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Assessing chronic and climate-induced water risk through spatially distributed cumulative deficit measures: A new picture of water sustainability in India

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[1] India is a poster child for groundwater depletion and chronic water stress. Often, water sustainability is measured through an estimate of the difference between the average supply and demand in a region. However, water supply and demand are highly variable in time and space. Hence, measures of scarcity need to reflect temporal imbalances even for a fixed location. We introduce spatially distributed indices of water stress that integrate over time variations in water supply and demand. The indices reflect the maximum cumulative deficit in a regional water balance within year and across years. This can be interpreted as the amount that needs to be drawn from external storage (either aquifers or surface reservoirs or interarea transfers) to meet the current demand pattern given a variable climate and renewable water supply. A simulation over a long period of record (historical or projected) provides the ability to quantify risk. We present an application at a district level in India considering more than a 100 year data set of rainfall as the renewable supply, and the recent water use pattern for each district. Consumption data are available through surveys at the district level, and consequently, we use this rather than river basins as the unit of analysis. The rainfall endogenous to each district is used as a potentially renewable water supply to reflect the supply-demand imbalances directly at the district level, independent of potential transfers due to upstream-induced runoff or canals. The index is useful for indicating whether small or large surface storage will suffice, or whether the extent of groundwater storage or external transfers, or changes in demand are needed to achieve a sustainable solution. Implications of the analysis for India and for other applications are discussed.

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1. Introduction

[2] The varying distribution of fresh water across the globe, involving complex patterns of rainfall in space and time, directly influences ecosystems and the infrastructure on which human societies depend. Water issues also feature prominently in assessments of economic development [*United Nations Development Programme (UNDP)*, 2006]. Variability in rainfall is a key factor for agricultural production and water management. *Brown and Lall* [2006] demonstrate statistically that rainfall variability may be a more important determinant of per capita income of nations than mean annual rainfall and is hence a significant factor in economic growth of a country.

[3] At the global scale, assessments have been done to project the current and future distributions of water-deficit areas worldwide Wallace, 2000]. These assessments use global hydrological models to estimate the distribution of runoff (renewable freshwater) and various statistics to estimate water use [*Oki and Kanae*, 2006]. However, they primarily consider only *per capita annual water availability* [*Arnell*, 1999, 2004] or the annual *withdrawal to availability ratio* [*Oki et al*., 2001; *Alcamo et al*., 2003] and not the impact of climate variability or the temporal variation of demand, as highlighted in *Brown and Lall* [2006]. A detailed review of the current water scarcity indices can be found in *Amber* [2011].

[4] A country like India has wide variations in population density, topography, and climate. These need to be addressed in developing water stress indices [*Perveen and James*, 2009]. The monsoonal rains in India occur over a few days (on average just 100 h per year, *Agrawal et al*. [2001]) in a 4 month season and account for almost 90% of the annual river flows [*Central Water Commission (CWC)*, 1998]. Lately, several attempts have been made to analyze water resources at a more refined spatiotemporal scales with essentially the same indicators as those employed at the global or national scale [*Alcamo et al*., 1997; *Meigh et al*., 1998; *Vörösmarty et al*., 2000]. The results obtained

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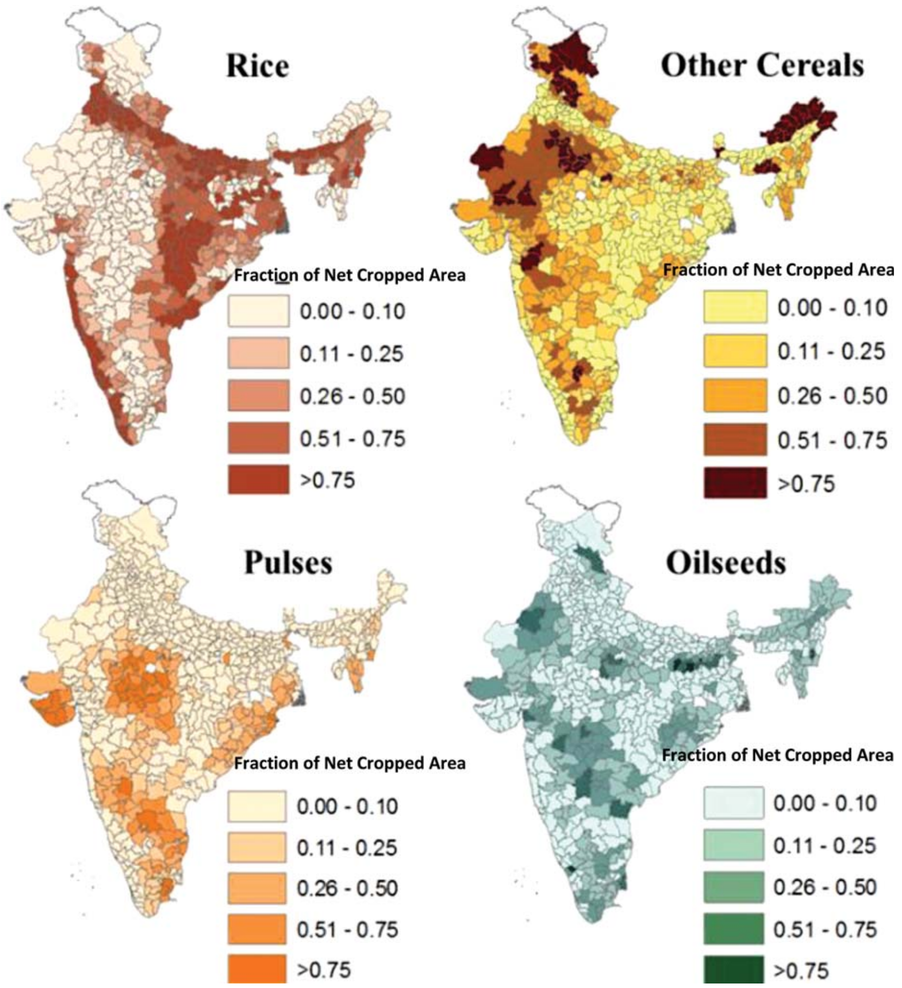

Figure 1. Districtwise cropping patterns of major food grains and oilseeds in India, shown as the fraction of net cropped area for each district.

from these studies corroborate the importance of using high spatial resolution data to analyze local water-scarcity problems [*Perveen and James*, 2011].

