from climate natural variability with a 500 member ensemble performed via a multivariate k-nearest neighbor bootstrap that maintains the lag 1 correlation (Lall and Sharma 1996). Each member contains 50 year (2001–2050) monthly runoff, reservoir evaporation, and irrigation requirement. We focus our analyses of these metrics on their distributions of relative decadal mean annual changes (2041–2050) from the baseline of the same period. We use MATLAB for all the data analyses.

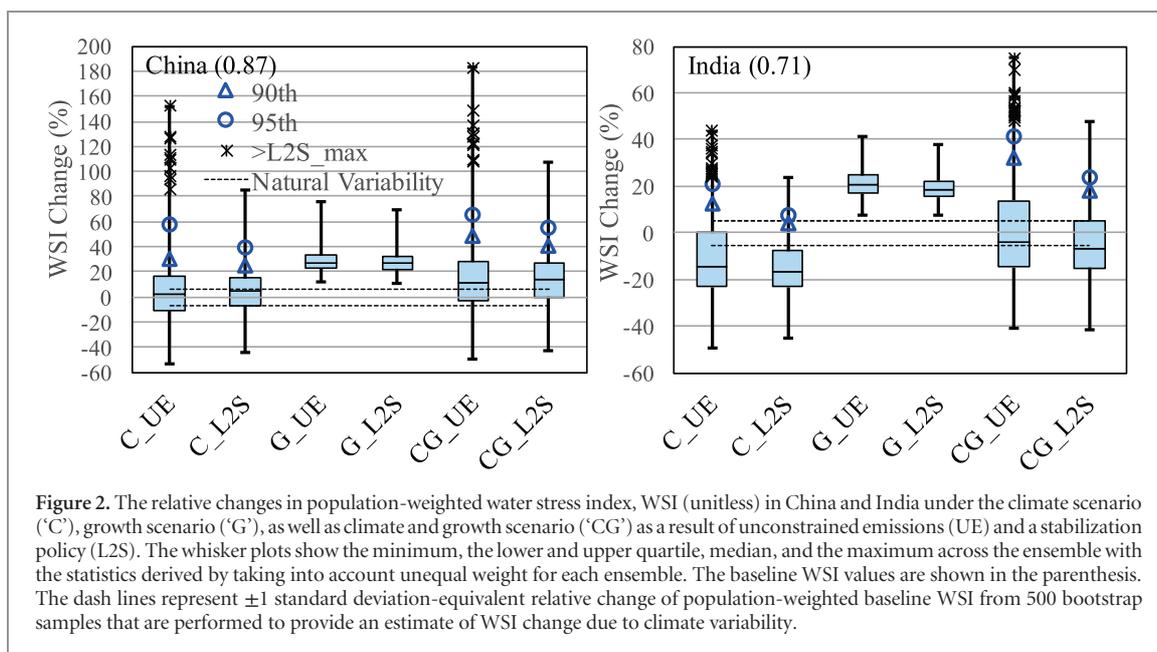
For the population at risk to water stress, we identify all ASRs in China, India, and SEA whose WSI values are larger than 0.6—and thus within the heavily to extremely exploited category and deemed exposed to ‘water stress’. We aggregate the populations across these ASRs for each of the ensemble under each of the six future scenarios. The future populations under this characterization of ‘water stress’ ( $POP_s$ ) are obtained for each of the six future scenarios as follows:

$$POP_s = POP * R_s \\ = POP * \frac{\sum_{e=1}^N \sum_{w=3}^5 POP_{e,w}}{\sum_{e=1}^N \sum_{w=1}^5 POP_{e,w}} \quad (1)$$

