ADAPTIVE AGRICULTURAL WATER RESOURCES MANAGEMENT IN A DESERT RIVER BASIN: INSIGHTS FROM HYDROLOGIC MODELING

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ADAPTIVE AGRICULTURAL WATER RESOURCES

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INSIGHTS FROM HYDROLOGIC MODELING

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Abstract: Many arid and semi-arid areas around the world are projected to experience increasing aridity levels throughout the 21st century. The increase in the frequency and severity of droughts and changing precipitation patterns will likely intensify the water shortages. The widening gap between water availability and demand in arid and semi-arid areas necessitates better understanding of water quantity and quality issues in these regions. The objectives of this dissertation are: (1) reviewing the challenges of applying Soil and Water Assessment Tool (SWAT) watershed hydrology and water quality model in arid/semi-arid regions with irrigated agriculture; (2) robust analysis of water availability in an example desert river basin under plausible future climate conditions; and (3) evaluating water and land management interventions for adaptive water resources management and agricultural water sustainability. The results show the possibility of dryer future and more saline water resources, increasing the risks of crop loss, especially for high-value crops like pecan. The current agricultural water management practices that support growing pecan orchards will be difficult to implement in the future due to growing water shortages. It is timely for agricultural producers to develop preparedness to use water with marginal quality or take action to reduce the net consumptive water use of their operations by improving agricultural water management. Changing the crop pattern and applying deficit irrigation for water intensive crops like alfalfa helps reduce the irrigation water consumption while growing more drought resistant crops such as pistachio and pomegranate could improve the resilience of agricultural producers to long-term droughts. Challenges of modeling agricultural watersheds in arid/semi-arid regions are addressed in this dissertation to provide a technical road map for watershed modelers interested in applying SWAT.

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CHAPTER I

INTRODUCTION

1. Background

Irrigated agriculture produces 40% of global food production and consumes more than 70% of water resources (Jägermeyr, et al., 2017; Word Bank, n.d.). It is estimated that agricultural land should expand significantly in order to feed the world's population in the future (Jägermeyr, et al., 2017). Sustainability of water resources in arid/semi-arid regions around the world is threatened by increasing water and food demands of the growing population and climate conditions (AghaKouchak et al., 2015; Tietjen et al., 2016). Impacts of irrigation water shortage on food security and economy of such regions necessitates detailed investigation of drought risks in future and adaptive planning and management to ensure sustainable water resources.

This dissertation offers a climate impact assessment methodology to characterize future water availability and examine the need for adaptation in a water-scarce river basin that supports irrigated agriculture. The study area is located in the desert-like climate of the southwest US in the US-Mexico border region. Agriculture in this region has faced the challenges of water quantity and quality in recent decades. Despite the general knowledge of future water stress challenges based on large scale synthesis (Cayan et al., 2010; Seager et al., 2013; Cook et al., 2015; Garfin et al., 2013; Dettinger et al., 2015), a robust analysis of future states of available water resources is critically needed to guide adaptive agricultural water management. This study provides a detailed analysis of plausible future climate conditions and water availability for agricultural activities and suggests possible options to mitigate the risks of droughts for crop production.

The Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) watershed hydrology and water quality model is used to simulate the impact of different climate scenarios and water conservation operations. The results can be used to initiate the water sustainability dialogue between the stakeholders in the watershed to optimize and secure future crop production under plausible risks of water shortage and salinization.

2. Objectives

The objectives of this dissertation are:

(1) Provide a thorough review of challenges and limitations of applying SWAT in arid/semi-arid regions with irrigated agriculture future application of the model;

(2) Conduct a robust analysis of water availability under plausible future climate conditions in the middle section of the Rio Grande Basin; and

(3) Analyze practical water and land management interventions for agricultural water sustainability in the study area under severe water shortage conditions.

3. Organization

This dissertation includes 5 chapters. Chapter I offers a general introduction of the dissertation and explains the objectives of the research. Chapter II provides the detailed review of literature on the application of SWAT in irrigated watersheds in arid/semi-arid regions, analyzes the challenges reported in the literature and suggests practical instructions for a reliable modeling in such watersheds. Chapter III studies the water availability and reliability of surface water and groundwater resources under plausible climate projections. Chapter IV investigates practical series of interventions in irrigated agriculture to conserve more water to adapt to a warm-dry future in the region. Chapter V summarizes the conclusion and suggests future works.

