Modeling water resource systems within the framework of the MIT Integrated Global System Model: IGSM-WRS*

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Modeling water resource systems within the framework of the MIT Integrated Global System Model: IGSM-WRS

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[1] Through the integration of a water resource system (WRS) component, the MIT Integrated Global System Model (IGSM) framework has been enhanced to study the effects of climate change on managed water-resource systems. Development of the WRS involves the downscaling of temperature and precipitation from the zonal representation of the IGSM to regional (latitude-longitude) scale, and the translation of the resulting surface hydrology to runoff at the scale of river basins, referred to as assessment subregions (ASRs). The model of water supply is combined with analysis of water use in agricultural and nonagricultural sectors and with a model of water system management that allocates water among uses and over time and routes water among ASRs. Results of the IGSM-WRS framework include measures of water adequacy and ways it is influenced by climate change. Here we document the design of WRS and its linkage to other components of the IGSM and present tests of consistency of model simulation with the historical record.

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1. Introduction

[2] Policy and decision makers have started to focus attention on the availability and reliability of water supplies in the coming decades based on concerns about projected global climate change and other pressures on our natural, managed, and built environments. As a result, there is a growing need for modeling and analyses tools that can provide quantitative insights into these issues while representing the full integration of the climate system with its socioeconomic drivers, hydrology and water supplies, water use sectors, and management strategies. A subgroup of the International Group of Funding Agencies for Environmental Change Research issued the Belmont Challenge [*International Group of Funding Agencies for Global Change Research*, 2013]: "To deliver knowledge needed for action to avoid and adapt to detrimental environmental change…." Additionally they selected freshwater security as one of the five priority foci, and the need for integrated research, influenced by natural hydro-meteorological processes as well as the many complex facets of the societal footprint, such as land use or water abstraction (for agriculture or industry) which in turn are governed by patterns of consumption or population change. While global water modeling tools have been developed [e.g., *Hirabayashi et al.*, 2008; *Okazaki et al.*, 2012; *Tang and Lettenmaier*, 2012; *Arnell and Gosling*, 2013; *Döll and Zhang*, 2010; *Fung et al.*, 2011; *Gosling et al.*, 2010; J. Schewe, et al., 2013], most of these studies are driven by exogenous climate forcing that is disconnected from consistent socioeconomic pathways and therefore fall short of the call to the Belmont Challenge for "critical interactions between natural processes and human activities." This paper reports on the integration of a water resource system (WRS) component into the MIT Integrated Global System Model (IGSM) framework. The IGSM is a comprehensive tool that analyzes interactions among humans and the climate system. It is used to study causes of global climate change and potential social and environmental consequences. The IGSM-WRS provides an integrated tool to study the effects of climate change on managed water-resource systems at the global and regional scales.

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2. The MIT Integrated Global System Modeling Framework

2.1. Framework Components

[3] Changing climate and growing population threaten to increase stress on available fresh water, with

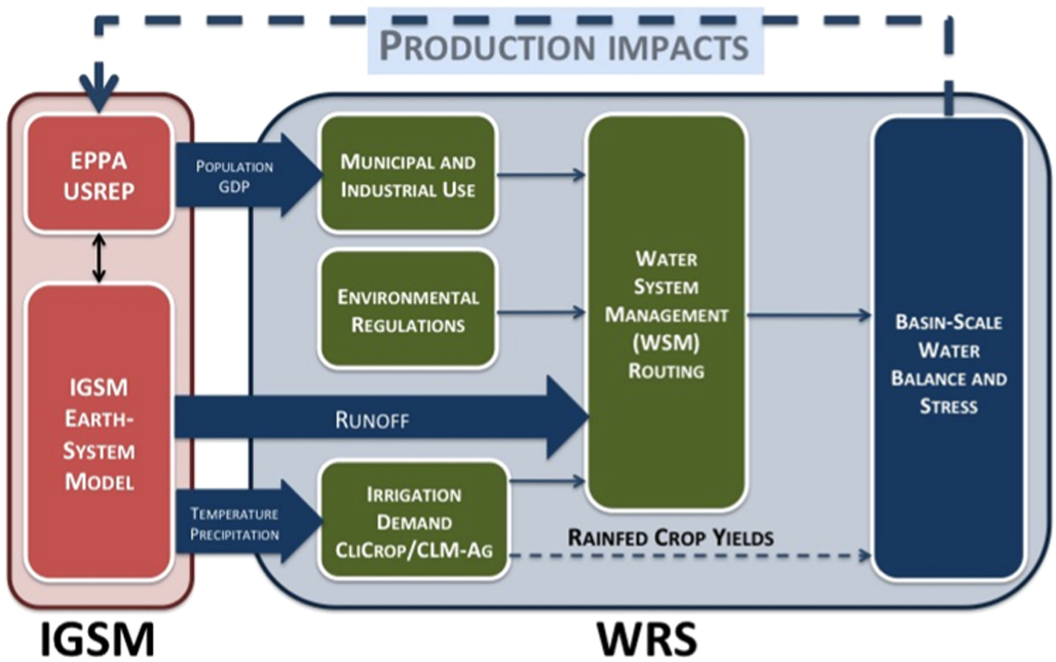

Figure 1. Schematic of the IGSM-WRS model illustrating the connections between the economic and climate components of the IGSM framework and the WRS component. Solid arrows represent connections utilized in this research; dashed arrows represent WRS links under development.

implications for irrigation, energy production and other uses and, in extreme cases, the stability of nations. The MIT Integrated Global System Model (IGSM) [*Sokolov et al.*, 2007] is designed to study global climate change and its social and environmental consequences, quantifying the associated uncertainties, and assess the cost and effectiveness of policies proposed to mitigate the risk. To support assessment of these issues, the IGSM has been expanded to include a water resource system (WRS) component that integrates the managed aspect of the hydrologic cycle. The resulting IGSM-WRS framework includes

[4] 1. *Water supply*: the collection, storage, and diversion of natural surface water and groundwater;

[5] 2. *Water requirements*: the withdrawal, consumption, and flow management of water for economic and environmental purposes; and

[6] 3. The supply/requirement balance at river basin scale and measures of water scarcity, particularly its effects on agriculture.

[7] In this report, we describe the IGSM-WRS framework and demonstrate its performance in a backcast of the 20th century. Parallel efforts apply the model to projections at the global scale [*Schlosser et al.*, 2013] and to the United States [*Blanc et al.*, 2013]. A more detailed discussion of the IGSM-WRS can be found in *Strzepek et al.* [2012].

[8] The WRS component of the IGSM framework draws on two lines of research on global water systems: one at the University of Colorado (CU) on the impacts of climate change upon hydrological systems, and another by the International Food Policy Research Institute (IFPRI), on global food and agricultural systems. Work at CU began with a national-level assessment of water resources supply-demand balances for the United Nations Comprehensive Fresh Water Assessment [*Raskin et al.*, 1997]. This national-level analysis was extended and incorporated in the Stockholm Environment Institute's Polestar model [*Raskin et al.*, 1998] and included by the World Water Council in an analysis for its World Water Vision 2000 [*Gangopadhyay et al.*, 2001; *Cosgrove and Rijsberman*, 2000]. Concerns about food security and trade led to an effort by IFPRI and partner collaborators to develop the IMPACT-WATER model, which integrates a global partial-equilibrium agricultural sector model, IMPACT, with a water simulation module that balances water availability and demands among economic sectors at global and regional scales [*Rosengrant et al.*, 2008].

[9] Figure 1 summarizes how the WRS is integrated within the IGSM framework. Given a scenario of global climate policy, the IGSM provides the WRS with economic drivers, relevant climate variables, and inputs to the estimation of runoff. WRS combines these inputs with estimates of water requirements and simulates the operation of the water management system to assess the ability to meet these requirements at the river basin level. Currently, this is a one-way connection between the economic and climate components of the water system. In subsequent stages of model development, the economic effects of changes in the water system will be fed back into the economic analysis, as indicated by the dashed line in Figure 1.