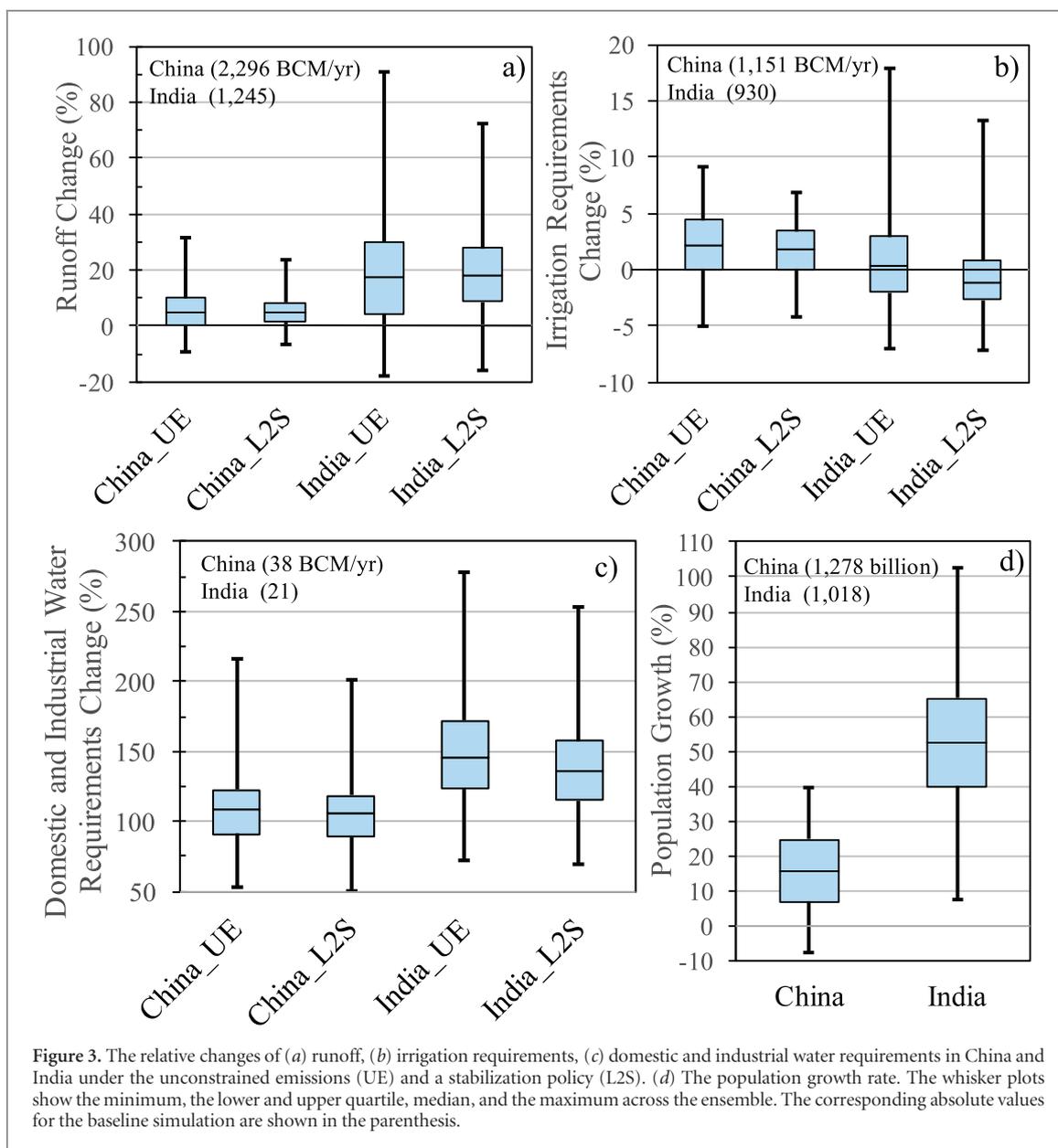
where POP is the projected 2041–2050 population calculated as the mean of 400 member ensemble.  $R_s$  is a pooled percentage-under-stress.  $e$  is the ensemble member,  $N$  is the total number of ensemble members (539 and 630 for UE and L2S scenarios, respectively).  $w$  is the WSI category:  $w = 1$  indicates  $WSI < 0.3$  (slightly water stressed);  $w = 3$  and  $w = 5$  indicate  $WSI \geq 0.6$  (heavily water stressed) and  $WSI \geq 2$  (extremely water stressed), respectively.  $R_s$  is calculated as the ratio of the sum of the population under our water stress characterization to the sum of the total population across all ensemble members.