[5] Among the major developing nations, India faces the most serious and persistent water deficits owing to a growing imbalance of supply and demand [*Lall et al*., 2008; *Briscoe*, 1999; *Dinar and Subramanian*, 1997; *Kinzelbach et al*., 2004]. Irrigated agriculture, to buffer climate variability, is the dominant water user in India, accounting for nearly 90% of all consumptive water use. Irrigation typically requires either surface water storage and distribution, or extraction from shallow or deep ground water storage. The latter has emerged as the dominant mechanism in India over the last 20 years. Today, it accounts for nearly 75% of water use in the main agricultural areas of the country [*Shah et al*., 2006]. Figure 1 shows the cropping patterns of major food grains and oilseeds in India [*Dacnet*, 2011] at the district level. The simultaneous effects of agricultural growth, industrialization, and urbanization coupled with declining surface and groundwater quantity, inefficiencies in water use practices, and rising concerns on the impacts of climate change on water supply patterns are crucial problems faced by India's water sector, leading to cross-sectoral and intrastate and interstate water disputes. Since groundwater use is not monitored, and data on groundwater levels are available only at a rather coarse resolution, one needs an alternate approach to estimate the potential water stress faced across the country, relative to the estimated renewable supply.

[6] From a sociopolitical perspective, water is a "local" subject. In India, and in other countries, water is often a state subject, while the central government is involved with the financial and approval of large infrastructure projects, and regulatory issues of water quality and interstate water allocation. Local or state governments typically administer permits for withdrawal and cross-sectoral disputes. In India, China, and other water-stressed countries, there is increasing emphasis on rain water harvesting for domestic as well as supplemental irrigation at the point of use. As these activities have intensified, water balance impacts on river systems have become evident. Upstream/downstream use tensions within and across states naturally emerge as a consequence [*Bandyopadhyay and Perveen*, 2008]. Given that streamflow available at a location is subject to upstream withdrawals, any analysis that assumes that currently available flows at a location will continue to be available in the future makes a strong assumption as to the nature of water resource endowments and conflicts.

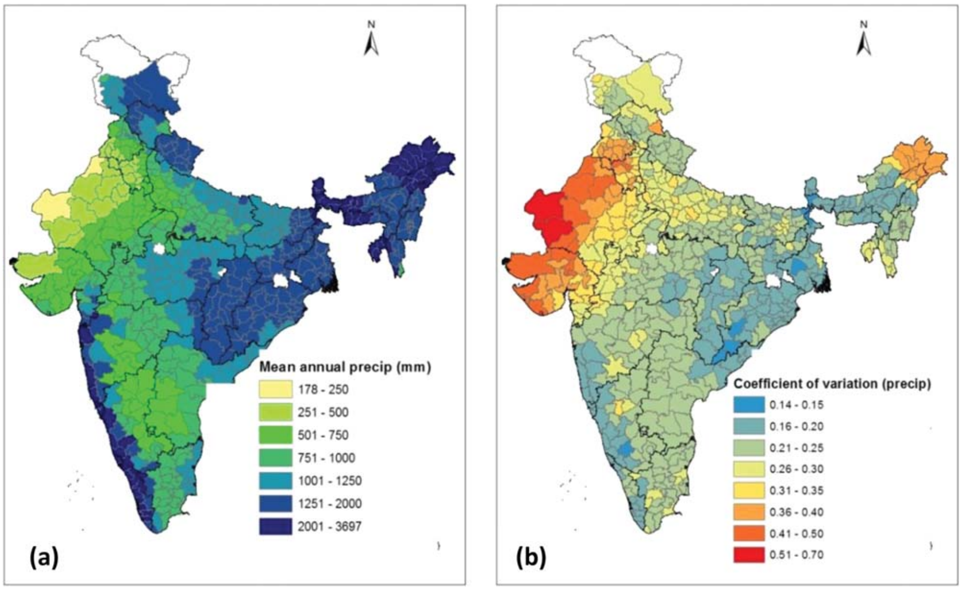

Figure 2. Spatial distribution of (a) mean annual precipitation and (b) variability in precipitation across the country.

Assessing water stress independent of such an assumption may better inform or bound the physical and institutional challenges associated with regional water resource development and allocation. A question that emerges is

[7] "If each district had to rely only on its indigenous water sources, what could be a sustainable water use strategy for that district"?

[8] Or equivalently,

[9] "What is a measure of water stress in this district given its current water use patterns, if it had to rely only on rainfall in that district"?

[10] A parametric analysis of these questions could help reveal the value of external water sources (e.g., deep groundwater that may currently be mined, or incoming river flows and their canal diversions) for that district. Likewise, modest temporal imbalances in demand and supply could be offset by using small or large endogenous surface or groundwater storage of water during the high intensity monsoon rainfall. Conditional on the current or proposed water use pattern, and a historical or projected rainfall pattern, what is the probability distribution of the storage needed to buffer the supply-demand imbalances? These questions provide the context for the present paper.

[11] A perusal of the past 100 years of meteorological data over India shows significant variation in rainfall across years and within the year. At the all-India level, the variation in the monsoon rains across years may only be 10% (coefficient of variation of all India monsoon rainfall is 0.096). However, at the district level, the variability can be dramatically higher (ranging from 15% to 20% over the Eastern parts of India to more than 50% over northwestern regions) (Figures 2a and 2b). Much of the country also experiences strong seasonality in rainfall. The monsoon occurs during June and September, and the rest of the year can be dry. Even within the monsoon season, there can be long periods of no rain or monsoon breaks [*Gadgil and Joseph*, 2003], as well as periods of intense rainfall (>10 cm/day), even in otherwise arid regions. A little reflection suggests that, in a monsoonal climate, such as in India, one needs to account for the cumulative water deficit for meeting water needs, at least at a daily time step (at which rainfall data and crop water requirements are available), consistent with the farmer's decision-making process to irrigate.

[12] Two components of water stress are thus of interest: (i) the relative difference between average demand and supply over the accounting unit and (ii) the implications of the temporal imbalance of supply and demand at a spatial resolution consistent with decision making. The index proposed here focuses on water stress as defined through a temporal integration of a cumulative deficit at a daily resolution and, hence, can be examined at different levels of aggregation, e.g., seasonal, annual, or over the period of record. Where stochastic rainfall sequences are available, given an existing or proposed water-use scenario, one can also evaluate the probability distribution associated with the index for a selected accounting unit and for a specific time scale of analysis.