[10] The economic analysis component of the IGSM is the MIT emissions prediction and policy analysis (EPPA) model for the globe [*Paltsev et al.*, 2005] and the United States regional energy policy (USREP)

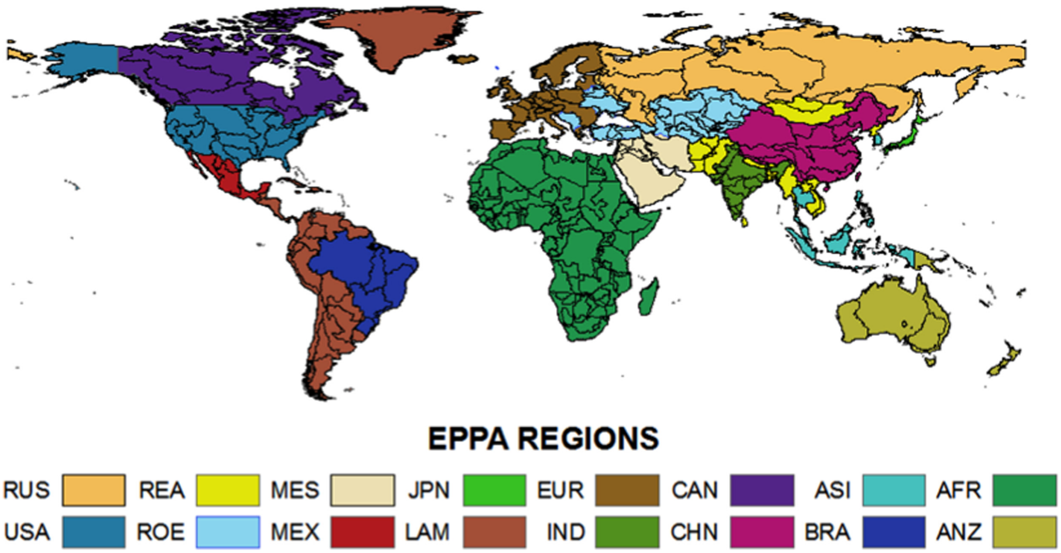

Figure 2. The 282 water ASRs of the IGSM-WRS with EPPA regions in color. Detailed listing of the ASRs and their mapping to EPPA regions is provided in *Strzepek et al*. [2012].

model, *Rausch et al*. [2009]. It provides emissions inputs to the Earth system part of the IGSM and supplies socioeconomic information used in the estimation of nonagricultural water demands. Runoff is calculated by a procedure that begins with the community land model (CLM) that is employed in the global land system (GLS) component of the IGSM's Earth system model [*Schlosser et al*., 2007]. The IGSM's atmosphere resolves zonal and altitude variations, and so the meteorological variables must be downscaled across longitude. The subsequent runoff calculation then proceeds through several steps of calibration and bias correction (section 2). The current application employs a deterministic representation of runoff. Subsequent stages of this research will incorporate uncertainty in the climate analysis [*Sokolov et al*., 2009; *Webster et al*., 2012] and the future patterns (resulting from human-induced climate change) used in downscaling, applying a method developed by *Schlosser et al*. [2012].

[11] Runoff and water requirements are then input to a water system management module (WSM) developed by IFPRI [*Rosengrant et al*., 2008] which simulates the water supply and demand balance, allocating available water among competing sectors (section 3). The Earth system component of the IGSM supplies simulated temperature, precipitation, and potential evapotranspiration, which are inputs to a model of irrigation water requirements, CliCrop [*Fant et al*., 2012], discussed in section 4.1. The estimation of nonagricultural water requirements, covered in section 4.2, is based on the IMPACT-WATER framework and draws on economic data from the EPPA model. A number of indicators of water system function, such as water stress, can be computed from the runoff and water use information and from the results of the supply-demand balance and water allocation.

[12] In section 5, we explore aspects of the model's performance by calibrating it to the period 1954–1977 and comparing results for various output measures with observations or other constructions of basin characteristics for the period 1981–2000. Section 6 reviews the results of the model development and summarizes the applications of the IGSM-WRS to analysis of the effects of projected climate change.

2.2. Application at Global Scale

[13] The IGSM-WRS at the global level is disaggregated into 282 assessment subregions (ASRs). The ASRs are based on IFPRI's IMPACT-WATER model's "food-producing units." These were created by first dividing the globe into 106 hydrologic regions or river basins, and then by separately defining 116 economic regions (mainly nations), which identify the political boundaries of management policy (details are provided by *Strzepek et al*. [2012]). The selection and scale of these regions seeks to isolate the most important river basins and countries in term of water use, especially for irrigation and energy purposes, and the 282 ASRs are then defined by their intersection.

[14] Figure 2 displays the ASRs, with color-coding showing their relation to the 16 region disaggregation of the EPPA model. China, India, and the United States, which produce an aggregate 60% of the world's cereal grains, have the highest level of subnational disaggregation, being divided into 9, 13, and 14 major river basins, respectively.

3. Hydrology and Runoff at ASR Scale

[15] The IGSM's climate and earth system component employs a numerically efficient two-dimensional (latitude zones and altitude) modeling approach, which makes it possible to develop large ensembles of climate predictions for purposes of studying uncertainty in the water resource effects of climate change. The downscaling from 2-D climate to flows at the basin level involves a number of steps: 2-D to 3-D climate, hydrology and

runoff projection, and a correction for bias common to the simulation of river flows in climate models.

3.1. Spatial Transformation of IGSM Climate

[16] The procedure developed by *Schlosser et al.* [2012] is applied to translate the zonal (latitude mean) field of any state or flux variable of the IGSM, $\overline{V}_y^{IGSM}$, to longitudinal detail (these variables are a function of time, but t is left out here for clarity:

$$V_{x,y}^{IGSM} = C_{x,y}\overline{V}_y^{IGSM} \tag{1}$$

where $C_{x,y}$, is a transformation coefficient that corresponds to the longitudinal point (x) along any given latitude (y) and maps $\overline{V}_y^{IGSM}$ to its corresponding longitudinal value, $V_{x,y}^{IGSM}$. While this transformation can apply, in principle, to any state or flux quantity, here the variables providing the links between the IGSM and WRS are surface-air temperature and precipitation, radiation, wind speed, specific humidity, and air pressure.

[17] As described in *Schlosser et al.* [2012] for the historical period, we calculate the monthly climatology of $C_{x,y}$ using available observational data sets which include, but are not limited to the Princeton Data Set [*Sheffield et al.* 2006], Climate Research Unit (CRU) [*Mitchell and Jones*, 2005], and the Global Precipitation Climatology Project (GPCP) of *Alder et al.* [2003], for all meteorological variables. Each of these observational data sets is provided at monthly timesteps, and we build the $C_{x,y}$ climatologies accordingly. We then employ the calculated $C_{x,y}$ coefficients in equation (1) with an IGSM simulation covering the corresponding observational record.

[18] We can evaluate the downscaled $\overline{V}_y^{IGSM}$ patterns by the spatial (i.e., pattern) correlation with observations for precipitation. For the period 1981–2000, we find spatial consistency between the downscaled IGSM seasonal means and observations, with correlations of 0.992 for December, January, and February (DJF) and 0.987 for June, July, and August (JJA). Strong spatial consistency also is found for surface air temperature (T).

[19] When applying this framework to projections of climate change, the associated shifts and/or amplification of the $C_{x,y}$ patterns can be calculated for any climate model to take account of its projected change in longitudinal distribution over time in response to changing climate. Analytically, the procedure is a Taylor expansion of the form:

$$V_{x,y}^{IGSM} = (\Delta T_{Global}) = C_{x,y}|_{t_0}\overline{V}_y^{IGSM} + \left[\frac{dC_{x,y}}{dT_{Global}}\Delta T_{Global}^{IGSM}\right]\overline{V}_y^{IGSM} \tag{2}$$

[20] The first term on the right side of the equation is the transformation coefficient evaluated at a reference historical time period (t_0) based on observations. In the second term, $\frac{dC_{xy}}{dT_{Global}}$ is the pattern-change kernel estimated from a climate model (see *Schlosser et al.* [2012] for details), which employs climate model results from the CMIP3 experiments [*Meehl et al.*, 2007] in support of the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). Numerically, the pattern-change kernel quantifies the shift in $C_{x,y}$ per unit change in global temperature (ΔT_{Global}). In climate change projections, these transformation patterns evolve over time as a result of the IGSM's projected global temperature change (from the zonal model). *Schlosser et al.* [2012] present a comprehensive evaluation of the application of equation (2) with every climate model from CMIP3.

3.2. Hydrology and Runoff Projections

[21] The IGSM-WRS requires monthly runoff of natural flows, i.e., streamflows without human intervention. Unfortunately, natural flow data are scarce because few series cover the period before intensive infrastructure development. Thus natural flow must be estimated using observed flow and data on human uses augmented by climate records and hydrologic modeling. Applying simulated climate variables from the IGSM downscaling methodology described above, natural flows at the ASR level are generated in a two-step process.

[22] First, the downscaled climate is input to the IGSM GLS component, which uses the Community Land Model (CLM) to generate raw natural flow. For reasons of scale, data, and model structure, CLM simulates historical raw natural flows for some ASRs that differ from observations in that they follow the climate signal but display a wetting or drying bias.