### 3. Results and discussion

Socioeconomic growth increases the risk of water stress across all ensemble members and scenarios for China and India (figure 2). While the ensemble medians of both countries indicate similar increases in water stress, China exhibits a wider range of relative increase (10%–75%) than India (5%–40%). These consistent increases resonate strongly with the changes in the domestic and industrial water requirements (figure 3(c)). China and India experience at least 50% to two- or three-fold increases in water requirements, highlighting the extensive growth anticipated for these



**Figure 2.** The relative changes in population-weighted water stress index, WSI (unitless) in China and India under the climate scenario ('C'), growth scenario ('G'), as well as climate and growth scenario ('CG') as a result of unconstrained emissions (UE) and a stabilization policy (L2S). The whisker plots show the minimum, the lower and upper quartile, median, and the maximum across the ensemble with the statistics derived by taking into account unequal weight for each ensemble. The baseline WSI values are shown in the parenthesis. The dash lines represent  $\pm 1$  standard deviation-equivalent relative change of population-weighted baseline WSI from 500 bootstrap samples that are performed to provide an estimate of WSI change due to climate variability.



**Figure 3.** The relative changes of (a) runoff, (b) irrigation requirements, (c) domestic and industrial water requirements in China and India under the unconstrained emissions (UE) and a stabilization policy (L2S). (d) The population growth rate. The whisker plots show the minimum, the lower and upper quartile, median, and the maximum across the ensemble. The corresponding absolute values for the baseline simulation are shown in the parenthesis.

developing countries. India exhibits larger relative increases than China in all distributional aspects (i.e. the medians and interquartile ranges), likely attributed to its projected higher population growth rate (figure 3(d)). Nevertheless, given that mitigation scenario employs the same distribution of future population as the UE scenario but slows the GDP growth rate, its relatively weak benefit out to the middle of the century is expected with small relative reductions (on the order of 5%) in the upper range and median of WSI change.

Climate change produces a broad mixture of responses with both positive and negative effects on water stress (figure 2). In terms of the central-tendency of WSI change, decreasing water stress is primarily associated with increased runoff from climate change, while increased water stress stems from growing withdrawals from agriculture sector. For China, already in a heavily water-stressed condition, the ensemble medians suggest that climate change will increase water stress in both UE and L2S scenarios. The increases are marginal, however, when viewed against estimated natural variability. In contrast, the central tendency (median) and the majority of the ensemble show reduced water stress for India. The combined climate-growth effect is dependent on how the two interact, and the interplay is ASR/basin specific which leads to distinct aggregate behaviors at the country scale (figure 2). The overall effect of socioeconomic growth is to exacerbate the marginally adverse effect of climate change on water stress for China, but the climate-growth interplay is predominantly counteractive across ASRs in India, with the resulting ensemble medians exhibiting net reductions in water stress.

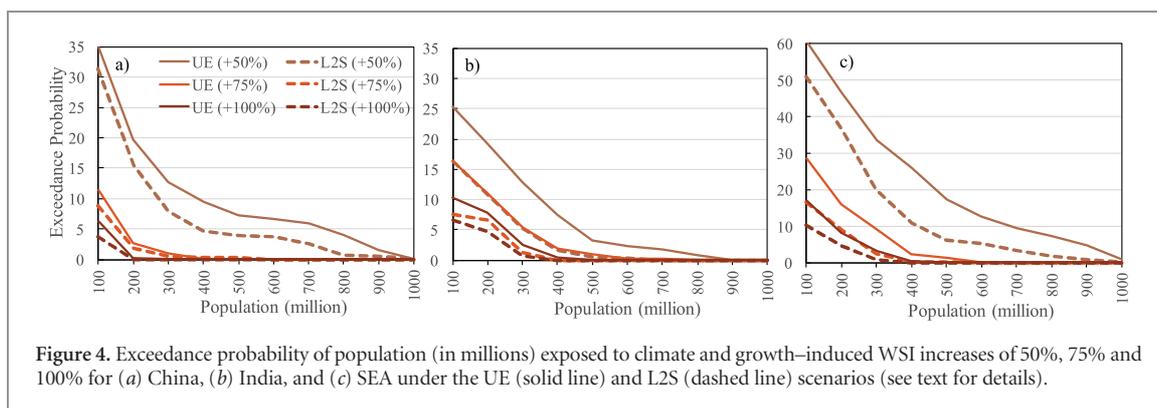
A critical aspect of the UE scenario is that unabated climate change produces a positively skewed (skewness 1.42 for China and 0.51 for India) and two to three times larger range of outcomes than that from socioeconomic growth (figure 2). The climate-induced WSI changes range from a decrease of 50% to increases of 150% and 50% for China and India, respectively. Particularly for China, the top 10% of the UE ensemble spans a substantially wide range of increase (30%–150%). Thus, the most salient risk to future water stress arises from regional climate extremes occurring within a subset of the UE ensemble. This subset of situations depicts countries already under ‘heavy’ water stress experiencing nearly (and in some cases exceeding) a doubling in the severity of water scarcity by midcentury. This facet of the results underscores the importance of using as much climate-model information as possible in order to capture the comprehensive range of climate-change outcomes for risk-based studies. Moreover, the interplay with socioeconomic growth causes a more pronounced positive skewness in water-stress changes (skewness 1.44 for China and 0.55 for India, figure 2), and thus an increased risk of a more severe water shortage condition by midcentury.