CHAPTER II

MODELING ARID/SEMI-ARID IRRIGATED AGRICULTURAL WATERSHEDS WITH SWAT: APPLICATIONS, CHALLENGES, AND SOLUTION STRATEGIES

1. Introduction

Irrigation is by far the largest single water user worldwide, accounting for more than 70% of total freshwater withdrawals in most regions of the world (Khokhar, 2017) in more than 300 million hectares of irrigated agricultural lands (Frenken and Gillet, 2012). Many arid/semi-arid irrigated agricultural watersheds around the world are projected to experience increasing aridity levels throughout the 21st century (e.g., Southwestern North America: Seager et al., 2007; Dettinger et al., 2015; Cook et al., 2015; Sub-Saharan Africa: Kotir, 2011; Middle East: Chenoweth et al., 2011; Central Asia: Lioubimtseva and Henebry, 2009; Southwest Australia: Silberstein et al., 2012). Increasing aridity causes concern about water sustainability, which is compounded with growing water demand due to socio-economic development and population growth in the face of hotter and drier climatic conditions (AghaKouchak et al., 2015). The increase in the frequency and duration of droughts and changing precipitation patterns will likely intensify surface water shortages (e.g., Tietjen et al., 2017; Mallakpour et al., 2018). Consequently, agricultural groundwater prospects are dire in arid/semi-arid regions in vast areas of the world (Gleeson et al., 2012; Amanambu et al., 2020) due to scarcity and variability of renewable water (Basso et al., 2013). As water availability diminishes, there is also a rising concern about deteriorating quality of available water resources (Parris, 2011) due to excessive sediment and nutrient pollution (US EPA, 2013) and salinity issues (Wurbs, 2002). The widening gap between water availability and demand necessitates better understanding of water quantity and quality issues in irrigated agricultural areas in arid/semi-arid climates.

Watershed models are used as a practical tool to investigate hydrological processes in agricultural lands of arid and semi-arid watersheds to improve our understanding of the watershed's response to irrigation and other agricultural management practices under changing climate (Singh and Woolhiser, 2002; Mirchi et al., 2010). Realistic representations of regional hydrologic fluxes, water management, and irrigation practices are a prerequisite for meaningful watershed modeling applications (Arnold et al., 2015), especially in agricultural regions where irrigated croplands are the dominant land use. Reproducing the hydrologic response of arid/semi-arid agricultural regions that face increasing aridity is particularly challenging due to complexities related to human interventions to modify the availability and flow of water in highly regulated irrigated watersheds. Model calibration in these watersheds can be a time consuming and costly process that involves expert judgment based on practical understanding of the regional hydrology, irrigation and agricultural management, quality data, and in some cases, good fortune to set up a representative model. A good model requires an accurate model setup with a reasonable level of data quality and quantity to represent most of the key watershed processes prior to calibration (Faramarzi et al., 2015). Once an accurate model is developed, minimum calibration is usually required to improve model performance, otherwise calibration will be challenging and subjective as the errors due to the lack of accurate model setup are counterbalanced with model parameters (Ahmadzadeh et al., 2016; Faramarzi et al., 2017; Marek et al., 2017). A "good" calibration requires identification of the parameters that govern the hydrological processes and their interactions within the given watershed (Kirchner, 2006; Abbaspour et al., 2015; Daggupati et al., 2015), and assigning them appropriate values, known as model parametrization (Malone et al., 2015). Application of irrigation to maximize crop production creates large inter- and intra-annual variations in water consumption, which in turn affects key components of the water budget (e.g., streamflow, ET, and groundwater recharge) in arid/semi-arid irrigated lands. Watershed models that are capable of representing these complexities offer an advantage when investigating hydrologic impacts of alternative climate and management scenarios.

The Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) is a widely applied public-domain semi-distributed, continuous-time watershed hydrology and water quality model (Gassman et al., 2007; Douglas-Mankin et al., 2010). It informs adaptive water management by facilitating quantitative analysis of different components of the water budget within a watershed. The model's ability to simulate hydrological processes under the impacts of water and land management practices, and different climate forcings has made it applicable in a wide variety of water resources studies. Some examples representing a latitudinal pattern of SWAT applications include high and low flows (Singh et al., 2005), floods and droughts (Ahn et al., 2018; Ammar et al., 2020), water quality (Abbaspour et al., 2007; Niraula et al., 2013; Abbaspour et al., 2015; Xu et al., 2016; Zarrineh et al., 2018; Du et al., 2020), irrigation (Srivastava et al., 2010; Xie et al., 2014; Ang and Oeurng, 2018), crop yield (Schierhorn et al., 2014; Wang et al., 2016; Heidari et al., 2019), climate impact assessment (Song and Zhang, 2012), water availability (Schuol et al., 2008; Ahn et al., 2018), and snow hydrology (Grusson et al., 2015), among others. SWAT has a global user community with an active technical support forum that facilitates its applications worldwide. The model delineates the watershed using a digital elevation model (DEM) of topography and divides it into Hydrologic Response Units (HRU) based on slope, land use/cover, and soil data (Fig. 2.1). Other primary inputs include available flow and water quality data, hydro-meteorological data, and selection of methods to model biophysical processes (e.g., potential ET and channel routing). Further, plant growth characteristics and options to introduce agricultural operations (application of fertilizers, pesticides, tillage, etc. listed under management data) are provided in various built-in databases that can be modified based on specific conditions of a given modeling application. Outputs can be reported in daily, monthly, and annual time scales for HRUs and sub-basins.

This paper offers a comprehensive review of SWAT applications in arid/semi-arid irrigated agricultural watersheds from 2000 to 2020. We provide an overview of different modeling applications in irrigated agricultural lands under the broad themes of water quantity, water quality and a combination of these themes, providing a sub-thematic

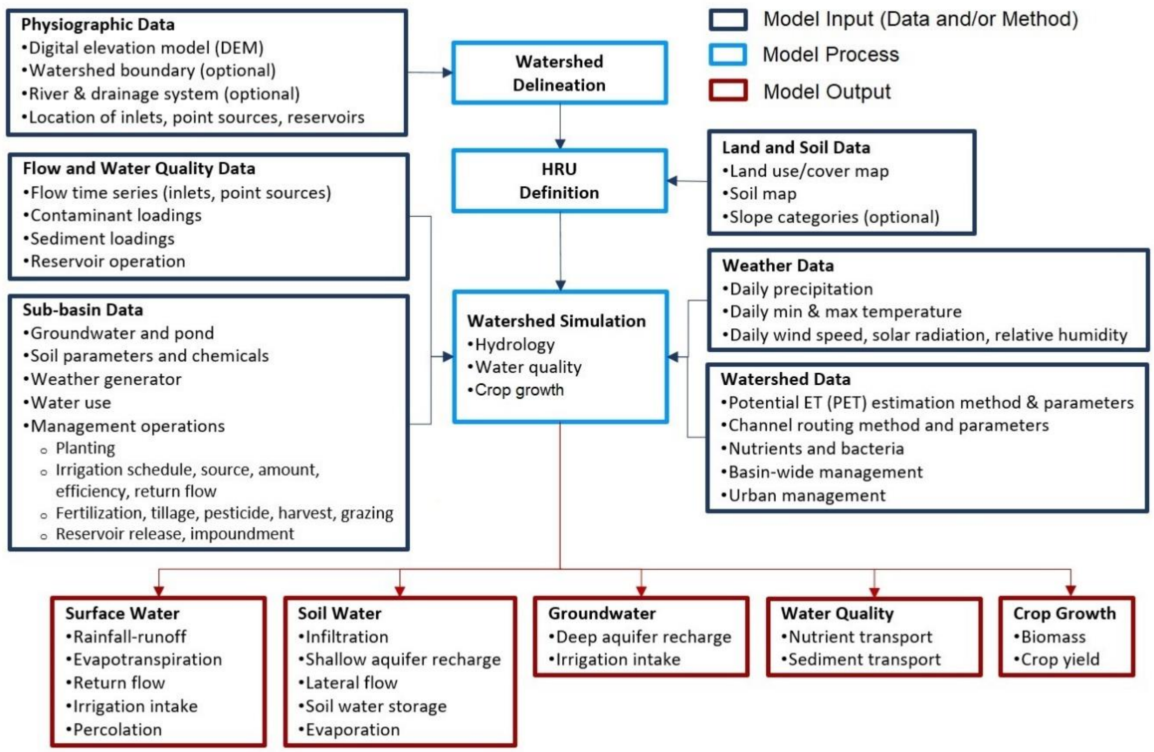


Figure 2.1. A general schematic of SWAT inputs (i.e., data and/or methods), processes, and outputs.