[23] Second, a bias-correction technique is applied that maintains the climate signal and runoff variability from the IGSM but adjusts the simulation to replicate the historical natural flow.

3.2.1. Land-Surface Hydrology

[24] Within the IGSM framework, CLM [*Oleson et al.*, 2004; *Lawrence et al.*, 2011] describes the biogeophysics of the terrestrial environment. The modeled processes include the hydrologic cycle and surface energy budget over land as well as interactions with the atmosphere. The IGSM atmospheric model drives CLM, which calculates the surface and subsurface water and energy balances at a grid resolution commensurate with the modeled (or observed) atmospheric forcing. For this application, we configure CLM with a horizontal resolution of 2° in latitude and 2.5° in longitude.

[25] In calculating surface runoff, CLM represents the effects of limited infiltration of soils (i.e., Hortonian flow) as well as runoff from saturated surface conditions, and it also considers the effects of frozen soil conditions and root density on soil hydraulic conductivity. For subsurface runoff (and in general vertical soil-water flow), a discretized treatment of vadose zone and saturated flow is the main determinant of the vertical transport through the soil column (10 soil layers to a depth of approximately 3 m); for details see *Lawrence et al.* [2011].

[26] Currently, CLM tracks only the natural vegetated land areas, and irrigation deficits for agricultural

areas are quantified by the CliCrop submodel (section 4). In the future, developments with CLM [*Gueneau*, 2012] will allow agricultural lands to be explicitly tracked within CLM, and groundwater recharge at the ASR scale of WRS will use CLM's treatment of unconfined aquifers, supporting a seamless link between the IGSM and WRS.

3.2.2. CLM-Based Flow at the ASR Scale

[27] For each 2° by 2.5° grid cell, CLM estimates energy and water fluxes including surface and subsurface runoff, and the two are added to produce total runoff per month in millimeters (mm/month). Considering the surface area of each CLM grid in an ASR, a new time series of monthly ASR runoff is computed as the weighted average of CLM grid contributions.

[28] While global databases of gauged flow are available [e.g., *World Meteorological Organization*, 2012], there is no corresponding database of natural flows to use in assessing the performance of this procedure at the global scale. *McMahon et al.* [2007] are developing a global natural flow database based on statistical charactertics of natural flow and recreating natural flows from gauged flow, but this effort is limited in scope and not appropriate for our application. Hydrologists have taken an alternative approach using global gridded databases of climate time series and using hydrologic models to simulate natural flows. For example, *Fekete et al.* [2002] at the University of New Hampshire's Global Runoff Data Centre (GRDC) have developed a composite runoff database that combines simulated water balance model runoff estimates with monitored river discharge. This data set consists of average monthly runoff values for each cell at a 0.5° by 0.5° global land grid.

[29] *Zhu et al.* [2012] at IFPRI have developed a global hydrological model for integrated assessment that was designed to provide natural flow at the same spatial scale (ASR) as the IGSM-WRS, and they use the GPCP preciptiation database and the CRU database for tempertature (same as IGSM) as the monthly climate drivers for the model for the historical period 1951–2000, which has been calibrated to naturalized observed data. For our global scale application, we have adopted this IFPRI modeled natural flow data set, and in subsequent notation we refer to it as a Modeled Natural Flow or MNF series.

[30] A linear regression through the origin comparing the average annual natural flow for the 282 ASRs from CLM versus IFPRI-MNF series for the period 1954–1977 results in an R^2 of 0.84, suggesting that the CLM runoff captures the regional wetness and dryness at the large spatial scale of the ASRs. However, the slope is 1.37, meaning that the CLM generated runoff is biased downward. *Milly et al.* [2005] found that this behavior is common for land-surface models incorporated into global circulation models (GCMs) of which CLM is one. In capturing the temporal variabilty and spatial signal of the climate, the CLM runoff will be a good tool for analysis of relative climate change impacts, but bias correction is needed if the model is to properly balance water supply with water demand and represent water stress.

3.2.3. Bias Correction of ASR Natural Runoff

[31] The goal of the bias correction procedure is to transform the raw CLM runoff values at the ASR level to have the same statistical properties as the IFPRI-MNF data set for 1954–1977, which includes not just mean and standard deviation but also roughly the same pattern over time. We employ the Maintenance of Variance Extension (MOVE) procedure [*Hirsch*, 1982] to achieve this result. MOVE is commonly used to transfer streamflow information from gauged to ungauged basins, and it standardizes streamflows with two parameters: the mean and standard deviation. The method is based on the hypothesis that, for each month, the standardized flows at a site of interest, y, and an index site, x, are approximately equal.

$$\frac{Q_x - \mu_x}{\sigma_x} = \frac{Q_y - \mu_y}{\sigma_y} \tag{3}$$

[32] A traditional standardization approach is used to produce a new standardized variable with mean 0 and variance 1, regardless of the probability distribution of the original flows.

[33] To apply MOVE to IGSM-CLM runoff to estimate ASR runoff, we first calculate the mean and standard deviation for the IFPRI-MNF flows, $\mu(m)_{\mathrm{MNF}}$ and $\sigma(m)_{\mathrm{MNF}}$. We then transform the CLM monthly runoff, $Q_{\mathrm{CLM}}(m,y)$, with mean, $\mu(m)_{\mathrm{CLM}}$, and standard deviation, $\sigma(m)_{\mathrm{CLM}}$. All moments are estimated over the period 1954–1977, which is assumed to be stationary. The MOVE formulation can be rearranged to produce an estimate of WRS basin runoff, RUN:

$$RUN(m,y) = \mu(m)_{MNF} + \frac{\sigma(m)_{MNF}}{\sigma(m)_{CLM}} * \left(Q_{CLM}(m,y) - \mu(m)_{CLM}\right) \tag{4}$$

[34] The bias correction factor is then:

$$\frac{\sigma(m)_{MNF}}{\sigma(m)_{CLM}} \tag{5}$$

[35] The IGSM-WRS bias-correction method uses the first two moments of the IFPRI-Modeled Natural Flow (MNF) and the IGSM-CLM simulated runoff over 1954–1977 for each ASR. The actual annual flow sequences are not identical due to the fact that the IGSM-WRS runoff is driven by the IGSM-GCM outputs from 1954 to 1977 with historic greenhouse gas emissions and the IFPRI-MNF annual global runoff is driven by historical climate from 1954 to 1977. However, the mean global runoff for IGSM-WRS and IFPRI-MNF averaged over 1954–1977 are almost identical at 40,099 and 39,995 billion cubic meters, respectively. A regression of the mean annual runoff of the IGSM-WRS runoff versus the IFPRI-MNF for the 282 ASRs for the assumed stationary period 1954–1977 results in the slope of the line through the origin of 1.0034 and an R^2 of 0.99, suggesting that geographical

climate signals driving both series are very similar. These results along with additional data analysis confirm that the bias-correction procedure works well, at least as compared with this constructed data set for undisturbed flows.

[36] The procedure is for stationary monthly stream flows, but under climate change modeled runoff exhibits monthly and seasonal nonstationaries. In some basins, warming can lead to early 21st century snowmelt runoff far greater than the 20th century average for a late winter month, and so the application of stationary techniques to map 21st century flow can result in erroneous estimates [e.g., *Milly et al.*, 2008].

[37] To handle these conditions, a nonstationary extension to the MOVE technique is applied to address the issue of seasonal regime change of runoff under future climates, especially for basins affected by snowmelt. The approach uses a 10 year moving average of the index variable, CLM monthly runoff, $\mu_{CLM_MA10(m,y)}$ and develops a trend relative to the 1955–1977 baseline:

$$TrCLM(m,y) = \frac{\mu_{CLM\_MA10(m,y)}}{\mu_{CLM(m)}} \tag{6}$$

[38] This modification is similar to that employed by [*Maurer*, 2007] where the 21st century GCM trend of temperature is removed, and then bias correction is applied to the residual magnitudes to create adjusted GCM estimates. The WRS projected runoff is then estimated based on the CLM trend and the CLM residual times the historical bias-correction factor and is expressed as

$$\begin{aligned} RUN(m,y) = {} & \mu(m) * TrCLM(m,y) \\ & + \frac{\sigma(m)_{MNF}}{\sigma(m)_{CLM}} * \left(Q_{CLM(m,y)} - \mu_{CLM\_MA10(m,y)}\right) \end{aligned} \tag{7}$$

[39] Figure 3 shows a diagram of the nonstationary MOVE technique.