Climate-driven WSI changes in China and India are supported by their runoff and irrigation require-

ment responses (figure 3). Under both UE and L2S scenarios, runoff is projected to most likely increase in China and India with more than 75% consensus across the ensemble members (figure 3(a)). This is consistent with previous studies (Arnell 2004, Haddeland *et al* 2014, Schewe *et al* 2014). India exhibits larger ensemble medians and substantially wider range of relative change (decrease of 20% to increase of 80%) than China. Irrigation requirement (figure 3(b)) features a considerably smaller range of relative changes (approximately –8% to 18%) than non-agricultural water requirements (figure 3(c)) but from much higher contemporary levels. Therefore in absolute terms, irrigation is the largest consumptive use of water. The majority of the ensemble (75%) for China indicates increases in irrigation requirement. The ensemble median for India is somewhat neutral under the UE scenario and shows a decrease under the L2S scenario, despite a notable skewness seen for stronger increase, particularly in the UE scenario.

The distinct skewness of large WSI increases seen in the UE scenarios (figure 2) calls attention to whether mitigation can alleviate these considerable risks. Overall, the differences in the projection of WSI change across the emissions scenarios are relatively small when compared with those across the climate change patterns, which is consistent with earlier work (Arnell *et al* 2011, Gosling and Arnell 2016). The mitigation trajectory has a weak effect on the central tendency and lower bound of WSI changes (figure 2), and generally speaking, affects the distributional changes in runoff and water requirements to a similar extent (figures 3(a)–(c)). This is due to inertia in the climate system that near-term climate is strongly conditioned by past greenhouse gas emissions and emissions scenarios are expected to differ more strongly beyond 2050 (Arnell *et al* 2011, Stocker *et al* 2013). Nevertheless, mitigation is clearly seen to eliminate the risk of extreme water stress increases (2~3% of the ensemble)—as evidenced by removal of the distinct skewness seen in all distributions (figure 2). The resulting skewness is 0.28 and 0.42 for China and India under the climate scenario as well as 0.45 and 0.48 under the climate and growth scenario, respectively.

We further assess the population exposed to various levels of water stress risk and the impact of the policy in emissions. For each ensemble member, we identify the basins (i.e. ASRs) which experience at least 50%, 75%, and 100% increases in WSI (relative to the baseline values) for the CG scenario and then aggregate the populations of the identified ASRs over China, India, and SEA, respectively. The exceedance probabilities of population under water stress increases are shown for the UE and L2S scenarios (figure 4). For China, the mitigation benefit is most evident for the population at risk to at least 50% water stress increase (figure 4(a)). The associated water stress risk is lowered to various extents across population of different sizes: i.e. the 1-in-10 chance is halved for 400 million people



**Table 1.** Changes in total population and population exposed to water stress (in million) for China, India, and SEA under three impact scenarios and two policy scenarios. The total population of 2041–2050 is the average from 400-ensemble projections. Bold numbers indicate decreases in population.

