Exploring the Implications of Modeling Choices on Prediction of Water Savings

Chinedum Eluwa[1], Baptiste Francois[1], Alec Bernstein[1] and Casey Brown[1]

[1]University of Massachusetts, Amherst.

Corresponding author: Chinedum Eluwa (celuwa@umass.edu)

Key Points:

- Predictions of water savings are highly sensitive to modeling choices, especially the choice of hydrologic model parameters
- The method used to represent non-beneficial losses (e.g., conveyance losses) can contribute to uncertainty in predicted water savings

Abstract

Improvements in irrigation technology are expected to yield water savings. Recent research highlights the need for accompanying institutional conditions (e.g., restricting irrigation expansion). However, estimating the expected quantity of water savings remains uncertain, even under such institutional conditions. This is because estimates of the water savings resulting from improved irrigation technology are subject to several methodological (sometimes arbitrary) choices. Three key choices are: (1) the underlying hydrologic model used to partition irrigation water into consumed (e.g., evapotranspiration) and non-consumed (e.g., runoff) components, (2) the selected hydrologic model parameters, and (3) the convention used to represent non-beneficial losses (e.g., non-crop evaporative losses during channel conveyance, on-farm application, off-farm storage, or unrecoverable seepage). This study is the first to explore the combined implications of these choices as regards predicting water savings. It is also the first to attribute the uncertainty in expected water savings to each of these choices. To explore these implications, we use an ensemble of water savings under all possible combinations of three different conceptual hydrologic model structures (HYMOD, HBV, SAC-SMA), a hundred equifinal parameter sets (for each model), and two conventions for representing non-beneficial losses - a total of 600 scenarios. The results show that parameter selection and alternative conventions of representing non-beneficial losses are the largest sources of uncertainty in water savings, contributing ~49% and ~33% respectively to overall uncertainty. These results provide a quantitative estimate for the minimum range of uncertainty one may expect when considering policy options that depend on quantified estimates of water savings.

1 Introduction

Improving the productivity of agriculture is a critical component of achieving food security, especially given intensified competition for water resources. There are a variety of possible interventions, many of which not only focus on developing and expanding irrigated areas but also on minimizing unproductive water losses via improved irrigation technology (Perry, 2017). It is sometimes claimed that water saved may be used further downstream in other activities, such as environmental preservation, without necessarily reducing crop production - for example experimental evidence shows that switching from furrow irrigation to subsurface drip used 57% less water yet maintained similar yields of the lettuce crop (Hanson et al., 1997). Richter et. al. (2017) document similar experiments. The monetary value to downstream users of expected water savings is often used to craft policies designed to incentivize upstream farmers to adopt improved irrigation technology. For example, in Australia (Williams & Grafton, 2019), India (Narayanamoorthy, 2004; Polak et al., 1997; Sivanappan, 1994), and the United States (Huffaker & Whittlesey, 1995; Scheierling et al., 2006).

However, erroneous estimates of expected water savings abound in policy practice (Williams & Grafton, 2019). *Apparent* savings - also known as *dry* or *paper* savings (Seckler, 1996) - are often mistaken for *real* savings (Grafton et al., 2018; Williams & Grafton, 2019). Such errors occur partly because of a lack of full water budget accounting – for example ignoring return flows (Richter et al., 2017); and partly because real water savings resulting from improved irrigation technology are only possible under certain policy conditions (Grafton et al., 2018; Huffaker, 2008; Huffaker & Whittlesey, 1995; Richter et al., 2017; Seckler, 1996). Such conditions have been well documented in the literature and include a general requirement that investments in improved irrigation technology are accompanied by other policy measures, such as restrictions on acreage expansion and limits on withdrawals (Grafton et al., 2018; Pérez-Blanco et al., 2020).

The expected savings resulting from such farmer incentivization (or other conservation) policies are commonly predicted using computational models (Berbel & Mateos, 2014; Berbel et al., 2015, 2018; Huffaker, 2008; Huffaker & Whittlesey, 1995; Huffaker & Whittlesey, 2003; Jägermeyr et al., 2015; Törnqvist & Jarsjö, 2012; Ward & Pulido-Velazquez, 2008; Williams &

Grafton, 2019). This is especially the case given that such policies are usually implemented across spatial scales much larger than typical plot-scale experimental studies, and some generalization of plot-scale experimental results is required. Such models can typically ensure that computed savings are *real* in three ways. First, by explicitly tracking the soil partitioning of irrigation water - into consumed (beneficial or non-beneficial) and non-consumed quantities. Second, by accounting for the additional policy constraints, such as restrictions on acreage expansion. Third, explicitly defining the spatial extent where the policy is implemented and computing savings downstream of that extent. Nevertheless, even when policies are evaluated using models that account for the physical fate of irrigation water and the necessary accompanying policy constraints, within well-defined extents, the proper quantification of real water savings is still uncertain. This time, plagued by arbitrary model and parameter choices that are necessary for mathematical specification and estimation of computational models. Such choices are inherently uncertain, and such uncertainty exists in the predictions of the model. This study is interested in quantifying the uncertainty in water savings predictions given computational modeling choices.

In terms of computationally predicting the expected *real* water savings from improved irrigation technology, for policy analyses, three modeling choices are inevitable. First, the selection of the accounting scheme used to partition irrigation water into consumed (e.g., evaporation, crop transpiration) and non-consumed (e.g., runoff, infiltration) quantities. In terms of accounting schemes, a spectrum - from simple to complex - of possible model choices exist. On the simple end, some studies use a static scalar value to represent the portion of irrigation water that is consumed (Huffaker, 2008; Ward & Pulido-Velazquez, 2008). On the complex end, the models used to partition irrigation water are dynamic, physically-based models (Jägermeyr et al., 2015; Malek et al., 2017). To account for hydrologic fluxes, and ensure predicted savings are real, the choice of partitioning scheme is inevitable. However, this choice implies a selection from alternative structural representations of the partitioning of soil moisture input (Mendoza et al., 2016). Ultimately, such a choice has implications for the predicted water savings.

The second inevitable choice is the selection of parameters used to fully specify the selected soil moisture accounting model structure. For the simple models, usually a scalar is specified. For example Ward & Pulido-Velazquez (2008) set a value where ~40% of irrigation water is depleted as evapotranspiration (see Tables 1 and 2 in that study). The partitions to other hydrologic fluxes, e.g., deep percolation and runoff, are similarly specified using scalar fractions. In studies that select more complex hydrologic partitioning schemes, the parameters are set via either manual or automatic calibration (Belder et al., 2007; Pool et al., 2021). The nonlinear nature of hydrologic processes implies that for a selected model structure, there are a non-trivial number of equifinal parameter sets that are practically identical (Beven, 2006), each of which presents a plausible representation of the hydrologic response. Little exists to discriminate among the members of that equifinal set (Efstratiadis & Koutsoyiannis, 2010). Thus, the choice of a parameter set from the equifinal collection of parameter sets is necessary, yet, inherently uncertain. Such a choice has implications for the predicted water savings.

The third inevitable choice with regards to prediction of *real* water savings, is selecting a convention to represent the hydrologic response to water saving measures. Water saving measures are the technologies intended to alter certain hydrologic flow pathways and reduce the irrecoverable, non-beneficial losses (e.g., non-crop evaporative losses during channel conveyance, on-farm application, off-farm storage, or unrecoverable seepage). For any given technology, there are a range of choices to represent the hydrologic response to that technology. For example, consider mulching, a technology that reduces non-beneficial evaporation and irrigation requirements. Alliaume et al. (2017) and Chukalla et al. (2015) represent the hydrologic effect of mulching by a simple reduction of the evapotranspiration (albeit using different models of evapotranspiration); while Filipović et al. (2016) represents mulching by altering the top boundary conditions of a hydrologic model. For another example, consider sprinklers, a technology used to apply irrigation water to fields. One can model sprinklers by adding an extra evaporative term to a hydrologic model (Malek et al., 2017), or by increasing the precipitation term without accounting for any extra evaporation (Leng et al., 2017), or by resetting soil moisture to field capacity during irrigation events (Khan & Abbas, 2007). A third example - which will be the focus of experiments in this paper - involves the generic representation of non-beneficial losses of water during channel conveyance and field application of irrigation water. Such losses are usually represented by the operation of a scalar. The scalar may be applied either on the irrigation withdrawals (Jägermeyr et al., 2015; Rost et al., 2008;

Siderius et al., 2020), or on the computed return flows (Huffaker & Whittlesey, 2000). In these examples, it is not evident whether alternative representational choices for the same technology are computationally or mathematically equivalent. As such, the selection of an alternative representation for the technologies in question likely has implications for predicting water savings.

The three modeling choices highlighted above: (1) the hydrologic model structure to use, (2) the hydrologic model parameters to select, and (3) the representation of the given technologies, are necessary given that full hydrologic accounting is crucial to estimate *real* savings. However, these choices are usually predominantly a function of factors such as the research question, analyst's familiarity with the tool (Addor & Melsen, 2019), computational tractability, data availability, fidelity with observations where they exist (Clark et al., 2015), and so on. Such factors, while pragmatic and non-trivial, are contingent and largely arbitrary. Such choices may reveal more about the model builder(s) than the geophysical process in question (Addor & Melsen, 2019) - in this case, the hydrologic response to irrigation technology. More importantly for this study, we hypothesize that each one of these modeling choices (and the interactions of these choices) has implications for the uncertainty in the predicted water savings. This study is concerned with quantifying the uncertainty that results from the above highlighted modeling choices. It is worth noting that there are a host of other choices aside from these three presented above. For example, the choices of forcing dataset (and any data pre-processing if necessary), model resolution (spatial and temporal), parameters to calibrate (if any), calibration metrics, calibration algorithm, calibration period, calibration bounds (Melsen et al., 2019; Mendoza et al., 2016). However, we limit the scope of this study to the three modeling choices outlined.

There is a consensus in the literature that accurately estimating real water savings requires full hydrologic accounting of irrigation water (Richter & Orr, 2017), alongside uncertainty quantification of all relevant terms of the mass balance (Grafton et al., 2018). Modeling studies to estimate water savings have increasingly adopted full hydrologic accounting (see review in Section 1.1 for justification). However, by doing so they face certain inevitable modeling choices, the combined uncertainty implications of which are unexplored in the literature – especially the literature regarding the prediction of water savings. Model estimates of water savings under improved irrigation technology are rarely accompanied by a rigorous exploration of the uncertainty implications of model methodological choices and assumptions. Furthermore, attributing total model uncertainty in water savings to individual choices is missing in the literature. The following literature review will explore these claims.

1.1 Literature review

1.1.1 The Growing Use of Hydrologic Models Estimating Water Savings

The risk of mistaking apparent savings for real savings, and the well-documented paradox of improved irrigation efficiency (Berbel et al., 2015; Grafton et al., 2018), have catalyzed studies that explicitly partition irrigation water into different consumed and non-consumed quantities and represent the water consumed in irrigation.

Many of such studies rely on hydrologic models as the standard tool to partition irrigation water into consumed and non-consumed fractions. For example, Malek et. al. (2017, 2018) couple the variable infiltration capacity (VIC) model with the crop model CropSyst to account for crop transpiration. They also directly modify the VIC equations using engineering-specified representations of evaporation components for specific irrigation technologies. Jägermeyr et al. (2015) and Rost et al. (2008) incorporate irrigation representations in the Lund-Potsdam-Jena managed Land (LPJmL) model to partition irrigation water and estimate water savings; Droogers et al. (2000) use the Soil-Water-Atmosphere-Plant (SWAP) model to partition irrigation water; Assefa et al. (2018) use the Agricultural Policy Environmental eXtender (APEX) model; (Jiang et al. (2015) and Xu et al. (2019) couple the SWAP with the Environmental Policy Integrated Climate (EPIC) crop model to partition irrigation water; Ahmadzadeh et al. (2016) and Santhi et al. (2005) use the Soil and Water Assessment Tool (SWAT) model; Shibuo et al. (2007) and Törnqvist & Jarsjö (2012) use the PCRaster model.

Other studies that do not explicitly include hydrologic models, directly specify the quantity of irrigation water consumed, including non-consumed return flows, under different forms of irrigation technology using exogenous parameters (Berbel et al., 2018; Huffaker, 2008; Huffaker & Whittlesey, 2003; Ward & Pulido-Velazquez, 2008; Zhang et al., 2019). These specified partitioning fractions can be interpreted as indirectly playing the role of the hydrologic models - albeit in a highly simplified manner.