[13] In sections 2 and 3, we present the methodology of the proposed water stress index and its application for India. Finally, in section 4, we summarize the findings for India, given the way we defined the problem context and discuss how they can be useful for local and national decision making and policy analysis.

2. Methodology

[14] The water stress index developed here is based on the sequent peak algorithm that is commonly used for the sizing of reservoirs [*Thomas and Burden*, 1963]. Applied to a time series of water supply and demand, the algorithm

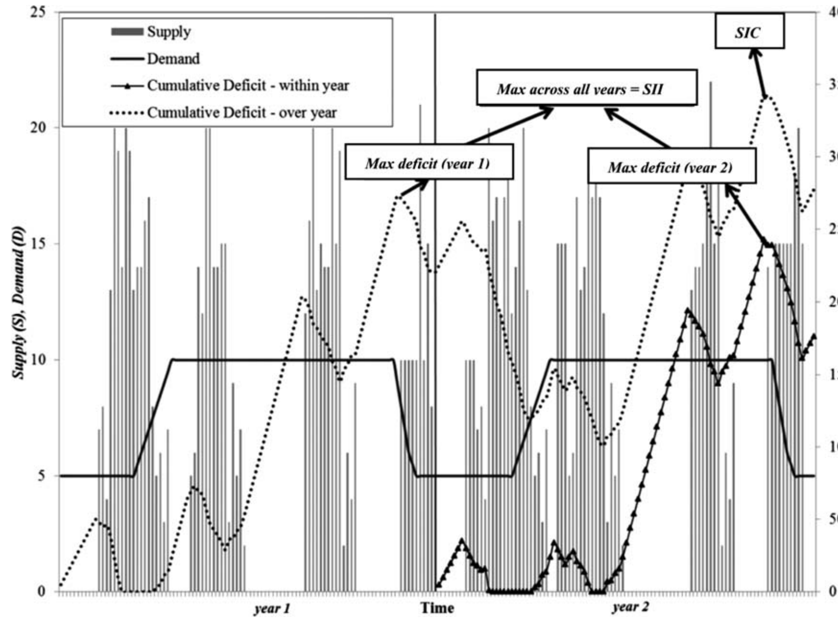

Figure 3. Conceptual representation of the stress indices SII and SIC using the sequent peak algorithm. Figure 3 shows a stochastic realization of the supply and demand over time for 2 years. The potential stress in each year is the maximum annual cumulative deficit for that year. Two cumulative deficit curves are shown. The first one (dots) plots the continuous cumulative deficit for the 2 years. The second curve (connected dots) shows the cumulative deficit for year 2, after a reset to 0 at the beginning of year 2. SII is the maximum of the cumulative deficit computed for year 1 and the one computed after reset for year 2. The maximum multiyear cumulative deficit (SIC) is obtained as the maximum of the continuous cumulative deficit curve (dots) over the 2 years.

identifies the stress as the maximum cumulative deficit over the period under consideration.

[15] For an *n*-year record, seasonal (or intra-annual) water stress can be evaluated as the maximum cumulative deficit in each of the *n* seasons, and hence, a probability distribution of the seasonal stress can be computed. Alternately, the maximum over the *n* computed values can represent the value that would provide an average annual reliability of supply of approximately ($n/(n+1)$). This is henceforth referred to as the *stress index intra-annual* (SII). Similarly, the maximum accumulated deficit, or *stress index cumulative* (SIC) over the *n*-year period of record can be estimated without breaking it into subperiods to provide a measure of the potential impact of multiyear droughts. Where stochastic realizations of supply and demand can be generated for a *n* year period, repeated applications of the method can be used to derive a probability distribution of the interannual storage requirement.

[16] A normalized deficit index (NDI) for each district in India is also computed by dividing the corresponding stress index (NDI for SII, NDC for SIC) by the average annual rainfall in that district. The normalization allows a comparative assessment of the water stress across districts. The basic steps for the computation of these indices are presented below, and the details of the estimation of the supply and demand for applications in Indian setting are presented in section 3.

[17] Consider a daily resolution of the time series of supply and demand. Then, for the *j*th geographical unit, define the following quantities:

$$\mathrm{deficit}_{j,t} = \max\left(\mathrm{deficit}_{j,t-1} + D_{j,t} - S_{j,t}, 0\right), \quad (1)$$

$$\mathrm{SIC}_j = \max{}_t\left(\mathrm{deficit}_{j,t}; t = 1 : n \times 365\right), \quad (2)$$

$$\mathrm{SII}_j = \max{}_y\left(\max{}_t(\mathrm{deficit}_{j,t(y)}; t = 1 : 365); y = 1 : n\right), \quad (3)$$

where $\mathrm{deficit}_{j,t}$ refers to the accumulated deficit, $D_{j,t}$ to total water demand, $S_{j,t}$ to the total water supply volume, for geographical location *j*, and day *t*, and *y* to a calendar or cropping year. The corresponding normalized indices are simply

$$\mathrm{NDC}_j = \frac{\mathrm{SIC}_j}{\mathrm{AP}_j}; \qquad \mathrm{NDI}_j = \frac{\mathrm{SII}_j}{\mathrm{AP}_j}, \quad (4)$$

where AP_j is the average annual rainfall volume (district area × average depth of precipitation) for district *j*. Figure 3 shows how the indices SII and SIC are computed for 2 years with variable supply for a region. The demand curve, as shown in Figure 3, represents the total demand (assumed to be the same for each of the 2 years).