4. Water System Management

[40] As shown in Figure 1, components of the IGSM provide inputs to a submodel of water management, termed the Water Management System (WMS). Its structure is the same as the water simulation module of IFPRI's IMPACT-WATER model [*Rosengrant et al.*, 2008]. It computes the balance of water supply and water demand (requirements) for the network of 282 ASRs, treating each as a single water balance area with no sub-ASR geographic representation of the water resource system. The term water "requirements" as used here does not convey the economic sense of a change in quantity demanded as a function of price and/or income but in the engineering sense of water needed to meet a specified target. Figure 4 is a schematic of the WMS at the ASR scale. It provides a map of the way water flows in the process of balancing water supply with water requirements in the presence of within-year and over-year storage. All reservoirs in the ASR are aggregated into a single virtual reservoir (STO) in the figure. It is from this virtual reservoir that all surface water releases are made. The maximum storage (STC) is the sum of all the maximum capacities of the reservoirs in the ASR. This section provides an overview of the water flow in and out of this storage for each month and ASR and how they are linked within the WMS component of the overall model. To simplify the notation, the indices for month and ASR are suppressed except where needed.

4.1. Water Supply

4.1.1. Surface Water Movements

[41] Surface water enters the ASR storage from two sources. Runoff (RUN) is the natural flow from the ASR area defined in section 2. Note that runoff as calculated may be diminished by surface water lost to groundwater recharge (GRW). RUN is then augmented by the flow into the ASR from one or more upstream ASRs (INF). The upstream-downstream links within the ASRs are established in the data set developed by IFPRI. Water then leaves the aggregated storage in three ways. Some is lost to evaporation (EVP); some is released to beneficial uses (REL), and some flows downstream to another ASR or to the sea (SPL).

4.1.2. Groundwater

[42] In this version of IGSM-WRS, groundwater is represented as a maximum monthly renewable (sustainable) supply, GRW, to meet water requirements. There is no modeled flow from groundwater to surface water. In future work, groundwater will be represented as a mass balance and elevation will be considered to better represent the effects of groundwater depletion. The current approach allows evaluation outside the model of the sustainability of the resource given the projected use and simulation of scenarios where maximum monthly renewable supply is adjusted to consider possible effects of depletion.

4.1.3. Desalination

[43] One additional source of water supply is provided by desalinization (DSL), and is based on data on installed capacity in an ASR.

4.1.4. Total Available Water

[44] The WMS computes the total available water (TAW) as the sum of surface water storage, groundwater supply, and the desalination supply:

$$TAW = STO + GRW + DSL \tag{8}$$

where monthly STO is constrained by the surface storage capacity, STC.

4.2. Water Requirements

[45] Water withdrawal is the total amount of water taken from the ASR water supply (surface, groundwater, and desalination) to provide for the various sectoral water uses, which then equals the total of consumption plus return flow (RTF). The following four sectoral water requirements (SWR in Figure 4) are modeled in the WRS, and their estimation is discussed in sections 4 and 5.

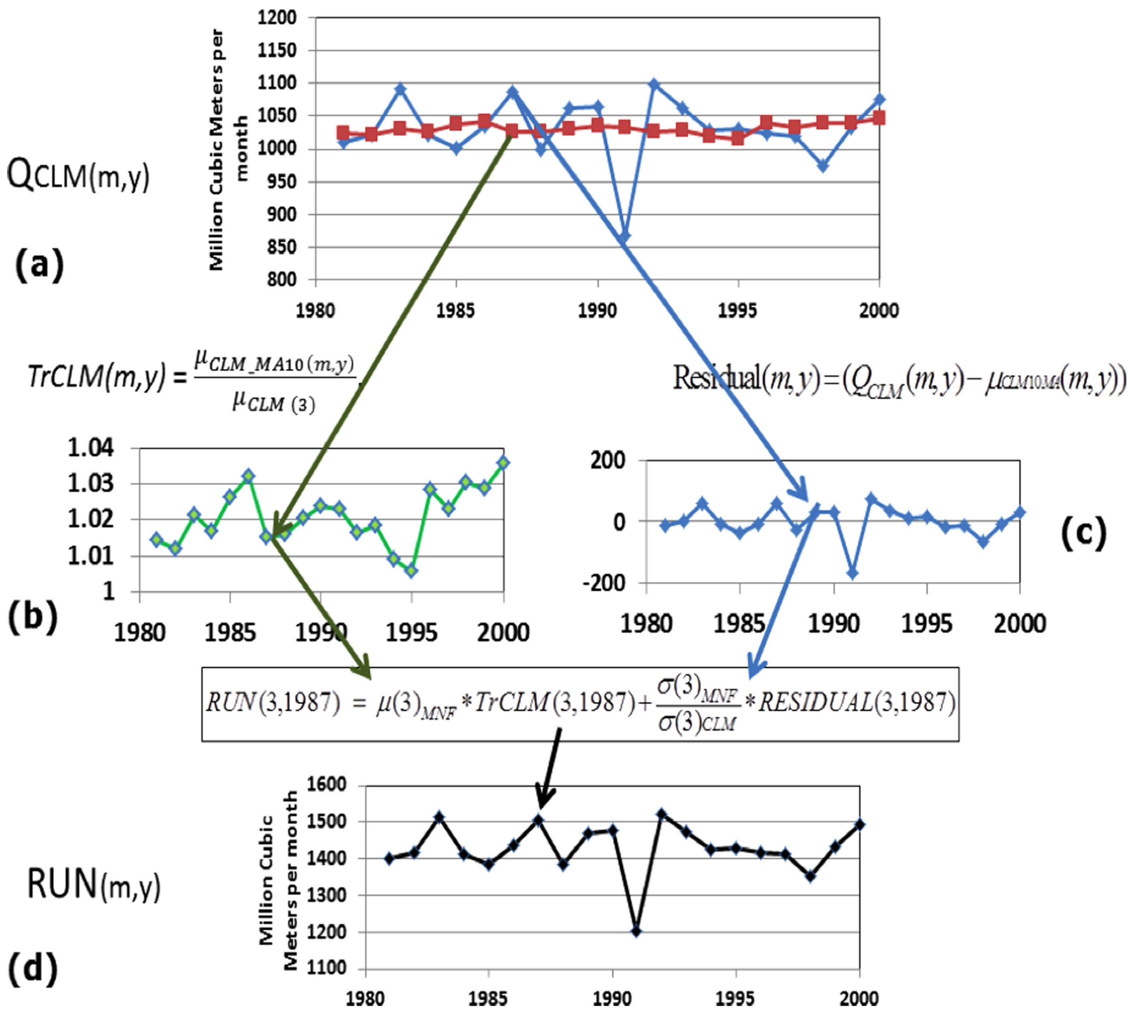

Figure 3. Illustration for a representative ASR and a representative month, 3, of the CLM runoff bias-correction methodology (the nonstationary MOVE technique) used to generate IGSM-CLM runoff for the postcalibration period 1978–2000. (a) The 23 yearly values of MNF from CLM (light blue line) with the 10 year moving average (red line) plotted on top, (b) the ratio of the 10 year moving average CLM MNF divided by the stationary mean (average from 1954 to 1977) (light green line), (c) the residual of CLM MNF with respect to its 10 year moving average MNF(light blue line), and (d) the biased corrected runoff (blue line) (RUN in Figure 9) constructed using Equation (6).

4.2.1. Irrigation

[46] The representation of ASRs as a single virtual storage renders the concept of classic irrigation system efficiency invalid because of the effects of recycling and a sequence of use cycles. Irrigation system efficiency (*SEF*) is defined as the ratio of crop consumptive use over the entire ASR to the total amount of water delivered to irrigated lands. In the WMS formulation, return flow from irrigation is downstream of the virtual reservoir and so is not available for other uses, and therefore the sector water requirement for irrigation is defined as

$$SWR_{IRR} = WTH_{IRR} = \frac{CON_{IRR}}{SEF} \tag{9}$$

where CON_{IRR} is the water consumption in irrigation, computed in section 4.1. The return flow from irrigation then is

$$RTF_{IRR} = WTH_{IRR} - CON_{IRR} \tag{10}$$

4.2.2. Nonirrigation

[47] Municipal, industrial, and livestock requirements are assumed to be independent of climate, while irrigation requirements are driven by monthly temperature and precipitation. The nonirrigation water uses (municipal, industrial, and livestock) consume only a small portion of the water withdrawal requirement. Because this return flow is near to the point of withdrawal (which is not the case for irrigation), it can be assumed that the return flow is to the virtual storage, and so the