1.1.2 Exploration of Hydrologic Uncertainty as regards Irrigation

The ubiquity of hydrologic models intended to prevent the misspecification of water savings raises other concerns - primarily related to model uncertainty. Hydrologic models are subject to well-known uncertainties stemming from model choices - specifically, model structure formulation and parameter identification (Beven, 1993, 2006; Oreskes et al., 1994). With respect to the hydrologic effects of irrigation technology and policy (of which water savings is one), Leng et al. (2017) demonstrate that predicted hydrologic response to irrigation technology is sensitive to the representation of irrigation sources and irrigation application type. This sensitivity suggests that the predicted results reflect the specific modeling choices to represent the hydrologic response to irrigation water saving measures. Given that such choices are inherently uncertain, it stands to reason that the results are uncertain as well. In the following sections, we review how the uncertainty from each of these choices has been covered in the literature.

1.1.2.1 Uncertainty from Model Structures

Section 1.1.1 outlined multiple examples of alternative model structures that have been used to estimate water savings. The models outlined have structural differences that are known to lead to differential partitioning of soil water input (Clark et al., 2008, 2015; Knoben et al., 2019). Multiple studies have investigated the effects of structural uncertainties on hydrologic model predictions such as runoff (Najafi et al., 2011), evapotranspiration (Jayathilake & Smith, 2020), and soil moisture (Andresen et al., 2020). From these studies, we learn that hydrologic model choices substantially influence the prediction of the water balance components of hydrologic models (Mendoza et al., 2016). However, these studies largely focus on unimpaired basins, with little anthropogenic modifications of irrigation. For the studies that compare hydrologic simulations including anthropogenic impacts, such as reservoir operations and irrigation, they have largely focused on improving simulation of river discharge (Veldkamp et al., 2018) or estimating the uncertainty in predictions of water scarcity (Greve et al., 2018). No studies have specifically investigated the implications of alternative hydrologic model structures used to model irrigation activities and predict water savings. Other studies model irrigation explicitly, but use only one hydrologic model (and so are rather silent on model structural uncertainty), or do not specifically investigate water savings (Leng et al., 2017). This situation is peculiar given the growing evidence that the representation of alternative irrigation technologies within the hydrologic model structure influences predictions (Pool et al., 2021) and model sensitivity (Han et al., 2021).

1.1.2.2 Uncertainty from Model Parameters

Model parameters are a source of uncertainty that is well explored as regards unimpaired hydrology (Efstratiadis & Koutsoyiannis, 2010). However, like studies of hydrologic model structure, most of the studies investigating parameter uncertainty have not included basins with substantial human impact. Thus, the implications of this source of uncertainty are not well understood especially regarding predicted water savings. To predict water savings, some models use static fractions to partition irrigation water into consumed and non-consumed portions (Huffaker & Whittlesey, 2000; Mateos, 2008; Ward & Pulido-Velazquez, 2008; Zhang et al., 2019). However, in these studies, there is no mention of the uncertainty in these predictions that is due to the specification of the static fractions. Recent evidence suggests that the selection of partitioning fractions in computational models can substantially alter estimates of water savings (Williams & Grafton, 2019). Thus, it is not clear the extent to which the results presented by studies such as Huffaker & Whittlesey (2000), Mateos (2008), Ward & Pulido-Velazquez (2008), and Zhang et al.(2019) are artifacts of the chosen fractions. This manual selection of partitioning fractions is analogous to the automatic calibration of hydrologic model parameters used in other studies of water savings (Ahmadzadeh et al., 2016; Assefa et al., 2018; Xu et al., 2019). However, no study has investigated the implications of equifinal parameter sets on predictions of water savings.

1.1.2.3 Uncertainty from Representing Non-Beneficial Losses due to Irrigation Technology

As discussed earlier (paragraph six of Introduction), numerical implementation of irrigation technologies in hydrologic models requires modeling choices to represent the non-beneficial losses that occur either during conveyance (to or from the farm), or during application of irrigation water. Such loss effects of irrigation technology are conventionally represented before or after the hydrologic model partitions the irrigation water on-farm. For example, the models used in some studies apply the losses on the irrigation withdrawals before such irrigation water is input to the hydrologic model (Jägermeyr et al., 2015; Rost et al., 2008; Siderius et al., 2020). To do this they include a scalar multiplier that depletes the withdrawn water quantity prior to field application. In contrast, the models used in other studies represent non-beneficial losses after the simulation of farm soil-moisture processes (Huffaker & Whittlesey, 2000, 2003). Their model includes a scalar operator on the quantity of non-consumed water that returns to the watercourse.

This difference in representing losses is meaningful when considered in the following manner. If non-beneficial losses are represented prior to the soil mass balance partitioning - as in Jägermeyr et al. (2015), Rost et al. (2008), and Siderius et al. (2020), then there is a systematic depletion of water input for hydrologic partitioning. The first order effect is on the soil moisture (a key hydrologic model state variable) which directly depends on water inputs to the hydrologic model. In the case when losses are represented after the on-farm partitioning of irrigation water, as in Huffaker & Whittlesey (2000) and (2003), the total withdrawn water is delivered without any losses. This means that a relatively higher quantity of water is systematically applied to the farm's soil. All else equal, these systematic differences in soil moisture are meaningful.

Current hydrologic models partition water input into consumed (e.g. evapotranspiration) or non-consumed (e.g. runoff) quantities depending on the current soil storage (Knoben et al., 2019). The quantity of water in soil storage itself is a direct function of the water input. This means that a systematic difference in the water input, will result in a systematic difference in the partitioning of the soil input. Given such non-linearities in the intervening soil moisture process, it is not immediately obvious whether the resulting effects on savings are mathematically equivalent under alternative choices to represent non-farm losses. Hence differences in representing non-beneficial losses add structural uncertainty worthy of scientific investigation.

Realistically, irrigation losses occur all along the irrigation process, however, the conventional representations (either applied on withdrawals or runoff) are stylized representations, whose implications have not been studied. Studies such as Leng et al. (2017) provide evidence of the sensitivity of hydrologic predictions (runoff, evaporation and water table depth) to the representation of irrigation technology. They show that hydrologic predictions vary with the technology used (i.e., sprinkler, flood, drip), and the water source used (i.e., surface vs groundwater). However, they rely only on one representation of three irrigation technologies, and only address changes in irrigation withdrawals - not water savings. So far, no study has investigated the uncertainty in predictions of water savings due to alternative representations of losses.

1.2 Objectives

Thus far, the preceding sections have reviewed the literature covering the estimation of water savings, the use of hydrologic models in such estimations, and the treatment of uncertainty in the representation of the hydrologic effects of irrigation technology. We summarize the literature in three points: (1) that investigations of the effects of model structural uncertainty on hydrologic predictions exist mainly for studies of unimpaired locations. Such studies have not covered predictions of water savings under anthropogenically impaired hydrologic conditions such as changing irrigation technology; (2) that investigations of the hydrologic effects of irrigation technology have not investigated the effects of parameter equifinality on the predictions of water savings; and (3) the implications of alternative conventions of representing the non-beneficial losses are unknown.

To address these gaps, we explore the implications of these identified sources of uncertainty for predictions of water savings. We do so by asking the following questions: (1) what is the minimum range of predicted water savings when we account for alternative choices in hydrologic model structure, parameter selection and representation of non-beneficial losses? (2) how important is each source to the overall uncertainty in predicting water savings?

In the sections immediately following, we outline the methods, data, models, and experiments used to address the questions raised. The rest of the paper presents the results and discusses the implications of these results for investments in improved irrigation technology.

2 Methods and Data

In this study, we delineate the range of uncertainty in estimates of water savings by comparing predictions across a 600-member ensemble of predicted water savings. The ensemble consists of three hydrologic model structures, 100 parameter sets for each model structure, and two configurations of non-beneficial losses. This section describes the study location, the selected hydrologic models, the experimental design, and the metric for estimating water savings.

2.1 Study Location

The study location is Weru-Weru, a sub-basin of the Pangani river basin in the Hai District of Northern Tanzania. The Weru-Weru river begins along the southwestern slopes of Mount Kilimanjaro and flows through small clusters of farms and irrigation schemes. The river then joins the larger Pangani river further downstream (see inset B, Figure 1). The Weru-Weru sub-basin is a good test location for investigating uncertainties in water savings because ideas and recommendations regarding the ability to generate substantial water savings from adopting improved irrigation technology arise often in policy conversations in Tanzania (IFPRI, 2016; Lankford et al., 2004).

In Tanzania, agricultural water use accounts for about 89% of national water use, and currently, about 500,000 hectares of land are irrigated. Of this irrigated land, small-holder farmers operate about 80%, while larger farmers and plantations operate 20% (van Koppen et al., 2016; MoWLD, 2002). In the case of the Weru-Weru sub-basin, smallholder farmers are upstream of larger farmers, who themselves are upstream of the Tanganyika Plantation Company (TPC), and the Nyumba ya Mungu lake used to generate hydropower (see Figure 1). Given that surface water is the key source of water in the region (Komakech, 2018), asymmetries based on proximity to the headwater sources result in conflicts among competing users (Komakech et al., 2011; Komakech & Condon, 2012; Ostrom & Gardner, 1993).

The literature covering ecosystem services in the region classifies downstream irrigation water as an ecosystem service worth conserving and proposes payments to redistribute benefits from irrigation water from downstream large-scale farmers to upstream small-scale farmers

(Hipel et al., 2015; Lalika et al., 2017; Lalika, Meire, & Ngaga, 2015; Lalika, Meire, Ngaga, et al., 2015). Such benefits are usually framed in terms of water saved for downstream use under more efficient upstream irrigation technology (IFPRI, 2016; Lein & Tagseth, 2009). However, it is not obvious how much water savings may result from such policies, especially under severe uncertainties resulting from arbitrary modeling choices.

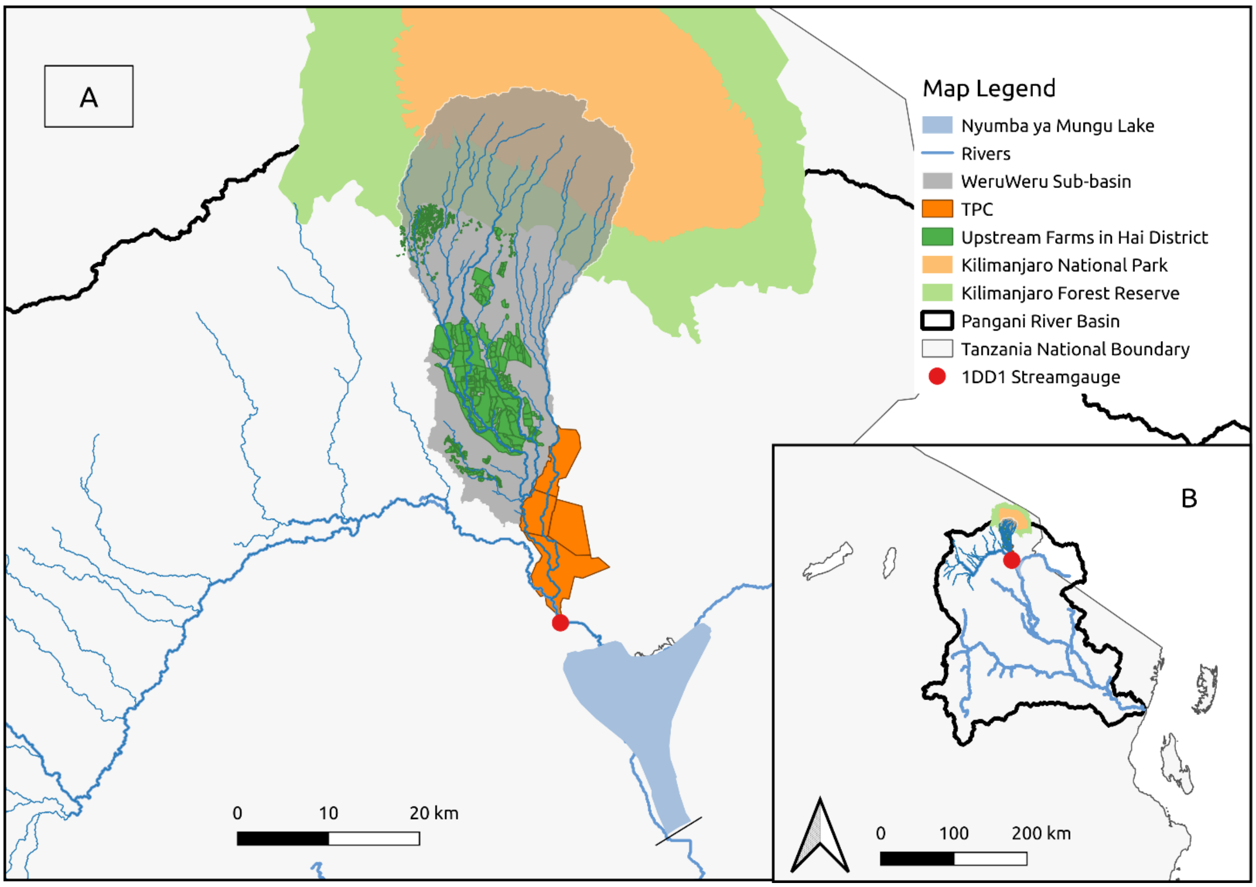

Figure 1: Study location. The main figure - labelled "A" - shows the Weru-Weru sub-basin (light grey). Upstream farms are depicted in dark green, downstream farms are shown in dark orange, and the Nyumba ya Mungu dam is shown as well. The inset figure ("B") shows the Weru-Weru sub-basin within the spatial context of the Pangani basin and Tanzania.