3. Data and Preprocessing

[18] The stress indices defined in the preceding section are computed for each of the 586 districts in India using a daily time step over the 104 years of climate record, and using the most recent national statistical surveys that can inform the current water use attributes. The estimation of

water balance and water stress analyses invariably requires the reconciliation of data collected at disparate time and space scales or resolution, locations and with varying spatial support. Global modelers often use regular grids to project the hydrologic balance, while regional modelers often use watersheds or country as a unit [*Cai and Rosegrant*, 2002; *Rosegrant and Cai*, 2002]. The interpolation of the data that drive the water balance at the accounting unit typically introduces biases and errors due to the need to reconcile the disparate data streams. Often, from a large-scale perspective these may not be as important. However, irrigation for agriculture accounts for 75% of the consumptive water use in India, and its application depends on climatic and crop factors among other factors. The political or institutional accounting unit in the country is a district, and the crop data are typically available for these units. Reallocation of these data to high-resolution watersheds that partition across district boundaries is not trivial. Further, streamflow and groundwater data, while collected extensively by government agencies, have not been publicly available. Similarly, the details of aquifer pumping and of the location and operation characteristics of the large number of small and large surface water storage units is also not available. Thus, while one could generate watershed level hydrologic balances, the ability to calibrate such a model to match runoff production and streamflow at a national scale would be very difficult. Even if one did that, it would be difficult to reflect actual water availability in the absence of spatially specific data on groundwater pumping and reservoir size and operation.

[19] In our experience, constraining such analyses at the daily time scale considering the data typically available is a challenge. For instance, if one took account of all stores and fluxes to assess stress, one would need to consider also the fluxes in and out of the deep groundwater, shallow groundwater, and natural and manmade reservoirs, and estimating these reliably is a challenge. Moreover, while water balance terms define actual water stress, this would be conditional on allocation or operation rules that are usually not available nationally. Changing the question to "how sustainable are the water resources in this accounting unit, if we consider only the renewable endogenous supply as defined by the rainfall in the unit," allows for a more direct assessment. This takes away the endowment issues and implicitly reveals dependence on exogenous supplies. Consequently, we chose districts as the accounting unit rather than watersheds. This respects the integrity of the dominant component of the water use data, as available, and also makes it possible to directly inform the social and political institutions of their relative stress and measures for possible reduction at a scale they naturally relate to as opposed to watersheds that typically cross-jurisdictional boundaries, and hence, pose more complex management challenges. The choice of using districts as accounting units here is similar to developing water balance studies at the fine-resolution water use regimes introduced by *Weiskel et al.* [2007] that better informs human interactions with hydrologic systems. Given the limitations in the data availability, an entire water balance study at the domain shown in *Weiskel et al.* [2007] is not feasible for the current problem at hand. However, the use of endogenous rainfall to define an upper bound on the renewable supply in a district allows one to compute a stress index that highlights the potential importance or value to that district of relying on exogenous supply (river water or mining groundwater) or storage within the district. Even where river basin authorities exist (there are only a few functioning in India), the district-level analysis exposing the reliance on water endogenous and exogenous to the district can help inform the macrolevel allocation and development discussions. Thus, if the indicated cumulative deficits (water stress) or equivalently the water storage needed to buffer supply-demand imbalances in a district is relatively small, then at the current use strategy, one could argue that a government program to stimulate small-scale storage to provide supplemental irrigation by rainwater harvesting could be locally effective. On the other hand, if the indicated water stress is very large, it exposes the degree of reliance of that district on either groundwater mining or transfers from river water, both of which are really resources for which there is growing competition across district boundaries. These arguments led us to the particular choice of the accounting unit and to the way the water balance components were considered.

[20] Gridded daily rainfall data from 1901 to 2004 (104 years) available at $1^0 \times 1^0$ spatial resolution from Indian Meteorological Department (IMD) [*Rajeevan et al.*, 2006, 2008] and gridded daily temperature data (at six hourly time step) from 1948 to 2000, available at the same spatial resolution from National Center for Environmental Predictions/National Center for Atmospheric Research (NCC) [*Ngo-Duc et al.*, 2005] were used in this study. Since the daily temperature data were available for only 53 years, the daily climatology, i.e., the mean daily temperature estimated from 1948 to 2000, was used for the earlier 51 years. The gridded daily climate time series were interpolated to each of the 586 districts [*Census of India*, 2001] in the country.

[21] For computing agricultural water demands, the most recent data on seasonal and perennial crops, and the respective cultivated area were extracted from the Ministry of Agriculture database [*Dacnet*, 2011]. The daily reference crop evapotranspiration (ET_o) for estimating crop water requirements was calculated using the time series data for minimum, mean, and maximum temperature along with the extraterrestrial solar radiation [*Hargreaves and Samani*, 1982]. The Hargreaves method is used to predict ET_o in regions where data availability is limited to air temperature data [*Allen et al.*, 1998]. Data for districtwise population were obtained from the *Census of India* [2001] estimates, which provides data every 10 years beginning 1872. Estimates on the industrial and livestock water use were obtained from the Water-Global Assessment and Prognosis model (WaterGAP 2.1) [*Döll et al.*, 1999; *Alcamo et al.*, 2003] at $0.5^0 \times 0.5^0$ and spatially aggregated using the district boundary layer for India.

[22] The renewable water supply $S_{j,t}$ is estimated as

$$S_{j,t} = \alpha_1 P_{j,t} \mathrm{AC}_j + \alpha_2 P_{j,t} (\mathrm{A}_j - \mathrm{AC}_j), \tag{5}$$

where $P_{j,t}$ is the rainfall for any day t over a district j. A_j is the geographical area of the district and AC_j is the net cropped area for the district. α_1 and α_2 are the factors that determine the usable fraction of rainfall for irrigation and for other uses. We selected α_1 to be 0.7, which is the effective rainfall [*Allen et al.*, 1998] that the crops can utilize from the total rainfall in a day over the net cropped area. We chose α_2, which is the fraction of rainfall that can be harvested and utilized from the noncropped area ($A_j-\mathrm{AC}_j$) to be 0.3. The parameters $\alpha_1$and α_2 can be varied regionally and parametrically based on the information available. They conceptually embody the processes one could model for bare soil evaporation, soil moisture dynamics, and runoff generation.

[23] Considering the fact that agriculture accounts for nearly 90% of water withdrawals in India [*Kumar et al.*, 2005], the demand is primarily controlled by the agriculture water use ($\mathrm{Ag}_{j,t}$). In addition to this, we also considered the domestic or household ($H_{j,t}$), industrial ($\mathrm{In}_{j,t}$), and livestock ($\mathrm{LS}_{j,t}$) water uses for each district.