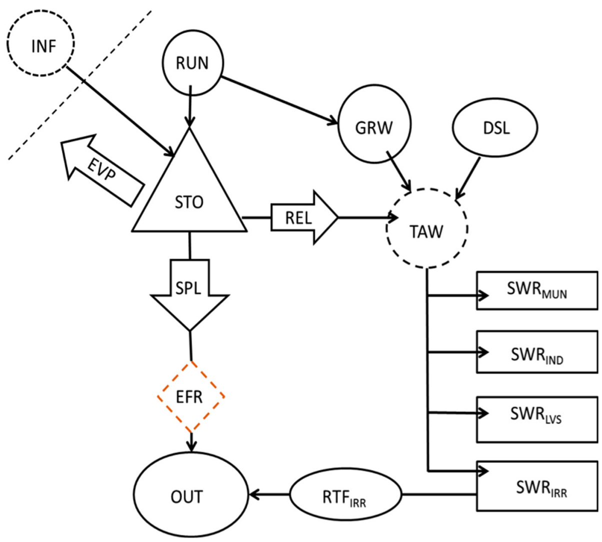

Figure 4. Water management system operation at ASR scale in the IGSM-WRS. The total water requirement (TWR) is calculated by summing municipal (SWR_{MUN}), industrial (SWR_{IND}), livestock (SWR_{LVS}), and irrigation (SWR_{IRR}) requirements. Surface water supply comes from inflow from upstream basins (INF) and local basin natural runoff (RUN), and it goes into the virtual reservoir storage (STO) where evaporation loss (EVP) is deducted. The reservoir-operating rules attempt to balance the water demands (TWR) with the total available water (TAW). Nonsurface supplies such as groundwater supply (GRW) and desalination supply (DSL) are used first and any remaining demands are met by a release from the virtual reservoir (REL). Additional releases (SPL) are made to meet environmental flow requirements (EFR).

sectoral water requirement, SWR, for each of the three above is estimated as its water consumption.

4.2.3. Total Water Requirement

[48] Each month, WMS determines the amount of water to be released from the virtual reservoir (*REL*) to be combined with the supply from groundwater (GRW) and desalination (DSL) to yield the total available water (*TAW*). The model attempts for TAW to meet the total water requirement (TWR) where:

$$TWR = SWR_{MUN} + SWR_{IND} + SWR_{LVS} + SWR_{IRR} \tag{11}$$

4.2.4. Environmental Flow Requirement

[49] Each month, WMS must release water from the virtual reservoir to provide minimum flows (*EFR*) for the maintenance of aquatic ecosystem services including floodplain maintenance, fish migration, cycling of organic matter, maintenance of water quality, or other ecological services [*Smakhtin*, 2008]. IFPRI has established minimum monthly and annual outflows from the 282 ASRs stated as a percentage of mean annual runoff. In some cases, these flow requirements are currently not being met due to extensive irrigation consumption. For the base case in 2000, these constraints have been adjusted to reflect current conditions.

4.3. Supply-Demand Balance

[50] Each month, the algorithm first balances water supply and demand in each ASR, beginning at the most upstream ASR and working downstream. If there is insufficient supply to meet all requirements in an ASR it then allocates the available water among its sectors.

4.3.1. The ASR Water Balance and Virtual Reservoir Operation

[51] The model is formulated as a mathematical programming problem, solved simultaneously for the 12 months of each year, *y*. The model objective is to keep as much water as possible in storage and maintain the minimum environmental flow while providing a total water supply, *TWS*, that satisfies as much as possible of the four sectoral water requirements. The algorithm used here is one of several developed by IFPRI [*Rosegrant et al.*, 2008], with four components.

[52] First, a variable, *RA*, is defined to capture the performance of the model in meeting the water requirement in each month:

$$RA(m) = \frac{TWS(m)}{TWR(m)} \tag{12}$$

where $TWS(m)$ is the water actually supplied and $RA < 1.0$ indicates shortage. Within this part of the objective, however, there is a desire not to penalize any particular month, so a minimum level of monthly shortage, *MRA*, also is included:

$$MRA(y) = \min_{y} [RA(m)] \tag{13}$$

[53] Then, to manage the available storage two variables are added, one to meet as much of the requirement as possible from runoff instead of groundwater, and one to limit unnecessary spillage. Following the IFPRI procedure, a simple sum of these components leads to the following expression:

$$\max \left[\sum_{m \subset y} RA(m) + MRA(y) + \frac{TWS}{RUN} - \frac{SPL}{RUN} \right] \tag{14}$$

subject to the storage accounting and limits on its capacity and a minimum level:

$$\begin{aligned} STO(m) &= STO(m-1) + RUN(m) + INF(m) + DSL(m) \\ &\quad - GRC(m) - REL(m) - SPL(m) - EVP(m) \\ STO(m) &\le STC(m) \\ STO(m) &\ge STC(m) * 0.1 \end{aligned} \tag{15}$$

[54] It includes the calculation of supply from the virtual storage and groundwater and imposition of the environmental flow requirement. Finally, there is the calculation of evaporation based on the average storage in the month,

$$TWS(m)=REL(m)+GRS(m) \quad \text{and} \quad SPL(m) \geq EFR(m) \tag{16}$$

$$EVP(m)=NET(m)\frac{(STO(m)+STO(m-1))/2}{STC(m)} \tag{17}$$

where NET is the net evaporation (potential evaporation minus precipitation) over the surface storage area.

4.3.2. Water Allocation

[55] The model allocates available water among sectors following simple priority rules, reflecting differences in the value of water in different uses. If the total water available is insufficient to meet total water requirements, water is first allocated equally among the municipal and industrial sectors, with each given the same fraction of the amount supplied. Irrigation and livestock sectors are last in priority and are served only if there is sufficient water to meet all industrial and municipal requirements. The algorithm can be easily changed to reflect institutional arrangements, such as legally established water rights that may lead to a different rule in any particular ASR.

5. Modeling Water Requirements

5.1. Irrigation Water Requirement

[56] Crop consumptive use is the main element of the irrigation system related to climate. Here we describe a formulation, used at the 282 ASR or global level, where the crop is given water at the root for maximum yield. This quantity is estimated using CliCrop, a generic biophysical crop model developed for integrated assessment frameworks. It is global, numerically efficient, and as used in WRS makes use of the limited set of inputs available globally [*Fant et al.*, 2012]. CliCrop requires the input of potential evaporation, which is estimated using the modified Hargeaves method as described in *Strzepek et al.* [2012].

[57] Monthly crop consumptive requirements for each ASR are provided to the WRS. CliCrop provides an estimate of the monthly crop consumptive use per unit of land (hectare) as irrigation depth in mm, $IRR_{mm}(crop)$. The area of each crop $IRR_{area}(crop)$ is an input to WRS and the crop consumptive use is then:

$$CON_{IRR}\sum_{crops}\left(IRR_{mm} * IRR_{crop}\right) \tag{18}$$

[58] Total water requirement requires an ASR level irrigation efficiency. The data on efficiencies and irrigated area by crop comes from FAO and IPFRI [*Strzepek et al.*, 2012].

5.2. Livestock Water Use

[59] Livestock water consumption SWR_{LVS} is estimated based on livestock numbers and water consumptive use per unit of livestock, which includes beef cattle, cows, pig, poultry, eggs, sheep and goats, and aquaculture fish production. Its projection of numbers is assumed to be proportional to demand in the agricultural sector in the EPPA model with no change in consumptive water use per head.

5.3. Nonagricultural Water Uses

[60] For the current version of the IGSM-WRS applied at the global scale, 2000 level nonagricultural water requirements are from IFPRI's IMPACT model [*Rosengrant et al.*, 2008]. These 2000 level requirements are projected to change as a function of projected population and economic growth, which for consistency with the climate projections we take from the EPPA model (see Figure 1). EPPA models the global economy in 16 regions, *r*, and the global configuration of the IGSM-WRS models nonagricultural water demand at 282 ASRs (Figure 2). An assumption of homogeneity of growth for the IGSM-WRS economic regions within each EPPA region was used to downscale EPPA projections. The method produces annual water requirements, which are distributed evenly across months. In this version of the IGSM-WRS system, we focus on representing water supplies and requirements and allocating available supplies among uses at a basin scale under varying scenarios of future climate, energy policy, and economic growth. The addition of feedbacks of changes in water availability on the economy and energy supply is scope for future research.

5.3.1. Municipal Water Use

[61] Municipal requirements include domestic use (urban and rural), public use, and commercial use connected to a municipal water system. The method is based on projections of growth rates of population and per capita income, ϕ_{POP} and ϕ_{PCI}, for each EPPA region. Income elasticities of demand for municipal water to GDP (η) also are estimated for each economic region, *n*. The annual growth rate of municipal water requirement for each economic region in each year *y*, $\phi_{MUN}(n)$ is then:

$$\phi_{MUN}(r)=\phi_{POP}(r)+\eta(r) * \phi_{PCI}(r) \tag{19}$$

for all economic regions *n* in EPPA region *r*.