This case in Tanzania provides a real-life example of long-standing scientific conversations regarding proper accounting for and quantifying the uncertainty of the benefits of improved irrigation technology (Grafton et al., 2018).

2.2 Meteorological Forcing

We force the hydrologic models, at a daily timestep, using the Climate Hazards Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015) for precipitation and Berkeley Earth Land/Ocean Temperature record (Rohde & Hausfather, 2020) for temperature. The precipitation data is downscaled from 0.05 degrees (~5km) to 0.02 degrees (~2km) to match the grid of the hydrologic models. The temperature data is also resampled from 1 degree to 0.02 degrees. To account for the effects of elevation on temperature, the 90m digital elevation model provided by the Shuttle Radar Topography Mission (SRTM) (Jarvis, 2008) is upscaled to match the 0.02-degree (~2km) grid by taking the average of all 90m pixels within the 2km gridcell. The aggregated elevation values are then used to downscale the temperature data using a lapse rate of -9.8oC per kilometer rise in elevation (Sheridan et al., 2010). The reference elevation is the lowest basin elevation. Potential evapotranspiration fluxes were then calculated using the Thornthwaite equation (Thornthwaite, 1948) using the downscaled temperature data.

2.3 Hydrologic Models

The hydrologic models used in this study are HYdrologic MODel (HYMOD) (Moore, 2007), Hydrologiska Byrans Vattenavdelning (HBV) model (Bergström & Singh, 1995), and the SACramento Soil Moisture Accounting (SAC-SMA) model (Duan et al., 2004). These models form a gradient of increasing complexity and have been used in various studies in Tanzania. Some studies have applied the HYMOD model to the Mara basin that spans southern Kenya and Northern Tanzania, (Roy, Gupta, et al., 2017; Roy, Serrat-Capdevila, et al., 2017). Mwanuzi & Mutabazi (1993) use the SAC-SMA model to the Ndembera catchment in central Tanzania and Yang & Wi (2018) use the HBV model in the Upper Ruaha catchment in central Tanzania.

The models are based on different hydrologic conceptualizations. They are also relatively parsimonious in terms of parameterizations and data requirements. For locations such as northern Tanzania where data is scarce, such models are useful. Herman et al. (2013) present evidence that highlights key structural differences resulting from the different parameterizations of these models. Herman's study shows that under different climatic events, different parameters control the soil moisture partitioning and runoff generation processes of these models. The parsimony of these models as well as their conceptual differences make them useful tools for the experiment described below. Clark et al. (2008) demonstrate that the choice of the model structure is as important as the selection of model parameters. Given a selection of alternative models, we select 100 alternative model parameter sets using a genetic algorithm. Each parameter set is behaviorally equivalent (i.e., there is no way to tell the difference in outputs of each parameter set) in terms of the selected objective (see the calibrated streamflow in Figure 2).

2.4 Model Calibration

We use observed monthly flow data at the stream gauge *1DD1* located near the Tanganyika Planting Company (TPC) (see Figure 1 for the location of gauge). The Pangani Basin Water Office (PBWO) provided the records. Records at this gauge begin in October 1928 and end in September 2006. Given that there are no records specifically for the Weru-Weru sub-basin, we compute the average basin runoff generated upstream of the available gauge – this upstream portion includes the Weru-Weru sub-basin. We then calibrate each hydrologic model to reproduce the average monthly runoff value. CHIRPS precipitation data is available starting 1981, therefore, we use the runoff in the twenty years 1985 to 2005 as the calibration set. The ten years 2006 to 2015 are used for the experiments.

We use the BORG multiobjective evolutionary algorithm (Hadka & Reed, 2013) to calibrate the hydrologic models. We initialize the BORG algorithm using 100 different seeds and set up two objectives for calibration. The first objective is the Nash-Suttcliffe Efficiency (NSE) value (McCuen et al., 2006). The second objective is the Nash-Suttcliffe Efficiency computed on the logarithm of the runoff values (log-NSE), which emphasizes model performance on low flow values. The evolutionary algorithm returns parameter sets that span the Pareto-front of the two objectives. We then select 100 parameter sets using the following process: (1) compute the percentile rank of each objective for each parameter set returned from the calibration tool; (2) set a threshold quantile, in this case, we begin with the 95th percentile; (3) select parameters sets whose NSE and log-NSE values are above the threshold quantile. (4) iteratively reduce the threshold quantile until there are 100 parameter sets selected.

Evolutionary algorithms require some stopping criteria. In our case, we stop the algorithm after 10000 function evaluations. This number of function evaluations is a tradeoff between model performance and computational time. This selection is based on the lead author's experience with the algorithm. Figure (S1) shows the convergence of the algorithm's selection of parameters.

2.5 Experiment

Given three hydrologic model structures, two conventions for applying non-beneficial losses, and 100 alternative parameter sets, we set up the experiment. The experimental design follows similar model intercomparison studies such as Kollet et al. (2017), where observations of the predicted variable of interest (in this case, water savings) are scarce or entirely unavailable, and therefore, it is not easy to validate such predictions. For such studies, it is meaningful to explore the range of possible predictions resulting from combining as many factors as possible that affect the prediction. As such, we compute the water savings for each irrigation technology scenario under the full combination of model structures, parameter selections, and representations of losses.

2.5.1 Representation of Alternative Non-Beneficial Losses

In the hydrologic literature, the hydrologic response to irrigation technologies is usually represented by the operation of a scalar on a quantity of interest. The scalar is widely termed "efficiency". This term is contentious and its multiple definitions have received much attention in the literature (Lankford, 2012; Perry, 2007). It is outside the scope of this paper to investigate the range of definitions of the term irrigation efficiency and what physical quantities are the correct inputs to the functions used to compute its value. Here, we focus on the common representations of the hydrologic effects of irrigation technology - especially in terms of the representation of non-beneficial losses that result from conveyance. Technologies deemed "low" or "high" efficiency are usually represented by low or high values of the scalar acting upon the physical flows in the conveyance channels. The value of the scalar is then used to modify different physical hydrologic quantities such as the water withdrawn to estimate the water lost during conveyance, such as through evaporation or seepage.

In this paper, we focus on the implications of two specific applications of such a scalar value. In studies such as Jägermeyr et al. (2015), Rost et al. (2008), and Siderius et al. (2020) the scalar value is applied to the water withdrawn prior to its application to the farm. In such models, the non-beneficial losses are computed as follows: $Loss\ = Withdrawals * (1 - e_c)$; where $e_c \sim [0, 1]$ is the model parameter that controls non-beneficial losses from the conveyance process and serves as a proxy for the efficiency of the irrigation system. In this method, as efficiency is increased, less water is lost non-beneficially.

The second representation of non-beneficial losses is depicted in studies such in Huffaker & Whittlesey (2000) and (2003). In such studies, the scalar value representing the efficiency of the conveyance process is applied on the runoff – after the hydrologic model partitions water into various consumed and non-consumed components. Irrigation withdrawals are input to the hydrologic model without losses. The losses are computed on the runoff component. The equation is: $Loss\ =\ Runoff * (1 - e_c)$; where $e_c \sim [0, 1]$ is identical to the model parameter defined in the paragraph above as representing the hydrologic effect of irrigation technologies on non-beneficial losses – albeit operating on a different quantity.

2.5.2 Irrigation Technology Scenarios

Komakech et al. (2011) report that irrigation efficiency in the Pangani river basin "lies in the range 15-25%", which is consistent with other reports from the country (Yang & Wi, 2018). Such efficiencies are associated with technologies such as surface flooding irrigation and open-channel furrows that are common in the region (Lankford, 2004). For such schemes, non-beneficial losses are primarily due to non-crop evaporation and irretrievable canal seepage (Roth et al., 2014).

Conversations about improving irrigation technology revolve around the implementation of certain technologies that can reduce such evaporative and seepage losses. For Tanzania, historical improvements in irrigation technology for small-holder farmers have resulted in only modest improvements in the efficiency of irrigation technology. For example, Mohan (2006) highlights a technology-induced improvement of about 16 percentage points (11% to 27%) in the dry season and about 10 percentage points (8% to 19%) in the wet season in Tanzania. These improvements are noted to have led to a "re-establishment" of base flows, now available for downstream users. The improvements in question have focused on non-intensive infrastructure modifications such as the re-engineering of intakes (Lankford, 2004), and modifications of on-farm practices (Mohan, 2006).

We, therefore, assume these historically documented characteristics of technology improvements constitute a reference class (Flyvbjerg, 2008) on which we anchor our scenarios of likely improvements due to investments in irrigation technology for small-holder farms. For this location, we do not expect dramatic increases in irrigation efficiency that are typically associated with the adoption of capital-intensive technologies such as drip and sprinkler systems.

As such, we experiment with two realistic scenarios of improved technology such that efficiency is raised from the current baseline efficiency (i.e., 25%; $e_c = 0.25$) to 30% ($e_c = 0.30$) in one scenario, and to 36% ($e_c = 0.36$) in the other scenario. These improved efficiency scenarios are further validated during on-site conversations with local experts. For demonstrative purposes, we include a theoretical scenario with a substantially higher efficiency of 75% ($e_c = 0.75$).

2.5.3 Water Savings Metric

In this study, we adopt the metric used in Williams & Grafton (2019) i.e. the net effect of irrigation technology on river flows. We measure this effect at the outlet of the Weru-Weru subbasin. Williams & Grafton (2019), decompose the net effect into its various constituent variables - (1) the expected net reductions in irrigation diversions (given by government estimates) and (2) the fraction of water savings that are due to changes in recoverable runoff. Their model bounds the range of water savings under different irrigation policies, by experimenting with alternative fractions of recoverable runoff. They achieve this without a hydrologic simulation of river flows. Our study is slightly different - we achieve the range of net effects on river flow using a hydrologic simulation under the identified technology scenarios. Based on the simulation of flow, we represent savings as either (1) increasing the fraction of withdrawn water that is delivered to the farm (i.e., decreasing the losses that are applied on the withdrawals), or (2) increasing the fraction of water that returns as recoverable runoff (i.e., decreasing the losses applied on the runoff). The combinatorial framework (combinations of hydrologic model structures, parameter sets, and non-beneficial loss representations) adopted in this study returns an ensemble of time-series for the streamflow variable. The ensemble consists of the combination of hydrologic models, parameter sets, and representations of non-beneficial losses for each scenario of irrigation efficiency. The equation for the water savings metric is:

$$Savings_{i,j,k} = \sum_{m} Q_{m,i,j,k} - \sum_{m} Q_{m,i,j,k=0.25}$$

Where $Savings$ is the predicted water savings; Q is the predicted streamflow summed across the long rainy months (m) March, April and May (MAM); i is an index representing the given hydrologic model, j is an index that represents a given parameter set for a given model, k is the index for the irrigation scenarios (0.25, 0.3, 0.36, 0.75). We compute the water savings metric relative to the baseline of current irrigation efficiency (i.e., 0.25).

3 Results

The results of the experiments are presented in six sections. The first section shows the results of calibrating the hydrologic models. The second section covers the water balance under alternative scenarios of irrigation technology, the third covers the effects of alternative representations of non-beneficial losses on the internal partitioning of soil moisture into consumed and non-consumed portions. The fourth section presents results that show the changes in the predicted hydrographs of evapotranspiration, runoff and streamflow under alternative model structures. The fifth section shows the baseline streamflow, while the last section of the results shows range of uncertainty in annual savings, and the attribution of uncertainty.