[24] The total water demand $D_{j,t}$ for a given district is calculated as

$$D_{j,t} = \mathrm{Ag}_{j,t} + H_{j,t} + \mathrm{In}_{j,t} + \mathrm{LS}_{j,t} \tag{6}$$

[25] We quantify the agricultural water demand ($\mathrm{Ag}_{j,t}$) as the estimated total crop water requirement for about 50 major crops cultivated in the country, including food grains, pulses, fruits, vegetables, and condiments. For each cultivated crop in a district, we estimate the water use based on the estimated crop growth stage and reference crop ETo on a daily time scale. Hence, $\mathrm{Ag}_{j,t}$ is given as

$$\mathrm{Ag}_{j,t} = \sum_{m=1}^{\text{number of crops}} k_{c,m}\mathrm{ET}_{oj,t}a_{j,m}, \tag{7}$$

where $k_{c,m}$ is the crop coefficient for the crop m. It is the ratio of actual evapotranspiration (ET_a) of a given crop under nonstressed conditions to reference crop evaporation (ET_o). It represents crop-specific water use at various growth stages of the crop and is typically derived empirically based on local climatic conditions [*Doorenbose and Pruitt*, 1977]. In this study, we use the Food and Agricultural Organization (FAO)-recommended crop coefficients that are estimated for various crops under tropical climatic conditions [*Allen et al.*, 1998]. $a_{j,m}$ is the cultivated area for each crop for a given district obtained from the Ministry of Agriculture database. We considered kharif (July–October), rabi (November–March), and summer (April–June) as the three main cultivating seasons within the year. In addition to this, we also consider the perennial crops such as trees and other plantation crops in our model, since those consume water throughout the year.

3.1. Stress Indices: Spatial Variation Over India

[26] The spatial distribution of within year and multiyear water stress maps for India is shown in Figure 4. The districts shown in blue have SIC = SII, i.e., maximum stress is prescribed just by the worst intra-annual cumulative deficit, and multiyear droughts are not the dominant factor. The maximum cumulative deficit occurs at the beginning of each monsoon period, and the monsoon rain each year is sufficient to reset the worst such deficit to zero. The regions in this category have high mean annual precipitation (between 1250 and 3500 mm) and low interannual rainfall variability (the coefficient of variation is ~0.2). Storage requirements to buffer the stress for this category are met by either wet season to dry season carryover or by groundwater recharge in the wet season or a combination thereof. A further subcategory could be identified if dry season agriculture were not important in a region (for instance, urban regions or regions with only two cropping seasons). In this case, it is likely that the storage requirements would be dictated by the "monsoon breaks" in the wet season and may be met by rainwater harvesting and small infrastructure. The current cropping intensity in India does not expose many cases where there is no dry season agriculture [*Dacnet*, 2011].

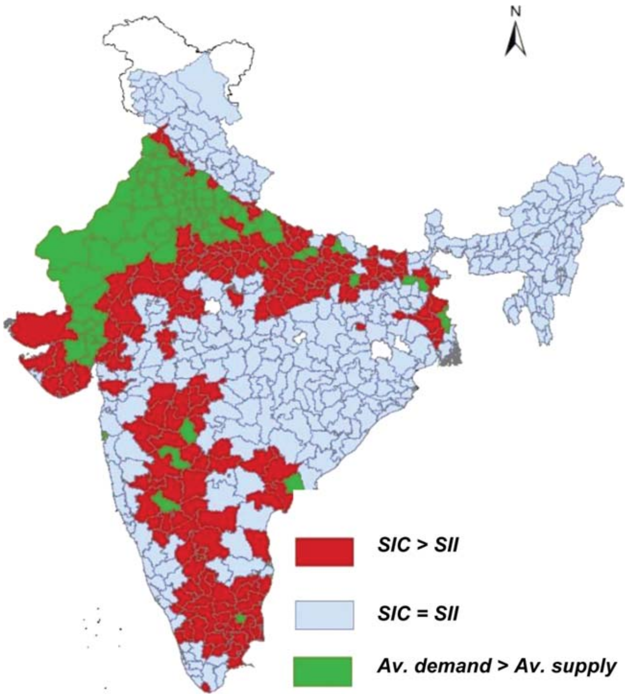

Figure 4. Spatial categorization of the magnitude and distribution of water deficits and storage requirements in India. Districts where SIC=SII are shown in blue. These districts do not require carryover storage across years. Districts where carryover storage across years is required, i.e., SIC>SII are shown in red. Districts where average consumption exceeds average annual rain are shown in green.

[27] The districts where the SIC is larger than SII are identified in red. These regions have high water deficits, experience multiyear droughts relative to current water use, and require large interannual or carryover storages to meet the existing demands, or there is significant potential for groundwater mining if the demand is met endogenously, or for exogenous imports.

[28] The regions in green have very large (>10 cu. km) cumulative deficits, where the average demand persistently exceeds that of supply, and consequently, the cumulative deficit increases monotonically over the period of record. The districts falling in this category in the northwest also happen to be the seat of green revolution in India and, consequently, one of the most intensively irrigated and populated in South Asia. These areas have unsustainable water use patterns with high groundwater extraction rates and depletion [*Tiwari et al.*, 2009].