synthesis of the multitude of hydrologic and water resources problems investigated with SWAT. We highlight modeling challenges such as data availability and quality issues, accuracy of results, and limitations in agricultural dominated watersheds, where irrigation is the major water management practice that governs the water balance. Further, we present example approaches reported in the literature to address these challenges, providing a synthesis of SWAT parametrizations for heavily irrigated arid/semi-arid agricultural areas to inform model set-up and calibration in future modeling efforts. Finally, we provide a critical discussion of the reviewed SWAT applications, calibration strategies, interpretation of results, and a roadmap for future model advancements and applications to expand the utility of SWAT for addressing water and food security questions.

2. Article Selection Process for Literature Review

We reviewed SWAT applications to arid/semi-arid irrigated agricultural watersheds from among >3000 papers on SWAT published in the last two decades (2000-2020). Papers were selected for inclusion in this synthesis if they: (i) were published in peer-reviewed scientific journals; (ii) applied SWAT in arid and/or semi-arid climates; (iii) explicitly mentioned a focus on the simulation of agricultural watersheds; and (iv) took irrigation into account. As illustrated in Figure 2.2, the paper selection process began with a general online search and targeted search of "water and environmental science journals" and determining the climate type and presence of agricultural lands. Many papers did not mention the climate type, requiring checking the study area's precipitation and evaporation and other sources of climate information to determine aridity (e.g., Köppen climate classification map (Kottek et al., 2006)). We initially identified 160 papers based on the first three criteria but eventually narrowed down the selection to 102 papers that offered substantial discussions about irrigation modeling using SWAT. We subsequently classified the papers that were selected for detailed review based on the primary modeling theme, including (1) water quantity analysis, (2) water quality analysis, and (3) a combination of both water quantity and quality issues. We also synthesized the literature in terms of modeling challenges and solutions, calibration parameters, and model performance.