3.1 Model Calibration

The model calibration results in parameters that predict the average daily runoff (millimeters) of the basin at low and high flows with reasonable accuracy. Average NSE values and log-NSE values computed using 100 parameter sets for each model are 0.6 (HBV), 0.11 (HYMOD), and 0.53 (SACSMA) - an average of ~0.43 across the models. The calibrated models also perform satisfactorily for the log-NSE metric - an average of 0.41 across the models. The three selected models show different performance across the performance metrics (see figure S2). The HYMOD model shows the largest range of values on both metrics.

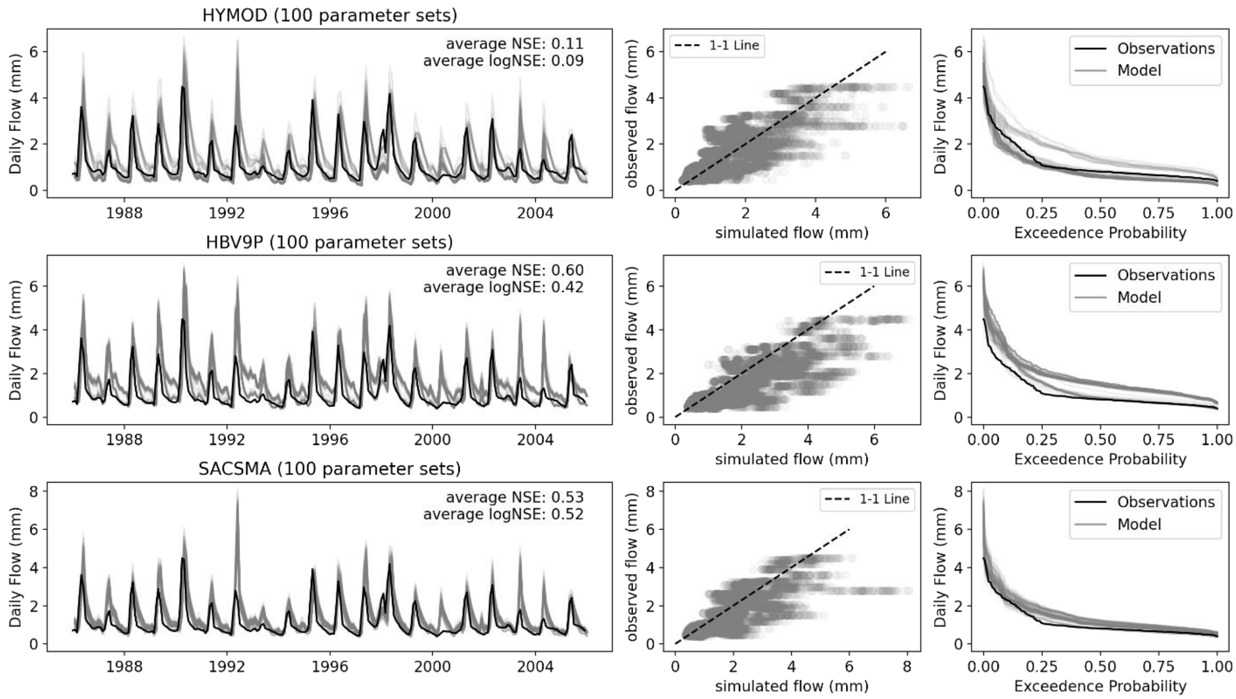

Figure 2: The results of calibrating the three selected hydrologic models. The rows show the individual models. The left column shows the timeseries and the average performance of the models (NSE and log-NSE). The middle column shows the scatter plot of observed runoff against predictions and the one-to-one line. The right column shows the flow duration curves of the observations and predicted flows.

3.2 Water Balance

In the models used in Jägermeyr et al. (2015) and Huffaker & Whittlesey, (2000), increasing efficiency results in decreasing losses. So, as expected, losses decrease with increasing irrigation efficiency. The decrease in losses can be seen in the decreasing hatched area on both rows. In figure 3, this effect is visible and consistent for all the models (see columns of figure 3). Also, when losses are applied before partitioning (top row), the quantity of water delivered to the grid cell increases. However, the quantity of water arriving at the grid cell is the same when losses are applied after partitioning. The implication is that the total quantity of water leaving the grid cell increases in the case where non-beneficial losses are applied on withdrawals. However, water leaving the grid cell remains the same when losses are applied after partitioning. When losses are applied on the runoff quantity (bottom row), the outputs are partitioned identically (see the unchanging fraction of ET a given hydrologic model e.g., 39% for

HYMOD, 3% for HBV, and 65% for SACSMA). However, improving the efficiency results in different partitions of runoff (for example, across the scenarios, runoff increases from 15% of the gridcell outflows to 46% in the HYMOD model, from 24% to 73% in the HBV model, and from 9% to 26% in the SACSMA model).

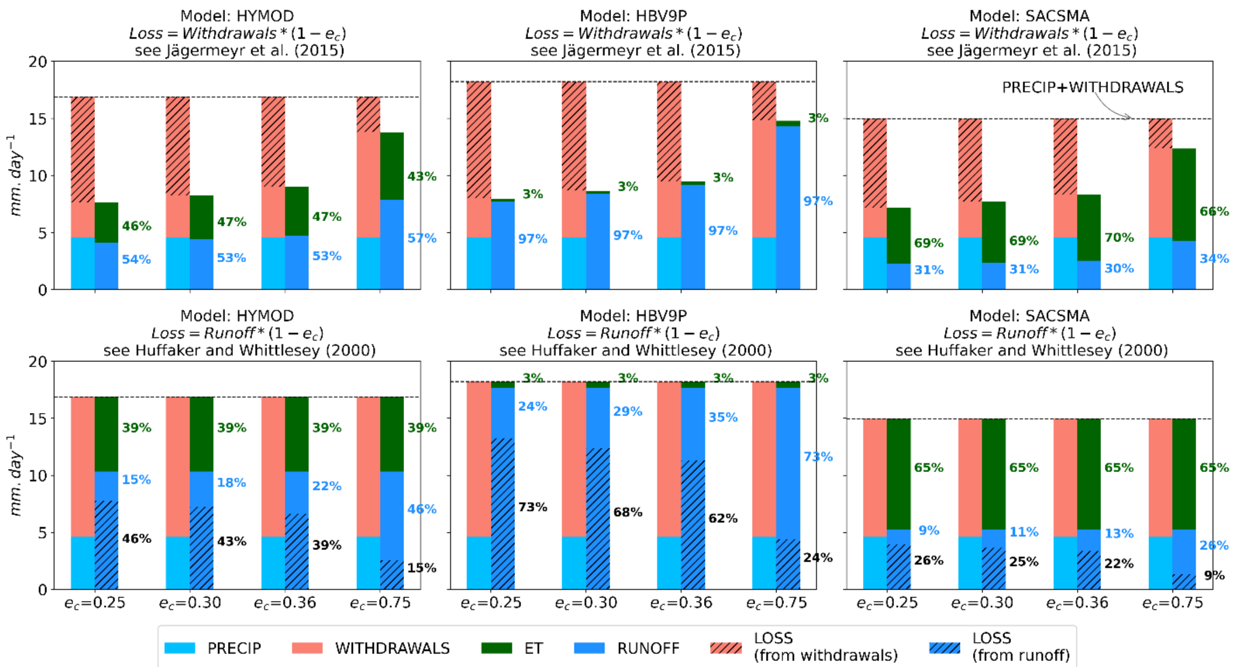

Figure 3: Shows the components of the water balance for a sample model grid cell that is fully irrigated. The area of this grid cell is 480 hectares, which is the maximum size of a 2km model grid cell. The contents of the water balance are grouped as inputs (precipitation and irrigation deliveries) and outputs (evapotranspiration and runoff). The panels on the top row show the results for each model when non-beneficial losses are applied to the withdrawn quantity (i.e., before hydrologic partitioning). The bottom row shows the water balance when losses are applied to the partitioned runoff quantity. The dotted line on each panel represents the sum of precipitation and irrigation withdrawals.

3.3 Effects of alternative representations of non-beneficial losses on soil moisture partitioning

The two identified methods of representing losses have immediate effects on the water input into the soil, the soil moisture state, and ultimately, the resulting soil moisture partitioning. Figure 4 shows the annual distribution of soil moisture states and the fraction of moisture that is not consumed for each hydrologic model (i.e., runoff) for the 100 calibrated parameter sets.

These results show that when losses are applied to the withdrawals, there is a systematic reduction of the soil moisture input to the hydrologic model. This leads to systematic differences in the quantity of soil moisture that is partitioned into non-consumption (residual soil moisture, seepage, and subsequently, runoff).

To illustrate these effects, we show the relative soil moisture state and non-consumed partition. These partitions are computed for each water-year (starting October 1st of a given year and ending on September 30th of the following year). The metric for relative moisture is the annual average soil moisture (x-axis) normalized by the maximum soil moisture of that timeseries. This metric represents a normalized value of the primary hydrologic state variable. The metric for the non-consumed partition (y-axis) is also calculated annually using the following formula: $non\ consumed\ partition = 1 - \frac{ET}{Precipitation + Irrigation\ Deliveries}$

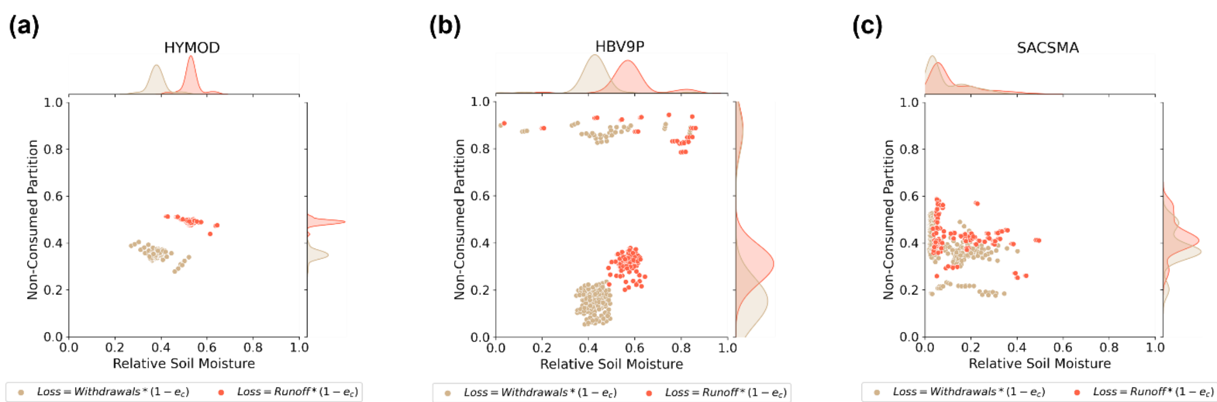

Figure 4: Soil moisture effects of implementing alternative non-beneficial loss conventions. On each panel (a, b, and c) the x-axis shows the relative soil moisture metric. The y-axis shows the non-consumed partition. The dots show the average value of relative soil moisture and non-consumed partition for each of the 100 parameter sets for the baseline irrigation scenario $e_c = 0.25$.

We use the Mann-Whitney U test to verify that the distributions are statistically distinct; see Table 1 in supporting information. The results in show that the differences in the resulting distributions of average soil moisture values and the partitioned factions are statistically significant. This figure demonstrates the resulting effects of the choice of loss representation on the internal hydrologic states.

3.4 Effects of model choice, parameter selection, and loss representation on the predicted evapotranspiration, runoff, sub-basin outflows

Figure 5 highlights the importance of the choices of hydrologic models, parameter sets, and the representation of non-beneficial losses. Some of the differences in hydrologic model structure are quite apparent. For example, the evapotranspiration from the HBV model (Figure middle row in 5a) is a much smoother curve than the predictions from the HYMOD or SACSMA models. Such differences in the hydrographs are due to functional differences in the models. Another important point from this figure is the crucial role of parameters. The parameters selected have a pronounced role in the predictions - see the shaded portions corresponding to the hydrographs. These shaded portions become wider as the represented irrigation efficiency improves (i.e., the modeled non-beneficial losses reduce). In the demonstrative scenario ($e_c = 0.75$), the differences in the average model predictions are almost indistinguishable (see rightmost columns in 5a, 5b). The differences due to the choice of equation used to represent non-beneficial losses seems apparent in the baseline scenario (leftmost column in 5a and 5b) and the two scenarios of modest change (middle columns in 5a and 5b) - for the evapotranspiration and runoff variables. The uncertainty from the equifinal parameter sets is visible in Figure 4, especially for the HBV model. We see that the equifinal parameters of the HBV model span a much wider range of the hydrologic model state-space. This manifests as very wide prediction uncertainties – even though the parameters are members of the same pareto set of parameters.