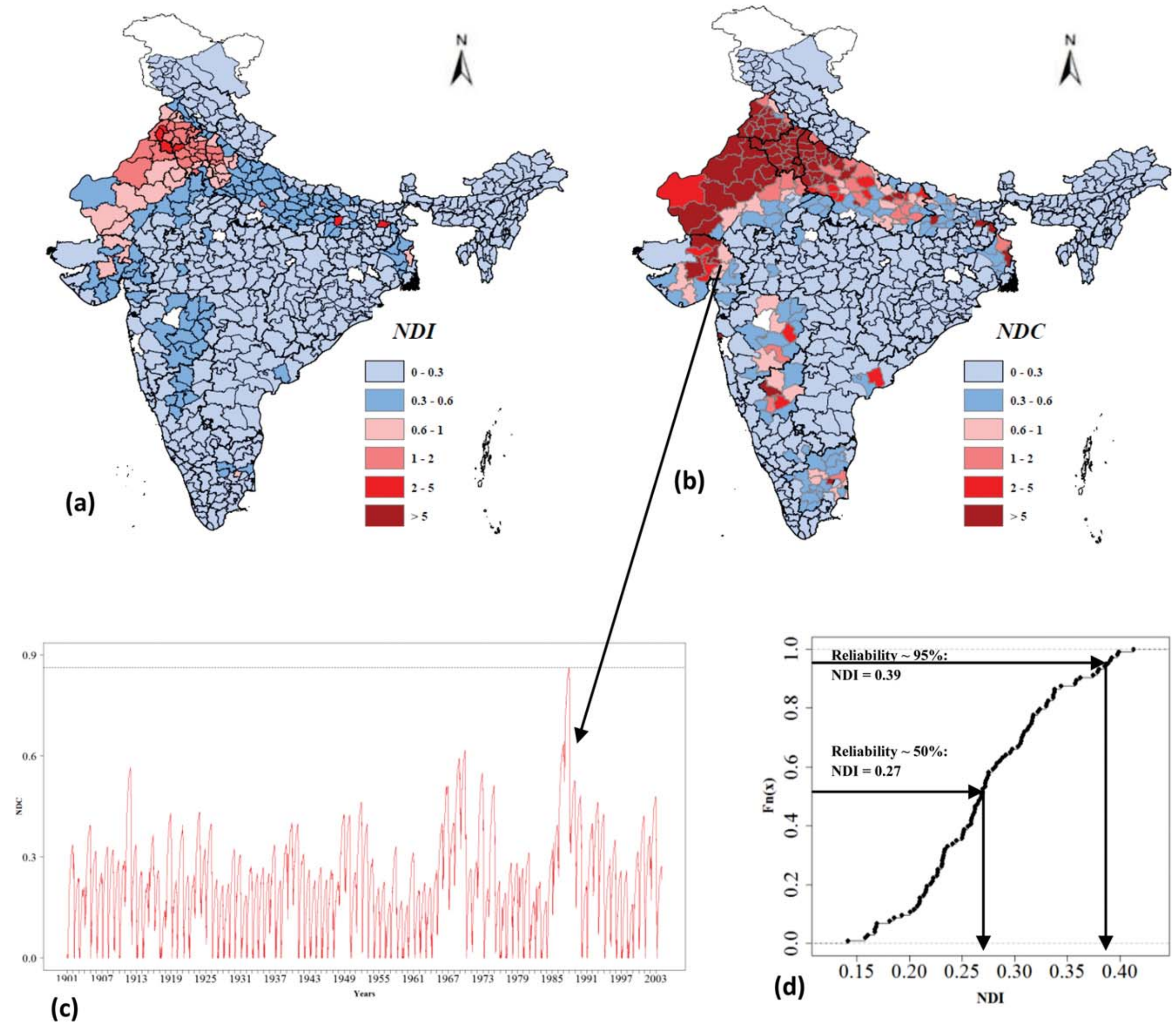

Figure 5. (a) Within year and (b) multiyear water stress across India. Many districts under low and moderate within-year stress (NDI < 1) show up as severely stressed (NDC > 1) in a multiyear analysis. (c) The time distribution of the NDC for Kheda district in Gujarat that experiences episodic multiyear droughts. (d) The cumulative distribution function using the 104 years of NDI for the same district. The 50th and 95th percentiles are highlighted.

3.2. Normalized Deficit Index

[29] The NDI, as shown in Figure 5, provides a comparative view of how conditions in a district may be out of kilter with its local climatology, i.e., relative to its average annual rainfall volume over the 104 years. NDI or NDC < 1 indicates that the storage required to meet the deficits is less than the average annual rainfall in the district. Similarly, regions with NDI or NDC > 1 correspond to the case where a storage greater than the average annual rain is needed to make it through the worst deficit year or a multiyear drought event. The annual rate of consumption in these regions could be higher than the average utilizable rainfall rates, or multiyear droughts may have a significant impact. Figure 5a shows that, for the year with the worst deficit, most of the country (except the northwestern states) has NDI < 1, indicating low storage requirements or low water stress. Regions with NDI > 1 correspond to a case where a storage greater than the average annual rain is needed to make it through the worst deficit year.

[30] Figure 5b illustrates the increase in stress when the required storage under the multiyear drought scenario is considered. Figure 5a highlights the deficits associated with an annual probability of exceedance of $1/(n+1)$ or 1/105 for this application, considering no persistence of climate across years. This is a potentially more informative stress indicator than the ratio of average demand to average supply, which is often the indicator used. However, as one considers persistence in climate beyond 1 year, we see that the current use patterns portend severe stress over much of the Indo-Gangetic plains as well as contiguous parts of peninsular India. The areas highlighted under NDC > 1 in Figure 5b correspond to the maps of groundwater depletion or

over exploitation published by the Government of India [*Central Ground Water Board (CGWB)*, 2011] and to the steady, large-scale water loss in this region, as recently recorded by the Gravity Recovery and Climate Experiment (GRACE) satellite mission and predominantly attributed to excessive extraction of groundwater [*Rodell et al.*, 2009]. Chronic or multiyear stress is hence the likely driver of the water-source exploitation than the mean value or even the worst annual deficit. This region is estimated to have lost groundwater at a rate of 54 ± 9 km^3/yr between April 2002 and June 2008; and the trend, if sustained, may lead to a major water crisis in this region when this nonrenewable resource is exhausted [*Tiwari et al.*, 2009]. Hence, in such regions, rainwater harvesting or groundwater recharge induced by small-storage structures would likely not solve the growing supply-demand imbalance, and efforts have to be directed toward water use reduction in existing crops, shifting the cropping pattern to less water-intensive crops, or interbasin transfers.

3.3. Implications for Water Storage Development

[31] It is well known that water-storage infrastructure can enhance both water security and agricultural productivity [*White*, 2005]. The right investment and planning for water storage can significantly reduce vulnerability and water-related risks, increase the resilience of the system to periodic shocks, and influence policy for altering the unsustainable use patterns. Through a combination of different storage systems like check dams, percolation ponds, farm ponds, and small dams, variations in agricultural water supply can be effectively buffered to meet crop water demands [*Li et al.*, 2000] and bridge the gap between potential and actual crop yields [*Muralidharan et al.*, 2007; *Panigrahi et al.*, 2005; *Srivastava et al.*, 2009]. Studies conducted by *Botha et al.* [2003] and *Pachpute et al.* [2009] have demonstrated that in situ rainwater harvesting systems can enhance water productivity and increase crop yields by 30%–50%.