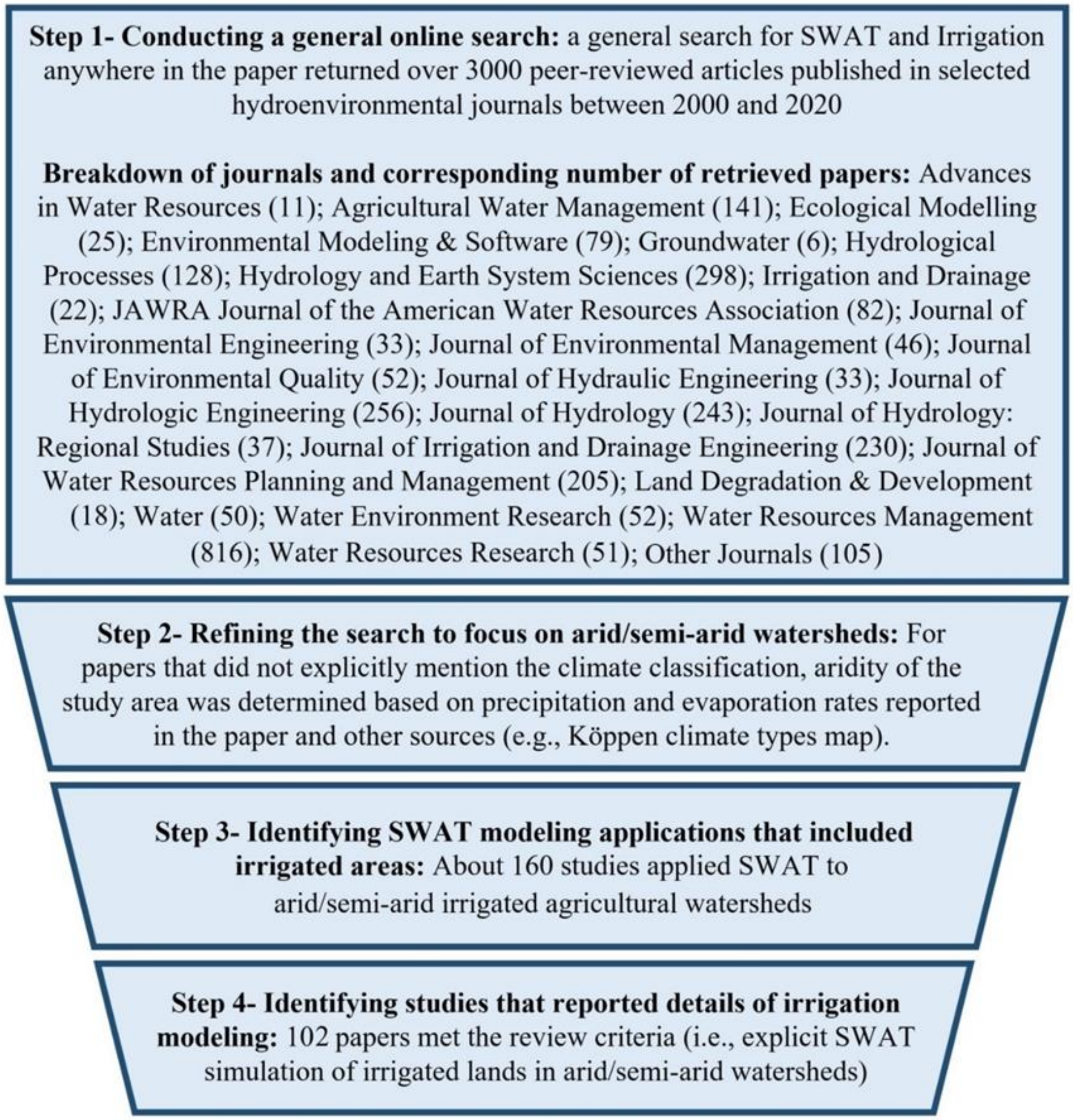


Figure 2.2. Selection of papers for inclusion in the literature review.

3. Applications of SWAT to Arid/Semi-Arid Irrigated Agricultural Watersheds

The reviewed SWAT arid/semi-arid irrigated agricultural watershed applications illustrate the global distribution and thematic foci of the selected studies (Fig. 2.3). The majority of the applications focused on water availability concerns, especially in East Asia, North America, and Middle East and North Africa (MENA). The second largest group of applications focused on a combination of water quantity and quality issues (e.g., MENA region, Europe, and North America). Only a few studies applied SWAT exclusively for water quality modeling of irrigated agricultural settings in arid/semi-arid regions (e.g., East Asia).

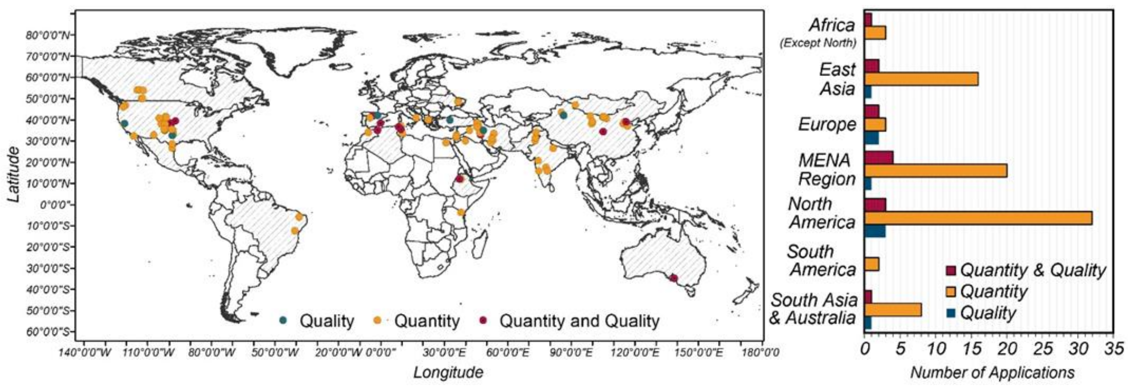


Figure 2.3. SWAT applications in arid/semi-arid irrigated agricultural regions in 24 countries, showing the global distribution and thematic foci of the selected studies.