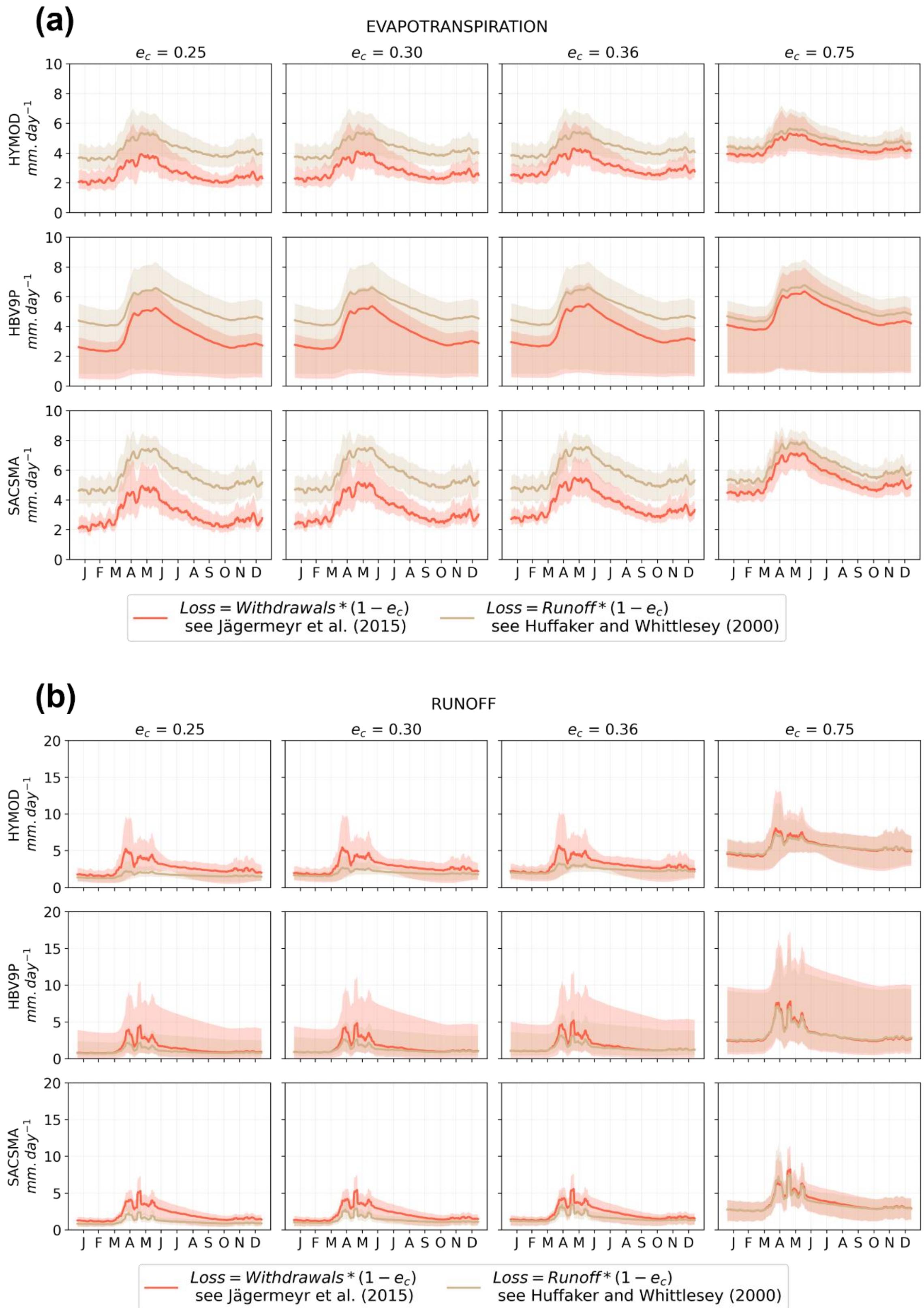

Figure 5: The annual hydrographs of the primary hydrologic outputs - evapotranspiration, runoff reported in millimeters per day.

3.5 Rainy season streamflow in the baseline scenario

Figure 6 shows the model predictions for streamflow in the baseline scenario ($e_c = 0.25$). Baseline streamflow is the sum of streamflow in the rainy season months of March, April, and May. This sum is computed each year and then averaged across all the years of the analysis (2006 - 2015). The annual average across all the models is about 18.7 million cubic meters of flow in the rainy months. Figure 6 shows some variation in this prediction due to the hydrologic models, parameter sets, and loss representations. The range around this mean from the combination of hydrologic models, parameters, and loss models is ~27MCM, spanning between ~7MCM (minimum) and ~34MCM (maximum). The figure also shows that the interquartile ranges of the computed savings are consistently higher when the non-beneficial loss model is applied on the withdrawals than when the non-beneficial losses are applied on the runoff.

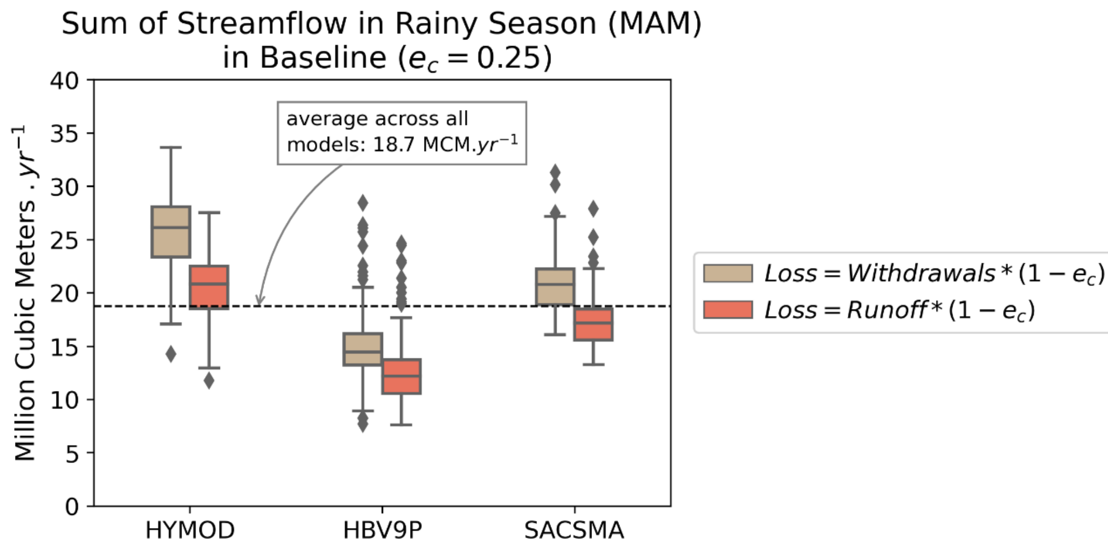

Figure 6: Sum of streamflow in the rainy season for all models. The boxplots show the values from each of the 100 parameter sets. The colors differentiate the alternative loss models applied.

3.6 Estimated water savings

Figure 7 shows the computed values of water savings in the long rainy season (March, April, May). The annual savings are reported in million cubic meters per year. The figure also shows the average across all hydrologic models, parameters, and loss representations in each scenario. The efficiency improvement from 25% to 30% results in an average savings of about 2%. Improving to 36% results in savings of ~5%, while 75% results in average savings of ~32%. For each scenario, the choice of the hydrologic model makes a substantial difference in the quantity of annual savings predicted and results in variations around the average value. The distributions of predicted water savings are different across each model. For example, given an improvement from 25% to 30%, the SACSMA predicts savings of 0.30MCM on average (range of 0.65MCM), HYMOD predicts about 0.48MCM (range 0.81MCM) on average and the HBV model predicts about 0.37 (range 1.08MCM).

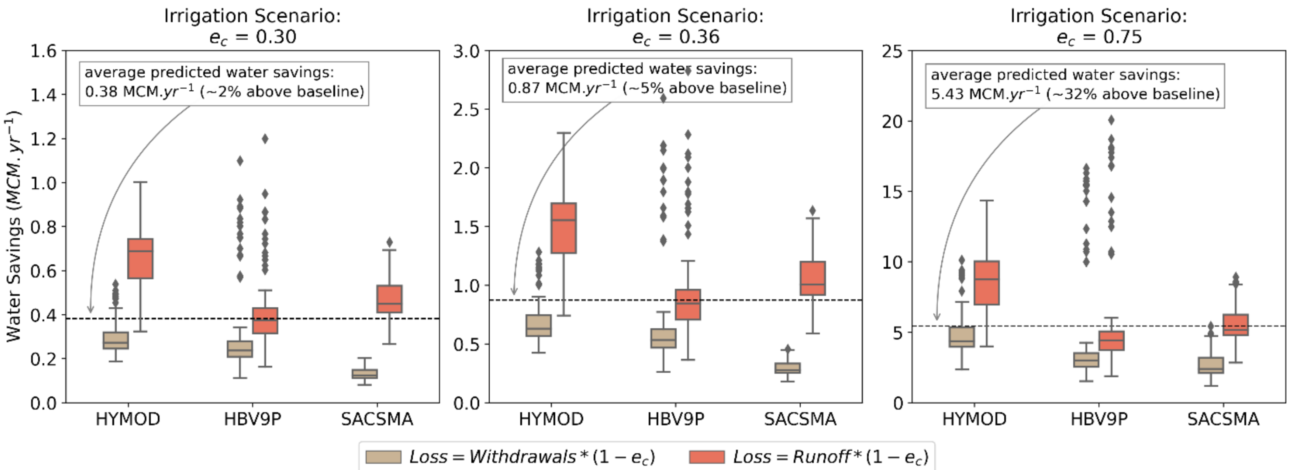

Figure 7: Water savings in the three scenarios, predicted for each model. The boxplots show the savings predicted for 100 parameter sets. The colors represent the alternative loss models.

The first research question asks: what is the minimum range of predicted water savings when we account for these three sources of uncertainty? Figure 7 addresses this question; it shows that there is a range of ~1.1MCM for the 30% scenario; a range of ~2.64MCM for the 36% scenario, and a range of ~18.9MCM for the demonstrative scenario. We use Welch's analysis of variance (ANOVA) to evaluate average model differences across each scenario. The results show significant differences (see Supporting Information Table 2); thus, we reject the null hypothesis that the predicted average water savings across the models are equal.

The results also show that there are important differences that result from the convention chosen to represent non-beneficial losses. For the hydrologic model structures in consideration, the choice of loss representation is significant. In the case of the SACSMA and HYMOD models, the variance due to the choice of loss model is more pronounced than the HBV9P model (the median and interquartile range in the tan and red box plots are much more spread apart for SACSMA and HYMOD, than for HBV). This is likely due to structural differences in the representation of evaporation and runoff processes. This difference is also visible in the hydrographs of evapotranspiration (Figure 5a), where we notice differences in the shape of the hydrographs of the HBV model when compared to the other two hydrologic models.

We use Welch's ANOVA to test the significance of the differences in the predicted averages across non-beneficial representations. Also, for each model, we perform a Mann-Whitney U test on the samples to verify any statistically significant difference in the distributions. Tables 3a and 3b in the Supporting Information show statistically significant differences in predictions as a result of the choice of alternative representations of non-beneficial losses.

Now, we turn to the second research question: how important is each source to the overall uncertainty in predicting water savings? We use a multi-factor ANOVA as performed in (Schlef et al. (2018) and Whateley & Brown (2016) to address this question. First, we formulate the ANOVA model as a two-factor model (factors are model choice and non-beneficial loss representation) with 100 replicates, where each parameter set is a replicate. Then, we fit the linear ANOVA model to predict water savings for each scenario. This allows the model residuals to capture the variance from the parameters. Results of this ANOVA are shown in Figure 8.