[32] Currently, however, it is unclear whether additional storage capacity in India should be centralized in the form of conventional large reservoirs and interbasin water transfer schemes, or decentralized and distributed in the farmers' fields and at the level of the microwatershed and village, or some combination of these two extremes [*Van der Zaag and Gupta*, 2008]; or if there is an effective mechanism for conjunctively using surface and groundwater storage given the millions of independent users. Groundwater use could potentially be controlled through electricity pricing for pumping in conjunction with climate forecasts [*Brown et al.*, 2006] or a systems-level resource assessment and canal water pricing.

[33] One can also use the index developed to explore the issue of small- versus large-storage infrastructure, assuming for instance that surface water storage is the mechanism of interest. This informs the current debate in India between those who lobby for large centralized storage and transbasin diversions e.g., the Indian River Linking project [*National Water Development Agency (NWDA)*, 2002], and those who argue that small, farm-level storages or a combination of both [*Van der Zaag and Gupta*, 2008] are needed. We consider an example of districts with low-to-moderate stress for the state of Gujarat (inset in Figure 5c). For each such district, using the total cultivated area in the district, and the NDC we estimate what fraction of this area would be covered if a storage with a dam height of 1, 5, or 10 m were considered, corresponding to farm-level impoundments to a moderately large central storage. From Figure 6, we note that, for districts with a NDC less than 0.4, the area required for water storage for a 1 m high dam ranges between 10% and 40% of the irrigated area in the district—clearly infeasible at the upper end of the range but feasible at the smaller range. Where the NDC is greater than 0.5, the 1 m dam based local impoundment strategy appears infeasible, while with a 5 or 10 m high dam, one needs about 15% to 7% of the irrigated area to create sufficient storage. In such districts, if physically and economically feasible, one would need to explore larger dams and/or a groundwater strategy. In practice, farmers may pursue deficit irrigation, practice conservation, and planners may beneficially consider a mix of on-farm and centralized storage and distribution systems. The index presented here does not prescribe such choices. It merely offers a better screening tool to inform such considerations than the existing indices.

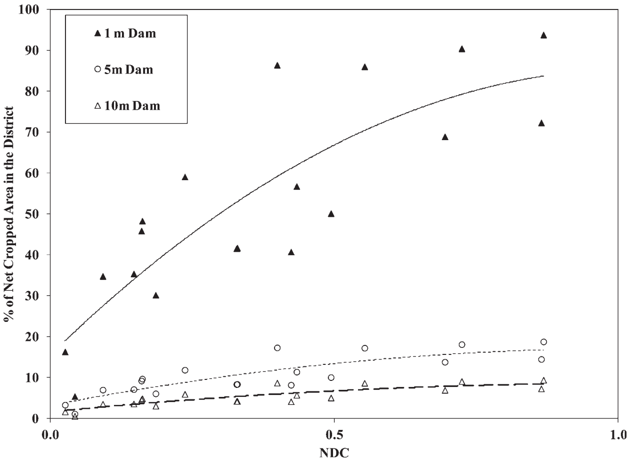

Figure 6. Fraction of the cropped area in the district that needs to be allocated to develop the water storage (impoundment) structures at 1, 5, and 10 m (height) for districts in Gujarat. Note the initially rapid increase in the % area with increases in NDC, for the 1 m high impoundment. A 5 m high impoundment is capable of addressing the need for all districts, using only about 15% of the land area, while a 10 m high impoundment requires no more than 7%.

3.4. Comparison of NDC With the Conventional Average Stress Index

[34] Many authors [e.g., *Oki et al.*, 2001; *Alcamo et al.*, 2003] propose the ratio of average use to average supply as a measure of water stress. A comparison of NDC with such an index is provided in Figure 7a. Districts that require (do not require) carryover storage are represented as red (blue) dots. For the same average stress index, the NDC is consistently higher for cases where multiyear deficits are important, relative to where a single year stress dominates highlighting its utility in discriminating between the two cases. Thus, stress induced from persistent low rainfall periods is not adequately revealed from the conventional