[62] If $\eta < 0$ and income growth is greater than population growth, municipal water requirements will decline, which has been observed in some developed countries. Where $\eta > 0$, municipal water requirements will increase.

[63] These growth rates are applied to each ASR within an economic region, weighted by population, so that for each ASR the water requirement becomes

$$SWR_{MUN}(y)=SWR_{MUN}(y-1) * (1+\phi_{MUN}) \tag{20}$$

where SWR_{MUN} for the 2000 base year for each ASR has been estimated from FAO AQUASTAT data and information on the population distribution within countries.

5.3.2. Industrial Water Use

[64] The model identifies three industrial water-use sectors: manufacturing and service, energy production and

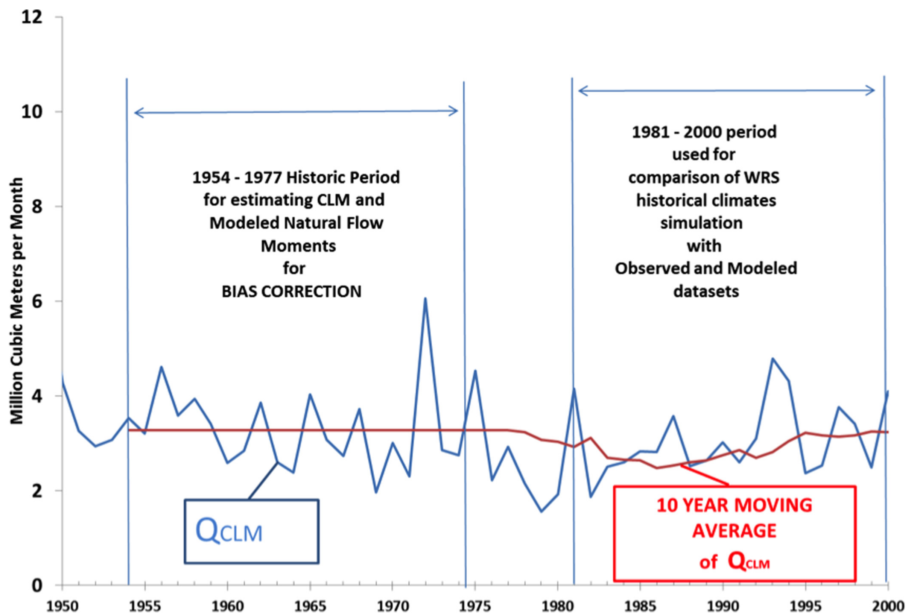

Figure 5. Timeline of calibration and comparison windows for IGSM-WRS (Q_{CLM}) and observed runoff data. For 1954–1977, climate is considered stationary with constant means and variance, and the period is used to calibrate model components and develop bias-correction parameters. After 1977, the climate is assumed to be nonstationary with runoff means having a trend from a changing climate, defined by a 10 year moving average (mean Q_{CLM}) while variances remain constant. IGSM-WRS simulations are then compared with observed and modeled historical data over the period 1981–2000.

thermal electric cooling, and agro-industrial. Changes in requirements for each industrial water-use sector are based on estimates of the elasticity of water use to per capita GDP, η_{GDPC}, with adjustments for time and the particular nation. For each of the three subsectors, α_n is the economic region intercept. This estimate is then augmented by a parameter for growth over time, γ_n, adjusted by factor, ADJ_n to account for countries where growth in GDP per CAPITA, GDPC does not properly capture structural changes or reflect climatic or water availability factors.

$$\log(SWR_{IND}) = \alpha_n + \eta_{GDPC}(n)\log[GDPC(r)] + \gamma_n * y * ADJ_n \tag{21}$$

[65] The general pattern observed is that industrial water requirements grow as a nation industrializes and then slows or even declines at higher levels of development with changing structure of industry and policies that lead to greater water reuse and recycling.

[66] The estimates of $SWR_{IND}(n)$ for each industrial subsector are then allocated among the ASRs within a nation according to the geographical distribution of industry, using population as a surrogate.

6. Assessment of Model Performance

[67] A challenge for global water model development is the lack of data against which the model performance can be evaluated. Many key variables are estimated using models, or where data exist it is often considered to be of poor or varying quality or available for a very limited period. Here we assess the performance of the IGSM-WRS in comparison with historical data where available, and in other cases we compare against other modeling exercises. Additional details are presented in *Strzepek et al*. [2012].

[68] The first step in this assessment is to calibrate the model over an initial historical period and then to simulate a second historical period that was not used in the model calibration. Figure 5 shows the IGSM-CLM runoff (Q_{CLM}) for these two periods and the 10 year moving average of IGSM-CLM runoff (Q_{CLM}) $\mu_{CLM_M A10(m,y)}$. The ratio of the 10 year moving average of Q_{CLM} after 1977 over the stationary mean of Q_{CLM} over the period 1954–1977, $\mu(m)_{CLM}$, becomes the normalized trend of Q_{CLM} ($TrCLM$) described in equation (5). As previously noted, the MOVE calibration of CLM is based on the period 1954–1977. Then the model is evaluated for the period 1980–2000, driven by the simulated climate. Model results are then compared with observations or observation-driven constructions of the water system performance.

6.1. Runoff

[69] The mean annual runoff for IGSM-WRS and IFPRI-MNF averaged over 1981–2000 was analyzed, and for the global scale the total was found to be 40,000 and 40,300 billion cubic meters, respectively. The spatial correlation of the mean annual runoff of the IGSM-WRS runoff versus the IFPRI-MNF for the 282 ASRs resulted in a slope of 0.97 and an R^2 as 0.99, which suggests that geographical climate signals driving both series are similar between the calibration and assessment periods. This vetting of the bias-correction method over

the assessment period provides more validation to effectiveness of the nonstationary MOVE extension. The raw CLM mean annual runoff before the MOVE bias correction was compared with gauged mean annual runoff data for four river basins will little human abstractions and thus limited impacts on runoff. Over the historic period 1960–1990, CLM mean annual runoff had relative error for the Amazon (+9%), the Congo (+16%), Niger (+6), and the Zambezi (−1%).

6.2. Irrigation Requirements by Crop

[70] IGSM-WRS annual irrigation demand exhibits the expected larger values in arid regions and lower values in humid regions. An analysis of the IGSM-WRS maize irrigation requirement is roughly consistent ($R^2 = 0.61$) with estimates for the IIASAs-FAO GAEZ model [*Fischer*, 2012], which is representative of historic conditions. The results show similar agreement for all other crops modeled in the IGSM-WRS. Tests in China and Brazil by comparing downscaled results based on statistics available on national level, with detailed subnational statistics on county- and microregion-levels revealed strong correlations between downscaled national statistics and county- or microregion-level statistics of harvested areas, yields, and crop production [*Fischer*, 2012].

6.3. Sectoral Water Requirements

[71] Global databases on water use are a recent phenomenon, and so historical time series data are lacking. The FAO has developed a comprehensive online database of water use: AQUASTAT [*Food and Agriculture Organization of the United Nations*, 2012]. The data are presented at a country level, requiring IGSM-WRS results to be aggregated to the economic region level. Also, AQUASTAT has limited temporal data, but its estimates for 2000 provide a basis for comparison. A comparison exercise was undertaken by running IGSM-WRS for the period 1981–2000 with irrigation areas and nonagricultural demands held constant at year 2000 base levels. The annual output of IGSM-WRS was averaged over the period and compared to FAO data on water requirements for 2000. The global climate over 1981–2000 is representative of the drivers in FAO 2000 data. A measure of IGSM-WRS's ability to adequately model the global systems would indicate the similarity of average 1981–2000 IGSM WRS outputs and the FAO reported data.

[72] For total irrigation demand, the spatial correlation shows close correspondence (R^2 of 0.81) with the exception of three outliers where the WRS estimate is below that in AQUASTAT. The two extreme outliers are for Indonesia and Japan, both island nations where the scale of the IGSM grids leads to lower irrigation demand due to differences in land and ocean temperature and precipitation.

[73] The same comparison for municipal requirements is also very close (R^2 of 0.81) with the exception of two outliers. There are a few outliers where the IGSM-WRS overpredicts water requirements and exhibits a slight bias toward overprediction of use compared to AQUASTAT.

[74] The IGSM-WRS estimation of industrial requirements is compared with the AQUASTAT data and correlates very closely (R^2 of 0.95). The outliers where the IGSM-WRS overestimates industrial withdrawal are India and Russia. This is the result of using a single global industrial withdrawal to consumption ratio, which varies depending on the structure of the economy.