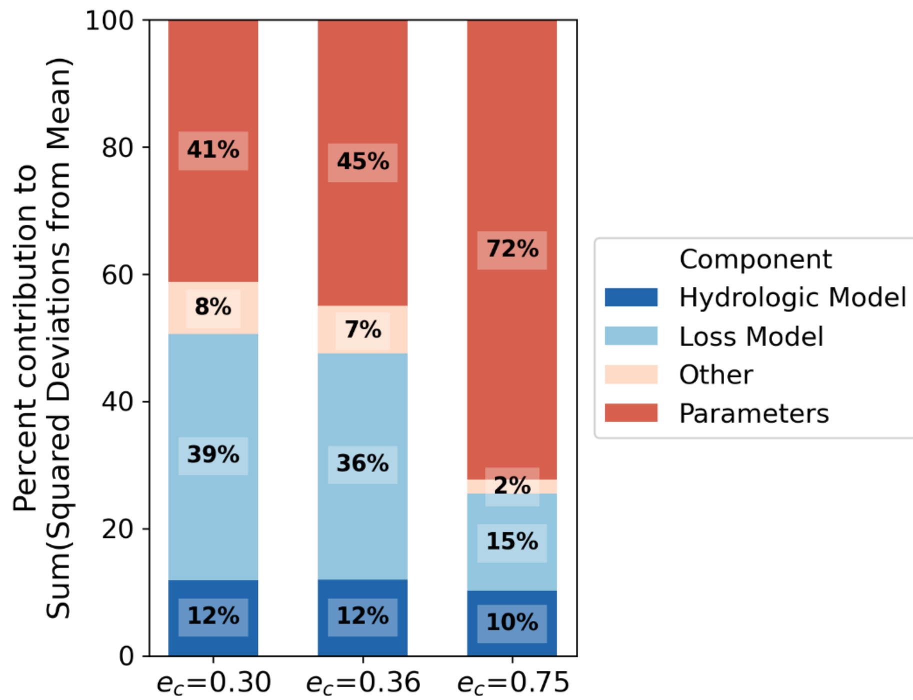

Figure 8: Relative contribution of each source of uncertainty to the overall prediction uncertainty in different scenarios

The ANOVA results show (not in the figure 8) that the total amount of uncertainty in the prediction of water savings increases as the irrigation technology improves. The total sum of squared deviations from the mean increases from ~27 in the 30% scenario to ~150 in the 36% scenario; at the 75% efficiency scenario, the sum of squared deviation is about 7000. Figure 8 shows relative contributions of uncertainty from the three modeling choices considered. The predominant source of uncertainty is the selected parameter set. This remains constant as the modeled irrigation technology improves - albeit with changing relative contributions from the three factors considered in this study. In all scenarios, the parameter sets contribute the most to the uncertainty of the predictions of water savings, and the contribution increases with increasing efficiency. The next most important source of variation in the results is the convention of the loss model to apply. Variance in the results due to the loss model decreased from ~39% (in the low-efficiency scenario) to ~15% (in the high-efficiency scenario). The relative contribution to the total uncertainty from the choice of hydrologic model is relatively constant (at ~ 11%) across the scenarios. While this is non-trivial, the choice of the hydrologic model is not a major source of uncertainty. Other interactions between the choices of hydrologic model and non-beneficial loss representation contribute some uncertainty (~7.5%) in the modest scenarios. However, the uncertainty from these other sources is negligible (~2%) in the demonstrative scenario. This low contribution from the hydrologic model structure may be an artefact of the decision by the authors to select three structures from the host of available hydrologic models. It is possible that an experiment considering more hydrologic model structures could show a larger contribution to total uncertainty from the choice of hydrologic model.

4 Discussion

The experiments in this study were designed to provide an ensemble of predictions of water savings given a set of modeling choices. Here we explore some of the implications of the findings: (1) the effects of model choices on water savings predictions (2) limitations of the study, and (3) relevance of the findings.

4.1 The Effects of Model Choices on Predictions

The first finding of interest is the substantial uncertainty of the predictions of water savings due to the choice to apply non-beneficial losses either on the withdrawn irrigation water (i.e., before hydrologic partitioning) or on the computed runoff (i.e., after the hydrologic partitioning). Uncertainty in hydrologic predictions stemming from model choices is commonplace in the literature. However, for predicting water savings, no studies have investigated either the effects of alternative hydrologic model structures and parameters or the effects of alternative conventions to represent non-beneficial losses. Few studies have started to investigate details in the representation of irrigation sources and application technology and their implications for irrigation modeling. For example, Leng et al. (2017) studied the effects of representing alternative water sources. Their findings show that the careful consideration of alternative water sources can account for a source of substantial uncertainties in predicting hydrologic variables in locations of heavy irrigation. Their finding that the representation of an irrigation process accounts for substantial model uncertainty is similar to the finding from this study. However, they do not account for alternative model representations of the application technologies. A reason for the large effect of the convention to represent non-beneficial losses is the non-linearities in the hydrologic models. Hydrologic models partition soil water into runoff and evapotranspiration based on the quantity of soil moisture available in the soil. This means that any convention that systematically alters the quantity of soil moisture will create large effects in the resulting predictions.

The representation of non-beneficial losses influences model predictions more than the hydrologic model used to partition the soil moisture. More interesting is that the uncertainty from the non-beneficial loss representations is almost as important as model parameters, especially for modest changes in irrigation technology. This is an interesting finding because while we use 100 equifinal parameters in the experiment, we have just investigated two approaches to represent non-beneficial losses. It is possible that there are many more ways to represent this non-beneficial loss process. For example, in this study, we assumed that all evapotranspiration from irrigated areas is beneficial. This is not necessarily the case. Other assumptions of the delineation of beneficial vs non-beneficial evapotranspiration that occurs on irrigated areas are possible (for example, see Malek et. al. (2017), where non-beneficial evaporation from irrigated areas is represented as a direct modification of the evaporation process within the VIC hydrologic model itself). In this study, rather than endogenize non-beneficial losses within the hydrologic model itself, we compute non-beneficial losses exogenously from the hydrologic model. This experimental decision possibly constrains the range of water savings due to alternative non-beneficial loss representations. It is possible that considering more increases the contribution of the loss model to the total uncertainty. Also, this finding is interesting because it suggests that studies that predict hydrologic variables in locations of heavy irrigation need to think carefully not only about the hydrologic model (and its parameters), but also about the numerical representation of other irrigation induced hydrologic processes such as non-beneficial losses. A point to note is that even the two conventions of non-beneficial losses adopted in this study are members on a spectrum of possible representations of non-beneficial losses. Non-beneficial losses do occur before, during, and after irrigation water is delivered to the soil. This means that this experiment explores but a portion of the minimum range of uncertainty that can arise from these stylized representations of these non-beneficial losses. This study considers losses applied strictly before and after hydrologic partitioning. The hydrologic interactions that occur under a systematic combination of a more comprehensive set of representations remains a point for future investigations.

4.2 Limitations of the study

While this study is useful to outline the implications for methodological choices in irrigation research, a host of factors limit the utility of the findings. One of such limitations is the experimental design that used entire model structures as experimental factors. It is well known that the complexity of hydrologic models prevents controlled comparisons (Clark et al., 2015). For this reason, multiple studies have focused on designing modular hydrologic frameworks that are useful for controlled experiments (Clark et al., 2008, 2015). In this study, it is thus difficult to isolate the effects of different specific processes that contribute to the component of hydrologic model structural uncertainty. The uncertainty from the hydrologic models cannot be apportioned in a controlled manner into its alternative components, and therefore, we cannot really attribute the differences in the hydrologic predictions - such as the shapes of the different hydrographs (see figure 5), and the differences in hydrologic partitioning (see figure 3) - to any internal process of the models.

Nevertheless, a few studies, such as Herman et al. (2013), have investigated the differences in the same three models used in this study. Herman et al. (2013) show that the predicted streamflow is strongly sensitive at different time periods to different parameters. Different combinations of parameters dominate the variation in streamflow predictions for different types of climate conditions. For example, of the three selected models, the SACSMA model is the most complicated (with the most parameter combinations and equations). This is probably not unrelated to the finding that the difference in predicted averages across non-beneficial losses is the widest, especially for scenarios with modest improvements. While a full investigation of model sensitivity to individual parameters is beyond the scope of this work, it is noteworthy to recognize that Herman et. al. (2013) focus on unimpaired hydrologic basins. It is likely that sets of parameter combinations different to those identified by Herman et. al. (2013) are at play in the hydrologic conditions in the study location (Weru-Weru) - a basin heavily influenced by anthropogenic processes such as irrigation. However, verification of such parameter combinations requires that the parameters themselves are well specified to capture the hydrologic response to anthropogenic activity such as irrigation.

This leads to another limitation of this study: the calibration of the model parameters without specific information on the specific predicted metric - water savings under irrigation technology. The absence of such information is common in the literature; thus, this study focuses on an exploration of a wide range of model structural and parametric uncertainty. This study specified the changes in streamflow, by calibrating to available information for high flows (NSE) and low flows (log-NSE), and then selecting a wide range of parameters. However, the calibration process did not consider a host of other relevant processes that are relevant for irrigation. For example, Pool et al. (2021) use spatially aggregated metrics related to evaporation, groundwater, and soil moisture to calibrate their model. A testament to the difficulty of using such information is their reliance on “expert knowledge”, and short records for calibration. Calibrating hydrologic models that include representations of human activities is incredibly difficult (Condon & Maxwell, 2014; O’Keeffe et al., 2018; Pool et al., 2021; Xu et al., 2019). This is partly because the hydrologic response to human activities is difficult to isolate from the hydrologic response to other environmental effects, and observations are scarce. This study used long observations of runoff available from local partners and optimized two metrics (NSE and log-NSE) related to streamflow prediction. The use of a stochastic multi-objective evolutionary algorithm to calibrate the parameters guaranteed a spread of parameter sets that can reasonably cover the space of hydrologic behaviors.

4.3 Relevance of the study

Despite the limitations of the study, the results take initial steps to a long articulated challenge in irrigation research - the quantification of hydrologic uncertainty in irrigation-relevant predictions (Grafton et al., 2018). This is especially important in the context of low-income countries such as Tanzania, where wrong estimates of water savings have the potential to lead to wasted funds in a society that can ill afford such. Indeed, reliable predictions (reported alongside associated uncertainties) are useful for planning and decision making. This study highlights some important considerations for modeling efforts to predict the hydrologic response to irrigation technology.

In addition to the practical relevance of this study, it improves the understanding of hydrologic predictions in locations that are heavily dominated by human activities. Understanding the hydrologic model parameter sensitivity to anthropogenic induced change is a potential next step for this study. Furthermore, most of the studies that represent irrigation technology in terms of its effects on non-beneficial losses do so with the convention that represents losses on the withdrawn quantity (i.e. before the hydrologic model) (Jägermeyr et al., 2015; Rost et al., 2008; Roth et al., 2014; Siderius et al., 2020). Much fewer studies represent non-beneficial losses after the partitioning (Huffaker & Whittlesey, 2000, 2003). This study has shown that the representation of non-beneficial losses is one significant choice in the prediction of water savings. That model choices influence model predictions is not a new finding. However, given an improved understanding of important factors that influence, researchers can use the findings from here to begin investigations into other factors that influence hydrologic responses in basins that are under human activity.

5 Conclusion

This study presents the first multifactorial exploration of the uncertainty in hydrologic prediction of water savings. Specifically, the experiment focuses on three important factors: (1) the choice of hydrologic model used to partition irrigation water on-farm soil, (2) the equifinal set of parameters, and (3) the representation of non-beneficial losses.

The results show that the prediction of water savings is highly sensitive to the parameters and the representation of non-beneficial losses. This is a new finding in the scientific literature covering the computational prediction of irrigation water savings. The study also partitions the total uncertainty into specific portions and attributes these portions to the specific factors in question. In regions where observations are scarce, a multi-model, multi-factor exploration, as performed in this study can help to outline the minimum range of uncertainty.

This study could be extended in a few ways: one way can focus on a detailed study of the hydrologic sensitivity, using a modular framework. This will help to clarify some of the missing intuition regarding the hydrologic model as a source of uncertainty. Another extension can focus on how such model uncertainty propagates in a decision-making framework. For example, if alternate predictions of water savings could lead to different economic investment decisions. Much has been written about the uncertainty of irrigation investment decisions to future changes, and other behavioral and socioeconomic uncertainties that are relatively exogenous to the water system and the representations of it. Studies that investigate investment decisions under severe model uncertainty are rare (Brown et al., 2015; Herman et al., 2019).

To conclude, this study demonstrates the need to take seriously the pervasiveness of severe model uncertainty in current representations of water systems. Loucks' remark that "*... we do not understand sufficiently the multiple interdependent physical … and political (human) processes that govern the [water system's] behavior …*" (Loucks, 1992) still holds true. Thus, it behooves researchers and investors engaged in designing irrigation systems for societal benefit to think carefully about the ways we can properly account for this uncertainty whilst making decisions.