|       | Total population |           |                    | 2000 | Population exposed to water stress (WSI > 0.6) |      |            |             |       |            |
|-------|------------------|-----------|--------------------|------|--|------|------------|-------------|-------|------------|
|       | 2000             | 2041–2050 | 2041–2050 (change) |      | 2041–2050 (changes relative to 2000)           |      |            |             |       |            |
|       |                  |           |                    |      | C_UE   | G_UE | CG_UE      | C_L2S       | G_L2S | CG_L2S     |
| China | 1278             | 1480      | 202                | 524  | 80   | 83   | 81         | 83          | 83    | 83         |
| India | 1018             | 1555      | 537                | 567  | <b>−96</b>                                     | 449  | <b>−11</b> | <b>−143</b> | 443   | <b>−73</b> |
| SEA   | 2930             | 4144      | 1214               | 1241 | 143  | 657  | 195        | 104         | 651   | 135        |

and 1-in-25 chance of 800 million people and above is nearly eliminated under L2S scenario. In India, mitigation reduces water stress risk across all three levels of WSI increases (50%, 75%, and 100%) (figure 4(b)). The 1-in-15 chance of 400 million people experiencing at least 50% WSI increase goes to approximate 1-in-60 chance, while the risk of a half billion people and above is almost eliminated under mitigation. The population at risk to at least a 75% or 100% WSI increase is upwards to 600 million, while under mitigation the corresponding population size is reduced to 350 million. Across the SEA, we see the reduction in risk to all the levels of WSI increases under mitigation (figure 4(c)). Specifically, the reduction in risk to a 50% WSI increase could benefit up to 900 million people. The 1-in-10 chance of 300 million people exposed to at least 75% WSI increase goes to a 1-in-40 chance, while 1-in-10 chance of 200 million people exposed to at least 100% WSI increase is nearly halved. Nevertheless, under the mitigation scenario there remains a 1-in-2 chance that 100 million people across SEA experience a 50% increase in water stress and a 1-in-10 chance they experience a doubling of water stress. These results highlight the need for widespread adaptive measures to be considered in order to adequately prepare for future water-stress risks by midcentury.

The population under water-stress is summarized in table 1 for all six future scenarios (see section 2 for details). In China, regardless of socioeconomic growth or climate change or their combination, the additional population under threat is approximately 80 million, equivalent to 40% of its projected population increase. In India, the population-under-stress attributed to socioeconomic growth nearly doubles the current estimate, with the resulting total population-

under-stress reaching up to 1 billion. The climate change, however, reduces the population-under-stress, mostly notable under the mitigation policy, by nearly 145 million. Overall, the mitigation policy results in 70 million fewer people in India under threat of water-stressed conditions. Across the entire SEA of our study-domain, all scenarios project increases in population under water stress, with more ubiquitous increases owing to socioeconomic growth than climate change, but combined we estimate an additional 200 million people are under threat of facing at least heavily water stressed conditions by midcentury. Nevertheless, a modest mitigation pathway could reduce this additional population-under-threat by 30% (60 million).

#### 4. Conclusions

By employing a large ensemble of scenarios that are consistent across the probability distributions of population, economic growth, regional hydroclimate changes, and emissions, we conduct a self-consistent risk-based assessment of water availability and use in response to climate change and socioeconomic growth by midcentury across SEA under two different climate trajectories. Our results highlight the large uncertainty associated with climate-driven WSI changes but also underscore a critical risk-abatement aspect of climate mitigation that removes the distinct positive skewness associated with extreme water stress increases under unconstrained emissions. A global effort to lessen the severity of climate warming with a modest mitigation policy can considerably reduce, and for some categories—eliminate, the rising risk to various

levels of water stress increase and thus benefit hundreds of millions of people. Overall, such a modest mitigation policy results in 60 million fewer people across SEA under threat of facing at least heavily water-stressed conditions. Nevertheless, several aspects of the implemented framework motivate subsequent investigation, that include: a broader sample of structural uncertainty in hydrological models that has been recently shown to be appreciable (Haddeland *et al* 2014); alternative metrics and categories of water stress that more explicitly account for physiological/health effects as well as unmet consumptive demands; higher granularity of water basins as the level of coarse resolution spatial units (river basins) may underestimate the assessment of water scarcity and hence the number of people under threat (Mekonnen and Hoekstra 2016); more explicit treatment of management measures; adjustments in irrigated acreage or in cropping patterns; alternative distributions of population projections; as well as adaptive and water-efficiency measures taken. Finally, for more comprehensive and rigorous assessment of the risk to future water availability—the impacts on water quality that result from the range of human activities and climate outcomes considered herein must be fully integrated. Improving the framework with these aforementioned considerations will ultimately lead to persuasive and actionable insights for water-related strategic planning and risk management in the face of unavoidable and preventable global changes.

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