6.4. Results at Basin Scale

[75] Because beneficial use of water and the impact of water management are felt year to year at the local or basin level, the usefulness of a model for impact assessment depends on its fidelity at this finer scale. Thus, we explore model performance in greater detail by considering four ASRs that represent a range of conditions: large irrigation demand, large reservoir storage, and large spatial area. Together, these basins present a broad range of water management conditions for a modeling framework like the IGSM-WRS to accurately model the following:

[76] • *The Nile Basin in Egypt*: No effective local runoff, large irrigation demand, large reservoir storage and downstream of a major transboundary river basin; homogeneous irrigation needs;

[77] • *The Nile Basin in Sudan*: Large irrigation demand, large reservoir storage, major downstream transboundary flow requirements, large internal local runoff; homogeneous irrigation needs;

[78] • *The Murray-Darling River in Australia*: Large irrigation demand, large reservoir storage, no downstream requirements and not a transboundary river basin; homogeneous irrigation needs;

[79] • *The Missouri Basin in the United States*: Large spatial area, nonhomogeneous, hydro-climatically, across the basin, large reservoir storage, supplemental irrigation needs.

6.4.1. Runoff

[80] The model results, if reasonable, should show a similar long-term mean and general pattern of variability. The performance of the IGSM-WRS runoff model is shown in Figure 6. The modeled results show similar overall levels of runoff and patterns of variability to that seen in the observations. Thus, the approach of linking IGSM output to the water system model appear to provide representative projections of runoff for actual river basins as outlined in detail in *Strzepek et al.* [2012].

6.4.2. Water Requirements

[81] The performance of the IGSM-WRS water requirement components model is shown in Figure 7 for three of the four ASRs. The one ASR that does not perform well is the Missouri River ASR, which is significantly different due to two key factors. One is irrigation—the Missouri basin is extremely large with substantial temperature and precipitation gradients and heterogeneous soils. Irrigation in this ASR is predominately in the Platte River subbasin of the Missouri where the climate is much hotter and drier than average ASR conditions. This scale issue is addressed in the U.S. version of WRS [*Blanc et al.*, 2013] where the

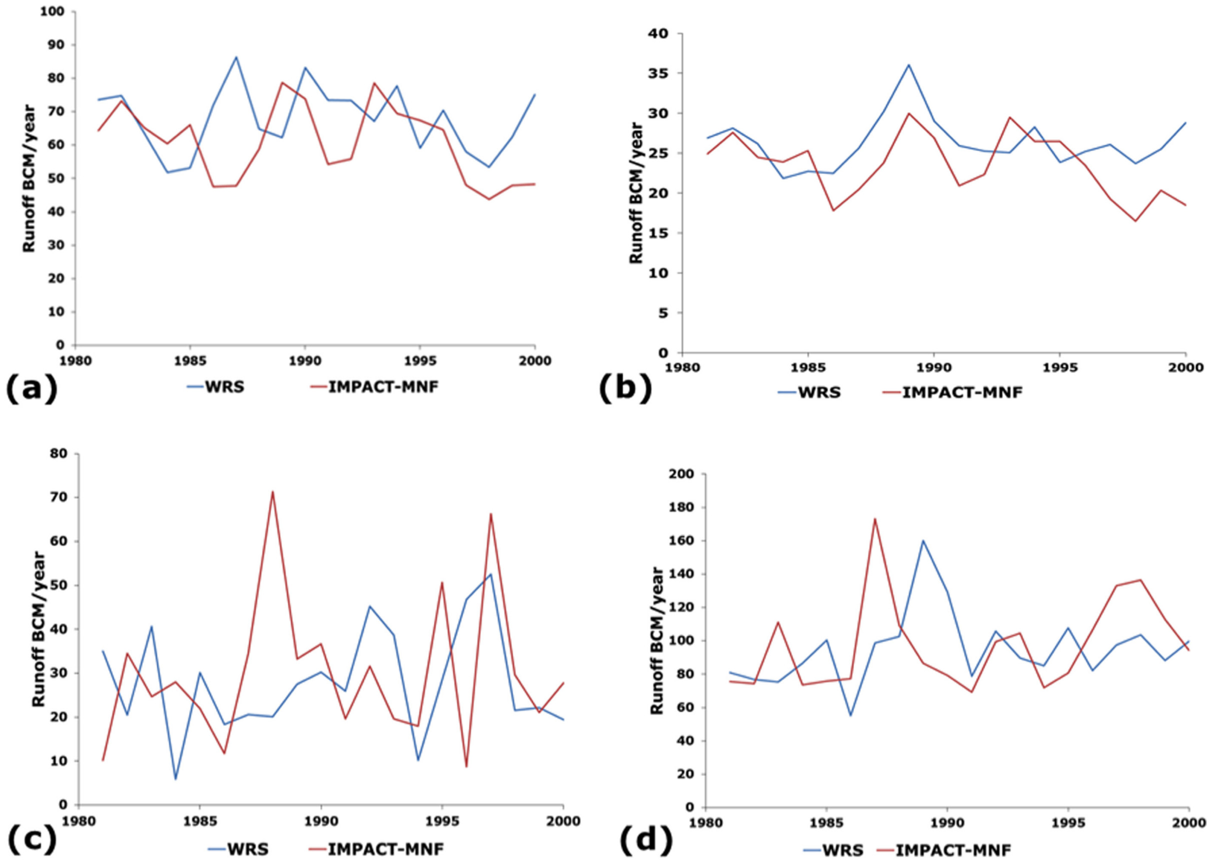

Figure 6. Comparison of the time series of annual natural flow (billion m^3) over the period 1981–2000 of IGSM-WRS (blue line) with IFPRI-MNF (red lines) for selected ASRs: (a) Nile-Ethiopia, (b) Nile-Sudan, (c) Murray-Darling, and (d) Missouri.

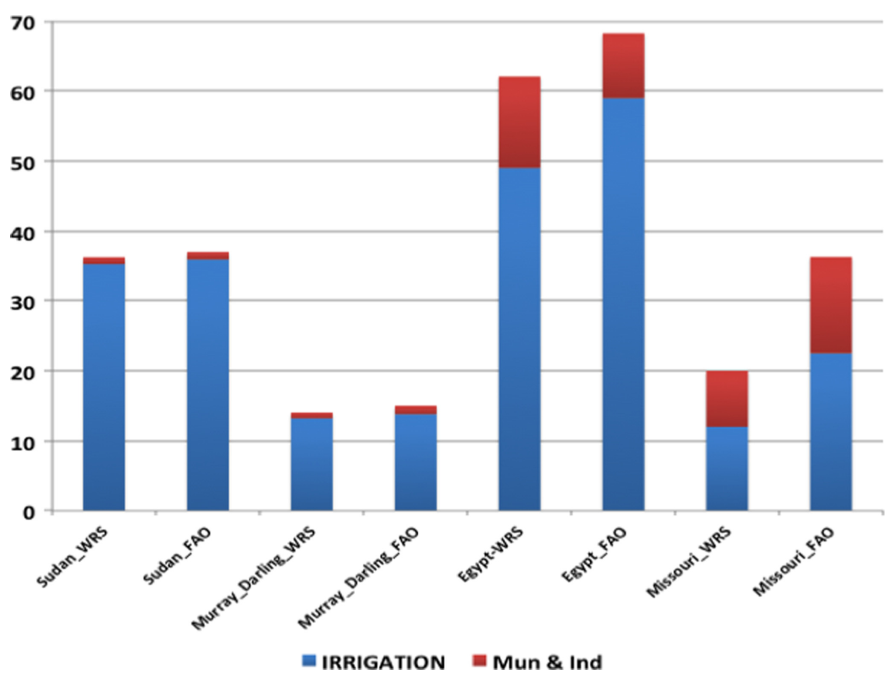

Figure 7. Comparison of the average annual irrigation and M&I water requirement (billion m^3) over the period 1981–2000 of IGSM-WRS (blue bar) with FAO 2000 (red bar) for selected ASRs: (a) Nile-Sudan, (b) Murray-Darling, (c) Nile-Egypt, and (d) Missouri.