6 References

Addor, N., & Melsen, L. A. (2019). Legacy, Rather Than Adequacy, Drives the Selection of Hydrological Models. *Water Resources Research*, *55*(1), 378–390. https://doi.org/10.1029/2018WR022958

Ahmadzadeh, H., Morid, S., Delavar, M., & Srinivasan, R. (2016). Using the SWAT model to assess the impacts of changing irrigation from surface to pressurized systems on water productivity and water saving in the Zarrineh Rud catchment. *Agricultural Water Management*, *175*, 15–28. https://doi.org/10.1016/j.agwat.2015.10.026

Alliaume, F., Rossing, W. A. H., Tittonell, P., & Dogliotti, S. (2017). Modelling soil tillage and mulching effects on soil water dynamics in raised-bed vegetable rotations. *European Journal of Agronomy*, *82*, 268–281. https://doi.org/10.1016/j.eja.2016.08.011

Andresen, C. G., Lawrence, D. M., Wilson, C. J., McGuire, A. D., Koven, C., Schaefer, K., et al. (2020). Soil moisture and hydrology projections of the permafrost region – a model intercomparison. *The Cryosphere*, *14*(2), 445–459. https://doi.org/10.5194/tc-14-445-2020

Assefa, T., Jha, M., Reyes, M., & Worqlul, A. W. (2018). Modeling the Impacts of Conservation Agriculture with a Drip Irrigation System on the Hydrology and Water Management in Sub-Saharan Africa. *Sustainability*, *10*(12), 4763. https://doi.org/10.3390/su10124763

Belder, P., Bouman, B. A. M., & Spiertz, J. H. J. (2007). Exploring options for water savings in lowland rice using a modelling approach. *Agricultural Systems*, *92*(1), 91–114. https://doi.org/10.1016/j.agsy.2006.03.001

Berbel, J., & Mateos, L. (2014). Does investment in irrigation technology necessarily generate rebound effects? A simulation analysis based on an agro-economic model. *Agricultural Systems*, *128*, 25–34. https://doi.org/10.1016/j.agsy.2014.04.002

Berbel, Julio, Gutiérrez-Martín, C., Rodríguez-Díaz, J. A., Camacho, E., & Montesinos, P. (2015). Literature Review on Rebound Effect of Water Saving Measures and Analysis of a Spanish Case Study. *Water Resources Management*, *29*(3), 663–678. https://doi.org/10.1007/s11269-014-0839-0

Berbel, Julio, Gutiérrez-Martín, C., & Expósito, A. (2018). Impacts of irrigation efficiency improvement on water use, water consumption and response to water price at field level. *Agricultural Water Management*, *203*, 423–429. https://doi.org/10.1016/j.agwat.2018.02.026

Bergström, S., & Singh, V. (1995). Computer models of watershed hydrology. *The HBV Model*, 443–76.

Beven, K. (1993). Prophecy, reality and uncertainty in distributed hydrological modelling. *Advances in Water Resources*, *16*(1), 41–51. https://doi.org/10.1016/0309-1708(93)90028-E

Beven, K. (2006). A manifesto for the equifinality thesis. *Journal of Hydrology*, *320*(1), 18–36. https://doi.org/10.1016/j.jhydrol.2005.07.007

Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagona, E. A., Ostfeld, A., et al. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resources Research*, *51*(8), 6110–6124.

Chukalla, A. D., Krol, M. S., & Hoekstra, A. Y. (2015). Green and blue water footprint reduction in irrigated agriculture: effect of irrigation techniques, irrigation strategies and mulching. *Hydrology and Earth System Sciences*, *19*(12), 4877–4891. https://doi.org/10.5194/hess-19-4877-2015

Clark, M. P., Slater, A. G., Rupp, D. E., Woods, R. A., Vrugt, J. A., Gupta, H. V., et al. (2008). Framework for Understanding Structural Errors (FUSE): A modular framework to diagnose differences between hydrological models. *Water Resources Research*, *44*(12). https://doi.org/10.1029/2007WR006735

Clark, M. P., Nijssen, B., Lundquist, J. D., Kavetski, D., Rupp, D. E., Woods, R. A., et al. (2015). A unified approach for process-based hydrologic modeling: 1. Modeling concept. *Water Resources Research*, *51*(4), 2498–2514.

Condon, L. E., & Maxwell, R. M. (2014). Feedbacks between managed irrigation and water availability: Diagnosing temporal and spatial patterns using an integrated hydrologic model. *Water Resources Research*, *50*(3), 2600–2616.

Droogers, P., Bastiaanssen, W. G. M., Beyazgül, M., Kayam, Y., Kite, G. W., & Murray-Rust, H. (2000). Distributed agro-hydrological modeling of an irrigation system in western Turkey. *Agricultural Water Management*, *43*(2), 183–202. https://doi.org/10.1016/S0378-3774(99)00055-4

Duan, Q., Gupta, H. V., Sorooshian, S., Rousseau, A. N., & Turcotte, R. (2004). *Calibration of watershed models.* American Geophysical Union.

Efstratiadis, A., & Koutsoyiannis, D. (2010). One decade of multi-objective calibration approaches in hydrological modelling: a review. *Hydrological Sciences Journal*, *55*(1), 58–78. https://doi.org/10.1080/02626660903526292

Filipović, V., Romić, D., Romić, M., Borošić, J., Filipović, L., Mallmann, F. J. K., & Robinson, D. A. (2016). Plastic mulch and nitrogen fertigation in growing vegetables modify soil temperature, water and nitrate dynamics: Experimental results and a modeling study.

Agricultural Water Management, *176*, 100–110. https://doi.org/10.1016/j.agwat.2016.04.020

Flyvbjerg, B. (2008). Curbing Optimism Bias and Strategic Misrepresentation in Planning: Reference Class Forecasting in Practice. *European Planning Studies*, *16*(1), 3–21. https://doi.org/10.1080/09654310701747936

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., et al. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, *2*(1), 150066. https://doi.org/10.1038/sdata.2015.66

Grafton, R. Q., Williams, J., Perry, C. J., Molle, F., Ringler, C., Steduto, P., et al. (2018). The paradox of irrigation efficiency. *Science*, *361*(6404), 748–750.

Greve, P., Kahil, T., Mochizuki, J., Schinko, T., Satoh, Y., Burek, P., et al. (2018). Global assessment of water challenges under uncertainty in water scarcity projections. *Nature Sustainability*, *1*(9), 486.

Hadka, D., & Reed, P. (2013). Borg: An auto-adaptive many-objective evolutionary computing framework. *Evolutionary Computation*, *21*(2), 231–259.

Han, P.-F., Istanbulluoglu, E., Wan, L., & Wang, X.-S. (2021). A new hydrologic sensitivity framework of unsteady-state responses to climate change and its application to catchments with croplands in Illinois. *Water Resources Research*, *n/a*(n/a), e2020WR027762. https://doi.org/10.1029/2020WR027762

Hanson, B. R., Schwankl, L. J., Schulbach, K. F., & Pettygrove, G. S. (1997). A comparison of furrow, surface drip, and subsurface drip irrigation on lettuce yield and applied water. *Agricultural Water Management*, *33*(2), 139–157. https://doi.org/10.1016/S0378-3774(96)01289-9

Herman, J. D., Reed, P. M., & Wagener, T. (2013). Time-varying sensitivity analysis clarifies the effects of watershed model formulation on model behavior. *Water Resources Research*, *49*(3), 1400–1414. https://doi.org/10.1002/wrcr.20124

Herman, Jonathan D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2019). Climate adaptation as a control problem: Review and perspectives on dynamic water resources planning under uncertainty. *Water Resources Research*, e24389.

Hipel, K. W., Fang, L., Cullmann, J., & Bristow, M. (Eds.). (2015). Paying to conserve watershed services in Pangani river basin, Tanzania. In *Conflict Resolution in Water Resources and Environmental Management*. Springer International Publishing. https://doi.org/10.1007/978-3-319-14215-9

Huffaker, R. (2008). Conservation potential of agricultural water conservation subsidies. *Water Resources Research*, *44*(7). https://doi.org/10.1029/2007WR006183

Huffaker, R., & Whittlesey, N. (2000). The allocative efficiency and conservation potential of water laws encouraging investments in on-farm irrigation technology. *Agricultural Economics*, *24*(1), 47–60. https://doi.org/10.1111/j.1574-0862.2000.tb00092.x

Huffaker, R., & Whittlesey, N. (2003). A Theoretical Analysis of Economic Incentive Policies Encouraging Agricultural Water Conservation. *International Journal of Water Resources Development*, *19*(1), 37–53. https://doi.org/10.1080/713672724

Huffaker, R. G., & Whittlesey, N. K. (1995). Agricultural Water Conservation Legislation: Will It Save Water? *Choices: The Magazine of Food, Farm, and Resource Issues*, *10*(4). Retrieved from https://econpapers.repec.org/article/agsaaeach/131316.htm

IFPRI. (2016). *New Directions for Irrigation Development in Tanzania | IFPRI : International Food Policy Research Institute*. Retrieved from https://www.ifpri.org/event/new-directions-irrigation-development-tanzania

Jägermeyr, J., Gerten, D., Heinke, J., Schaphoff, S., Kummu, M., & Lucht, W. (2015). Water savings potentials of irrigation systems: global simulation of processes and linkages. *Hydrology and Earth System Sciences*, *19*(7), 3073–3091. https://doi.org/10.5194/hess-19-3073-2015

Jarvis, A. (2008). Hole-field seamless SRTM data, International Centre for Tropical Agriculture (CIAT). *Http://Srtm. Csi. Cgiar. Org*.

Jayathilake, D. I., & Smith, T. (2020). Understanding the role of hydrologic model structures on evapotranspiration-driven sensitivity. *Hydrological Sciences Journal*, *65*(9), 1474–1489. https://doi.org/10.1080/02626667.2020.1754421

Jiang, Y., Xu, X., Huang, Q., Huo, Z., & Huang, G. (2015). Assessment of irrigation performance and water productivity in irrigated areas of the middle Heihe River basin using a distributed agro-hydrological model. *Agricultural Water Management*, *147*, 67–81. https://doi.org/10.1016/j.agwat.2014.08.003

Khan, S., & Abbas, A. (2007). Upscaling water savings from farm to irrigation system level using GIS-based agro-hydrological modelling. *Irrigation and Drainage*, *56*(1), 29–42. https://doi.org/10.1002/ird.284

Knoben, W. J. M., Freer, J. E., Fowler, K. J. A., Peel, M. C., & Woods, R. A. (2019). Modular Assessment of Rainfall–Runoff Models Toolbox (MARRMoT) v1.2: an open-source, extendable framework providing implementations of 46 conceptual hydrologic models as continuous state-space formulations. *Geoscientific Model Development*, *12*(6), 2463–2480. https://doi.org/10.5194/gmd-12-2463-2019

Kollet, S., Sulis, M., Maxwell, R. M., Paniconi, C., Putti, M., Bertoldi, G., et al. (2017). The integrated hydrologic model intercomparison project, IH-MIP2: A second set of benchmark results to diagnose integrated hydrology and feedbacks. *Water Resources Research*, *53*(1), 867–890. https://doi.org/10.1002/2016WR019191

Komakech, H., van Koppen, B., Mahoo, H., & van der Zaag, P. (2011). Pangani River Basin over time and space: On the interface of local and basin level responses. *Agricultural Water Management*, *98*(11), 1740–1751. https://doi.org/10.1016/j.agwat.2010.06.011

Komakech, H. C. (2018). Differentiated Access: Challenges of Equitable and Sustainable Groundwater Exploitation in Tanzania, *11*(3), 15.

Komakech, H. C., & Condon, M. (2012). The role of statutory and local rules in allocating water between large- and small-scale irrigators in an African river catchment, 11.

van Koppen, B., Tarimo, A., van Eden, A., Manzungu, E., & Sumuni, P. (2016). Winners and losers of IWRM [Integrated Water Resources Management] in Tanzania. *Water Alternatives*, *9*(3), 588–607.

Lalika, M. C. S., Meire, P., & Ngaga, Y. M. (2015). Exploring watershed conservation and water governance along Pangani River Basin, Tanzania. *Land Use Policy*, *48*, 351–361. https://doi.org/10.1016/j.landusepol.2015.06.010

Lalika, M. C. S., Meire, P., Ngaga, Y. M., & Chang'a, L. (2015). Understanding watershed dynamics and impacts of climate change and variability in the Pangani River Basin, Tanzania. *Ecohydrology & Hydrobiology*, *15*(1), 26–38. https://doi.org/10.1016/j.ecohyd.2014.11.002

Lalika, M. C. S., Meire, P., Ngaga, Y. M., & Sanga, G. J. (2017). Willingness to pay for watershed conservation: are we applying the right paradigm? *Ecohydrology & Hydrobiology*, *17*(1), 33–45. https://doi.org/10.1016/j.ecohyd.2016.12.004

Lankford, B. (2004). Irrigation improvement projects in Tanzania; scale impacts and policy implications. *Water Policy*, *6*(2), 89–102.