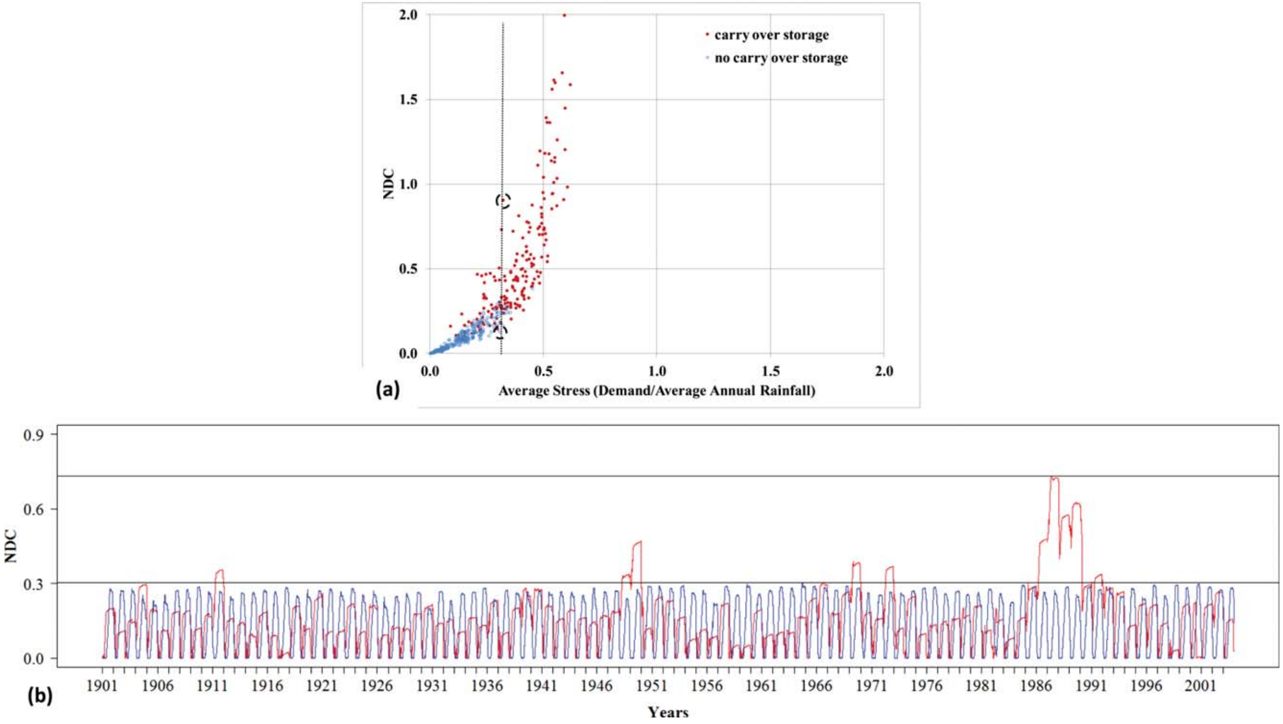

Figure 7. (a) Comparison with average stress index (average demand/average annual rainfall) and NDC. Districts classified as requiring carryover storage (red dots) and not requiring carryover storage (blue dots). For the same average stress index, the NDC is consistently higher for cases where multiyear deficits are important, relative to where a single year stress dominates, highlighting its utility in discriminating between the two cases. (b) Comparison of the daily cumulative deficit for two districts (identified in a) with dotted circles) with similar average stress (0.30). While one district (Jamui, Bihar; blue line) is not prone to multiyear droughts, Gandhinagar, Gujarat (red line) is prone to multiyear droughts. The NDC reflects the higher multiyear and within-year variability at Gandhinagar.

average stress index. The NDC can reveal both the magnitude of stress induced by climate variability and also its relative frequency. A comparison of the daily cumulative deficit for two districts (identified in Figure 7a) with dotted circles) with similar average stress (0.30) is presented in Figure 7b. While one district (Jamui, Bihar; blue line) is not prone to multiyear droughts, Gandhinagar, Gujarat (red line) is prone to multiyear droughts. Six multiyear droughts are in evidence in the Gandhinagar record. The NDC reflects the higher multiyear and within-year variability at Gandhinagar.

4. Summary and Discussion

[35] River and aquifer systems are essentially linked or shared systems that can have significant spatial externalities with respect to development, and so it is interesting to explore a solution set conditional on endogenous renewable supply that does not tap either the groundwater or the river system (beyond what is indicated in the rainfall into the region) and hence levels the spatial playing field. We realize that long-established downstream river or canal users will not like this proposal, but in essence, their dependence on a trans-accounting unit (an institutional one) is exposed. Of course, one could develop the index accounting for all fluxes if desired, but in this case, the real-world reduction of the fluxes by upstream use and diversion would need to be accounted for through the construction of "naturalized flows." There is no clear, pragmatic choice, and we preferred the use of endogenous rainfall in the application presented to make for a more transparent story for both comparative and absolute stress. This also detaches the analysis from equity considerations inherent in the use of shared aquifers and upstream-downstream considerations for the allocation and use of river water. By computing the local cumulative deficits relative to rainfall, one also gets an indication of the relative stress imposed by each accounting unit on a larger river basin or shared aquifer system.

[36] With regard to temporal variations, we consider intraannual and interannual variations in precipitation input, and in the nature of demand. Demand variations in time are most pronounced for agricultural water use. Since this is a large use sector of both "blue" and "green" water [*Falkenmark and Rockstrom*, 2006], and much of the water crisis in a country like India is associated with the use of groundwater for irrigation, an explicit accounting of this sector is warranted.

[37] Since long-term groundwater data is not readily available, the indices developed provide a surrogate measure for the local and spatial imbalance in supply and demand that translates into long term or drought period draws on the groundwater reservoirs. This provides a window to the risk to users in each district from increasing

water scarcity using the indices developed. There is strong interest today in the water sensitivity to climate variations given the high ratio of demand to supply and the indices developed can directly address this question. The potential climate risks for water supply operations and agricultural supply chains that are specific to businesses are indexed at high spatial resolution, considering endogenous renewable supply. Future climate scenarios or season-ahead climate forecasts can be readily accommodated for any location to provide the projected risk.

[38] Extensions of the approach indicated here to formally consider all aspects of the hydrologic balance in a watershed and explicitly address groundwater and surface water sources as they exist are of course conceptually possible. Where such an approach accounted for existing storage and diversions and pumping, it would represent the existing conditions better than the analysis presented here. Indeed, such an approach could be hypothetically useful to directly quantify whether shifting groundwater use to surface water or vice versa would lead to better outcomes, especially, under climatic exigencies. Ecological impacts on surface waters due to groundwater depletion could also be highlighted. Typically, such issues have been modeled for much smaller domains. However, given the lack of data on these aspects, an effort to add these factors would considerably increase the uncertainty in the resulting analysis, especially for a national analysis where a relatively high level of spatial detail is also reflected.

[39] For India, the analyses presented highlight the difference between a within-year and a long-term perspective and how the combination of population and agricultural intensity with the climate patterns has generated hotspots of stress. The impact of proposals for moving rice from the Punjab, in the Northwest, to say a wetter region, in the Northeast, can be assessed in this context. An interesting question that emerges here is whether the low rice yields in the unirrigated east can be improved if a modest amount of irrigation storage, as indicated in our analyses were to be provided in that region. As illustrated for Gujarat, the NDC can allow such a discrimination to be made. If this is feasible from a social, institutional and biophysical perspective, then much of the concern with India's water and food security could be alleviated without significant modifications of the landscape or aquifers. Our current research is exploring such options.

[40] We indicated briefly in Figure 5d, the interpretation of the probabilistic approach to the index proposed. Since there is much interest in scenarios for future sustainability, one would need plausible daily climate realizations for the future, in conjunction with proposed agricultural and other scenarios for water use. Each of these is feasible to develop under appropriate assumptions, and could be pursued to develop integrated assessment style scenarios for supply and demand (e.g., assuming conservation programs or changes in spatial crop allocation), and one could report the storage needed assuming different levels of reliability (as shown in Figure 5d). The probability distribution of stress (storage needed) would also allow consideration of formal risk management strategies or risk exposure economic analysis. An insurance or tradable water-risk portfolio could price indicated storage risk relative to existing utilizable storage in an area, offering a new financial risk management option. Likewise, trade-offs between food and water storage strategies could be examined in a probabilistic framework. One could also pursue crop allocation optimization at a national scale considering food storage and water storage as decision variables targeting desired reliability levels and contingency strategies to cover potential failures in food security. These are our current areas of research.

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