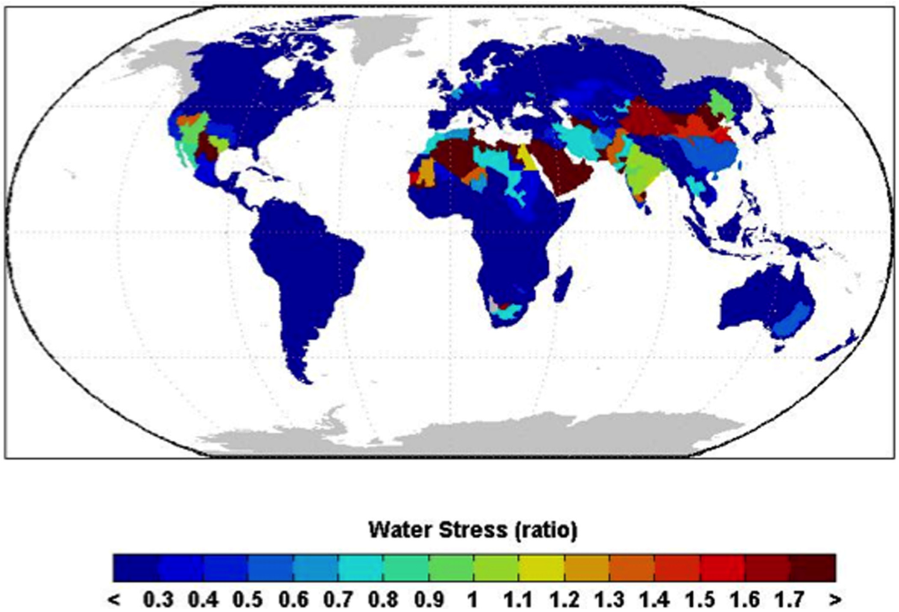

Figure 8. Results for the water stress index (WSI) from the IGSM-WRS averaged over 1981–2000 presented as (a) a map of the 282 ASR annual values (unitless). The IGSM-WRS WSI by country averaged over 1981–2000 was regressed against the FAO AQUASTAT WSI, based on observations from the year 2000. The estimated slope was 1.09 while R^2 was 0.96. Outliers were found due to two reasons: (1) spatial aggregation, which can lead to biases in irrigation demands as we saw for the Missouri River Basin and (2) biases in supply due to hydroclimatic data issues.

Missouri Basin is divided into 10 subbasins. The second is thermal electric cooling—the difference in the nonagricultural withdrawal is that the current global IGSM-WRS does not distinguish between industrial and electric cooling demand.

6.5. Water Stress

[82] A simple but useful indicator of the state of water systems is water stress. *Brown and Matlock* [2011] describe a variety of indicators used to estimate water stress. We apply a measure that is used extensively in global water resource assessments, the water stress indicator (WSI) developed by *Raskin et al*. [1997] and extended by *Smakhtin et al*. [2004]. *Smakhtin* [2008] defines the index as:

$$\mathrm{WSI} = \frac{\text{Average Annual Withdrawals}}{\text{Mean Annual Runoff}} \tag{22}$$

[83] The index is computed over a series of years, and withdrawal is totaled across all sectors representing water demand, and mean annual runoff is used as a proxy for total water availability.

6.5.1. Global Water Stress

[84] Water stress results from the IGSM-WRS for the globe using the Smakhtin et al. index are shown in Figure 8. The patterns resemble those published in the literature [*Brown and Matlock*, 2011]. An assessment of the skill of the IGSM-WRS in estimating global water stress was performed by comparing results with FAO-AQUASTAT data. The FAO-AQUASTAT data for 2000 are only reported at the national scale, whereas IGSM-WRS output is by ASR. We therefore aggregate the ARS data to the national level to make this comparison.

6.5.2. ASR Level Water Stress

[85] Water management and impacts occur at the ASR level not the national level. To examine the performance of the IGSM-WRS in estimating water stress, results for the four ASRs explored above are compared with observations as recorded by AQUASTAT, Australian water authorities, and the USGS (Figure 9). The categorization of stress is shown by the three colored lines designating the Smakhtin et al. categories described above. For the Nile-Ethiopia, Murray-Darling, and Missouri, the IGSM-WRI results are very close to observations. For the Nile-Sudan IGSM-WRS underestimates the stress index because the local Nile flows in Sudan include the very complex Sudd wetlands, and IGSM-WRS estimates higher internal Sudan-Nile runoff than FAO reports. Additionally, irrigation is the predominant sectoral water withdrawal, and differences are found between irrigation demand estimated with IGSM-WRS and what is

Table 1. Water Requirement Sectors. Rosegrant, et al, 2008.

Sector	Abbreviation	Description
Municipal	MUN	Domestic, commercial, and public uses
Industrial	IND	Agro-industries, manufacturing, and energy
Livestock	LVS	On-farm and stockyard
Irrigation	IRR	Crop consumptive use, conveyance, and on-farm loses

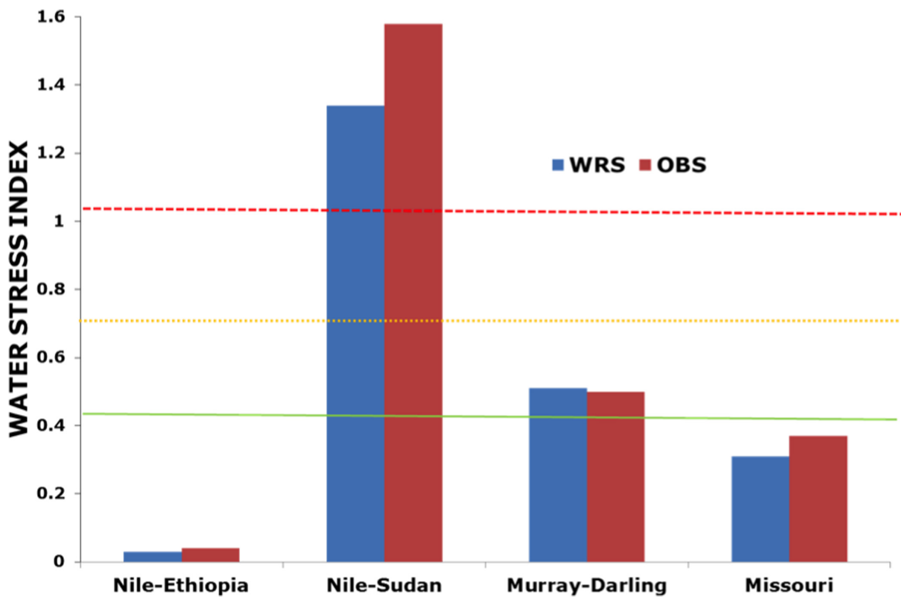

Figure 9. Comparison of water stress index (WSI, unitless) from IGSM-WRS mean over simulation years 1981–2000 (blue bars) with observed data for 2000 (red bars). Results are provided for selected ASRs: Nile-Ethiopia (observations based on FAO AQUASTAT); Nile-Sudan (observations based on FAO AQUASTAT); Murray-Darling (from Murray-Darling Basin Authority); and Missouri (observations from *U.S. Geological Survey* [2012]). Colored lines show Smakhtin stress categories: $WSI > 1$ is overexploited, $0.6 > WSI > 1$ is heavily exploited, $0.6 > WSI > 0.3$ is moderately exploited, and $WSI < 0.3$ is slightly exploited.

reported in AQUASTAT. While there is difference in the water stress index between the IGSM-WRS based value and the AQUASTAT based value, both estimates find that the Nile-Sudan falls in the overexploited water stress classification. This classification warns that there is extreme human pressure on the water resource in this region.

7. Summary and Applications

[86] The water resource systems framework presented here is a significant step forward in linking together a numerically efficient model that represents the economic, hydrologic, and climatological determinants of the performance of water resource systems. It provides a useful tool for assessment of conflicts between alternative water uses as they may evolve with future population and economic growth, considering the effects on water supply of climate change. A more detailed presentation of the material presented here can be found in *Strzepek et al*. [2012]. *Schlosser et al*. [2012] have applied the model to assessment of the effects of projected climate change at the 282 ASR level, applying the model specification presented here. Effects on water systems are explored under climate change to 2100 according to two different climate models under a no-new-policy reference case and policies limiting atmospheric greenhouse gas concentrations to 450 ppm CO_2e. *Blanc et al*. [2013] apply the model to a 99 ASR specification of the continental United States, imposing changes in characterizations of water requirements made possible by more complete data inputs for this particular region. The same two policy scenarios and two climate models are employed, and a number of measures of system stress and adequacy are studied.

[87] In putting together a global modeling system, the need for computational efficiency and data limits leads to inevitable compromises. Even with these compromises, this system provides a tool for screening for regions where water stresses may arise, providing global coverage. For detailed evaluation and resource planning for an individual river basin, a more detailed model would be needed. In that regard, the IGSM-WRS provides a framework where detail and resolution can be added where data are available and where resources are available to carry out improvements.

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