Lankford, B. (2012). Fictions, fractions, factorials and fractures; on the framing of irrigation efficiency. *Agricultural Water Management*, *108*, 27–38. https://doi.org/10.1016/j.agwat.2011.08.010

Lankford, B., Koppen, B. van, Franks, T., & Mahoo, H. (2004). Entrenched views or insufficient science?: Contested causes and solutions of water allocation; insights from the Great Ruaha River Basin, Tanzania. *Agricultural Water Management*, *69*(2), 135–153.

Lein, H., & Tagseth, M. (2009). Tanzanian water policy reforms—between principles and practical applications. *Water Policy*, *11*(2), 203–220. https://doi.org/10.2166/wp.2009.024

Leng, G., Leung, L. R., & Huang, M. (2017). Significant impacts of irrigation water sources and methods on modeling irrigation effects in the ACME Land Model. *Journal of Advances in Modeling Earth Systems*, *9*(3), 1665–1683. https://doi.org/10.1002/2016MS000885

Loucks, D. P. (1992). Water Resource Systems Models: Their Role in Planning. *Journal of Water Resources Planning and Management*, *118*(3), 214–223. https://doi.org/3(214)

Malek, K., Stöckle, C., Chinnayakanahalli, K., Nelson, R., Liu, M., Rajagopalan, K., et al. (2017). VIC-CropSyst-v2: A regional-scale modeling platform to simulate the nexus of climate, hydrology, cropping systems, and human decisions. *Geoscientific Model Development*, *10*(8).

Malek, K., Adam, J. C., Stöckle, C. O., & Peters, R. T. (2018). Climate change reduces water availability for agriculture by decreasing non-evaporative irrigation losses. *Journal of Hydrology*, *561*, 444–460. https://doi.org/10.1016/j.jhydrol.2017.11.046

Mateos, L. (2008). Identifying a new paradigm for assessing irrigation system performance. *Irrigation Science*, *27*(1), 25–34. https://doi.org/10.1007/s00271-008-0118-z

McCuen, R. H., Knight, Z., & Cutter, A. G. (2006). Evaluation of the Nash–Sutcliffe Efficiency Index. *Journal of Hydrologic Engineering*, *11*(6), 597–602. https://doi.org/10.1061/(ASCE)1084-0699(2006)11:6(597)

Melsen, L. A., Teuling, A. J., Torfs, P. J., Zappa, M., Mizukami, N., Mendoza, P. A., et al. (2019). Subjective modeling decisions can significantly impact the simulation of flood and drought events. *Journal of Hydrology*, *568*, 1093–1104.

Mendoza, P. A., Clark, M. P., Mizukami, N., Gutmann, E. D., Arnold, J. R., Brekke, L. D., & Rajagopalan, B. (2016). How do hydrologic modeling decisions affect the portrayal of climate change impacts? *Hydrological Processes*, *30*(7), 1071–1095. https://doi.org/10.1002/hyp.10684

Mohan, P. C. (2006). Tanzania - River Basin Management and Smallholder Irrigation Project. Retrieved from https://agris.fao.org/agris-search/search.do?recordID=US2014605544

Moore, R. (2007). The PDM rainfall-runoff model. *Hydrology and Earth System Sciences*, *11*(1), 483–499.

MoWLD. (2002). *National Water Policy*. Retrieved from http://www.tawasanet.or.tz/files/Tanzania%20water%20policy%20-%202002.pdf

Mwanuzi, F., & Mutabazi, A. (1993). A conceptual approach to water resources management for a catchment in Tanzania. *Tanzania Journal of Engineering and Technology*, *17*(2).

Najafi, M. R., Moradkhani, H., & Jung, I. W. (2011). Assessing the uncertainties of hydrologic model selection in climate change impact studies. *Hydrological Processes*, *25*(18), 2814–2826. https://doi.org/10.1002/hyp.8043

Narayanamoorthy, A. (2004). Drip irrigation in India: can it solve water scarcity? *Water Policy*, *6*(2), 117–130. https://doi.org/10.2166/wp.2004.0008

O'Keeffe, J., Moulds, S., Bergin, E., Brozović, N., Mijic, A., & Buytaert, W. (2018). Including Farmer Irrigation Behavior in a Sociohydrological Modeling Framework With Application in North India. *Water Resources Research*, *54*(7), 4849–4866. https://doi.org/10.1029/2018WR023038

Oreskes, N., Shrader-Frechette, K., & Belitz, K. (1994). Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. *Science*, *263*(5147), 641–646. https://doi.org/10.1126/science.263.5147.641

Ostrom, E., & Gardner, R. (1993). Coping with Asymmetries in the Commons: Self-Governing Irrigation Systems Can Work. *Journal of Economic Perspectives*, *7*(4), 93–112. https://doi.org/10.1257/jep.7.4.93

Pérez-Blanco, C. D., Hrast-Essenfelder, A., & Perry, C. (2020). Irrigation Technology and Water Conservation: A Review of the Theory and Evidence. *Review of Environmental Economics and Policy*, *14*(2), 216–239. https://doi.org/10.1093/reep/reaa004

Perry, C. (2007). Efficient irrigation; inefficient communication; flawed recommendations. *Irrigation and Drainage*, *56*(4), 367–378. https://doi.org/10.1002/ird.323

Perry, C. (2017). *Does improved irrigation technology save water?* (No. 57) (p. 57). FAO.

Polak, P., Nanes, B., & Adhikari, D. (1997). A Low Cost Drip Irrigation System for Small Farmers in Developing Countries1. *JAWRA Journal of the American Water Resources Association*, *33*(1), 119–124. https://doi.org/10.1111/j.1752-1688.1997.tb04088.x

Pool, S., Francés, F., Garcia-Prats, A., Puertes, C., Pulido-Velazquez, M., Sanchis-Ibor, C., et al. (2021). Hydrological modelling of the effect of the transition from flood to drip irrigation on groundwater recharge using multi-objective calibration. *Water Resources Research*, *n/a*(n/a), e2021WR029677. https://doi.org/10.1029/2021WR029677

Richter, B., & Orr, S. (2017). Chapter 16 - Water Budgets to Inform Sustainable Water Management. In A. C. Horne, J. A. Webb, M. J. Stewardson, B. Richter, & M. Acreman (Eds.), *Water for the Environment* (pp. 347–360). Academic Press. https://doi.org/10.1016/B978-0-12-803907-6.00016-4

Richter, B. D., Brown, J. D., DiBenedetto, R., Gorsky, A., Keenan, E., Madray, C., et al. (2017). Opportunities for saving and reallocating agricultural water to alleviate water scarcity. *Water Policy*, *19*(5), 886–907. http://dx.doi.org/10.2166/wp.2017.143

Rohde, R. A., & Hausfather, Z. (2020). The Berkeley Earth Land/Ocean Temperature Record. *Earth System Science Data*, *12*(4), 3469–3479. https://doi.org/10.5194/essd-12-3469-2020

Rost, S., Gerten, D., Bondeau, A., Lucht, W., Rohwer, J., & Schaphoff, S. (2008). Agricultural green and blue water consumption and its influence on the global water system. *Water Resources Research*, *44*(9).

Roth, G., Harris, G., Gillies, M., Montgomery, J., Wigginton, D., Roth, G., et al. (2014). Water-use efficiency and productivity trends in Australian irrigated cotton: a review. *Crop and Pasture Science*, *64*(12), 1033–1048. https://doi.org/10.1071/CP13315

Roy, T., Serrat-Capdevila, A., Gupta, H., & Valdes, J. (2017). A platform for probabilistic Multimodel and Multiproduct Streamflow Forecasting. *Water Resources Research*, *53*(1), 376–399. https://doi.org/10.1002/2016WR019752

Roy, T., Gupta, H. V., Serrat-Capdevila, A., & Valdes, J. B. (2017). Using satellite-based evapotranspiration estimates to improve the structure of a simple conceptual rainfall & runoff model. *Hydrology and Earth System Sciences*, *21*(2), 879–896. https://doi.org/10.5194/hess-21-879-2017

Santhi, C., Muttiah, R. S., Arnold, J. G., & Srinivasan, R. (2005). A GIS-based regional planning tool for irrigation demand assessment and savings using SWAT. *Transactions of the ASAE*, *48*(1), 137–147.

Scheierling, S. M., Young, R. A., & Cardon, G. E. (2006). Public subsidies for water-conserving irrigation investments: Hydrologic, agronomic, and economic assessment. *Water Resources Research*, *42*(3). https://doi.org/10.1029/2004WR003809

Schlef, K. E., Steinschneider, S., & Brown, C. M. (2018). Spatiotemporal impacts of climate and demand on water supply in the Apalachicola-Chattahoochee-Flint Basin. *Journal of Water Resources Planning and Management*, *144*(2), 05017020.

Seckler, D. W. (1996). *The New Era of Water Resources Management: From “dry” to “wet” Water Savings*. IWMI.

Sheridan, P., Smith, S., Brown, A., & Vosper, S. (2010). A simple height-based correction for temperature downscaling in complex terrain. *Meteorological Applications*, *17*(3), 329–339. https://doi.org/10.1002/met.177

Shibuo, Y., Jarsjö, J., & Destouni, G. (2007). Hydrological responses to climate change and irrigation in the Aral Sea drainage basin. *Geophysical Research Letters*, *34*(21). https://doi.org/10.1029/2007GL031465

Siderius, C., Biemans, H., Conway, D., Immerzeel, W. W., Jaegermeyr, J., Bashir, A., & Hellegers, P. J. G. J. (2020). Financial feasibility of water conservation in agriculture. *Earth and Space Science Open Archive ESSOAr*. http://dx.doi.org/10.1002/essoar.10503946.2

Sivanappan, R. K. (1994). Prospects of micro-irrigation in India. *Irrigation and Drainage Systems*, *8*(1), 49–58. https://doi.org/10.1007/BF00880798

Thornthwaite, C. W. (1948). An Approach toward a Rational Classification of Climate. *Geographical Review*, *38*(1), 55–94. https://doi.org/10.2307/210739

Törnqvist, R., & Jarsjö, J. (2012). Water Savings Through Improved Irrigation Techniques: Basin-Scale Quantification in Semi-Arid Environments. *Water Resources Management*, *26*(4), 949–962. https://doi.org/10.1007/s11269-011-9819-9

Veldkamp, T. I. E., Zhao, F., Ward, P. J., Moel, H. de, Aerts, J. C., Schmied, H. M., et al. (2018). Human impact parameterizations in global hydrological models improve estimates of monthly discharges and hydrological extremes: a multi-model validation study. *Environmental Research Letters*, *13*(5), 055008.

Ward, F. A., & Pulido-Velazquez, M. (2008). Water conservation in irrigation can increase water use. *Proceedings of the National Academy of Sciences*, *105*(47), 18215–18220.

Whateley, S., & Brown, C. (2016). Assessing the relative effects of emissions, climate means, and variability on large water supply systems. *Geophysical Research Letters, 43*(21), 11,329-11,338.

Williams, J., & Grafton, R. Q. (2019). Missing in action: possible effects of water recovery on stream and river flows in the Murray–Darling Basin, Australia. *Australasian Journal of Water Resources*, *23*(2), 78–87. https://doi.org/10.1080/13241583.2019.1579965

Xu, X., Jiang, Y., Liu, M., Huang, Q., & Huang, G. (2019). Modeling and assessing agro-hydrological processes and irrigation water saving in the middle Heihe River basin. *Agricultural Water Management*, *211*, 152–164. https://doi.org/10.1016/j.agwat.2018.09.033

Yang, Y. E., & Wi, S. (2018). Informing regional water-energy-food nexus with system analysis and interactive visualization: A case study in the Great Ruaha River of Tanzania. *Agricultural Water Management*, *196*, 75–86.

Zhang, L., Ma, Q., Zhao, Y., Wu, X., & Yu, W. (2019). Determining the influence of irrigation efficiency improvement on water use and consumption by conceptually considering hydrological pathways. *Agricultural Water Management*, *213*, 674–681. https://doi.org/10.1016/j.agwat.2018.11.016