SWAT applications that focused on various water quantity issues around the world are summarized in Table 2.1. A common SWAT application is to quantify the water budget components and examine the impacts of different watershed attributes (e.g., soil type and land use) on hydrologic processes under baseline business-as-usual conditions (Yu et al., 2011; Brouziyne et al., 2018; Aouissi et al., 2016; Tarawneh et al., 2016; Worqlul et al., 2018; Luan et al., 2018). SWAT has also been applied to investigate water availability (surface water and groundwater recharge) under demand growth (Perrin et al., 2012; Reshmidevi and Nagesh Kumar, 2014; Faramarzi et al., 2017; Chen et al., 2017 & 2018a; Luan et al., 2018), climate change (Van Liew and Garbrecht, 2003; Abbaspour et al., 2009; Awan and Ismaeel, 2014; Ronco et al., 2017; Naderi, 2020), adaptive management (Ahmadzadeh et al., 2016; Ahn et al., 2018; Chen et al., 2019b), mitigating groundwater depletion (Hu et al., 2010; Marek et al., 2017), and different combinations of these issues (Molina-Navarro et al., 2016; Jordan et al., 2018).

The model and its extensions have effectively facilitated the analysis of various water, land, and nutrient management practices (e.g., irrigation, cropping change, and fertilizer application) on water use and crop production at different scales. Examples include total annual irrigation water use in a large, transboundary basin (Cheema et al., 2014) and crop yield improvements through fertilization management to alleviate potential water conflicts due to the need to increase crop production by changing pasture to croplands in a harsh environment in Mongolia (Jordan et al., 2018). The SWAT-SSA model was developed for Sub-Saharan Africa to examine the potential for expanding "smallholder irrigation" farms in the region (Xie et al., 2014). SWAT-FARS (customized version of SWAT model for Fars region), showed water usage decrease by removing rice cultivation, and water usage increase by pressurized irrigation (Delavar et al., 2020). SWAT's auto-irrigation function has been applied to estimate optimum irrigation water demand irrespective of available water resources to quantify water scarcity (e.g., Mikosch et al., 2020). Masud et al. (2018) used SWAT simulated crop yield and crop water consumption to investigate impacts of climate change on water footprint.

Table 2.1. SWAT applications examining water quantity in arid/semi-arid agricultural watersheds.

Scope	Example application	Significant results	Country (Citation)
Baseline water management and hydrologic budget analysis	Improving simulation of irrigation methods/BMPs (e.g., SWAT-MAD)	Simulated BMPs improved water resources; accounting for irrigation return flows improved results; irrigation values differ by water	USA (Chen et al., 2018b); USA (Kannan et al., 2011); Australia (McInerney et al., 2018)
	Evaluating and improving SWAT performance using hard data (lysimeter, surface soil moisture)	Underestimated ET; Default LAI parameters might cause errors; Soil moisture and ET improved mostly for upper layers; streamflow and groundwater flow were unaffected.	USA (Marek et al., 2016); USA (Chen et al., 2011)
	SWAT/SWAT-MODFLOW calibration and validation in watersheds with more than one outlet, diverse crop patterns, etc.	Wet year data impacted parametrization more in two-way calibration-validation; land use-based ET improved calibration; model limits in "multiple domains" should be considered.	Canada (Rahbeh et al., 2011); Pakistan (Becker et al., 2019); USA (Acero Triana et al., 2019)
	Modeling surface water-groundwater interaction	Simulated daily groundwater table successfully; estimated seasonal recharge, shallow aquifer evaporation, and annual water budget; modified ET module improved modeling of interactions.	China (Luo and Sophocleous, 2011); Canada (Melaku and Wang, 2019)
	Modeling heavily managed watersheds; investigating sensitivity to soil characteristics; estimating water footprint of crop production.	Soil type and canal seepage impacted water balance and hydrology; scheduled manual irrigation improved flow simulations; detected streamflow decline and flow pattern change due to groundwater pumping and return flow; suggested ways to improve modeling LAI, crop yield and soil water; improved water yield and ET results by simulating crop yield at HRU level.	China (Wu et al., 2016); Ethiopia (Worqlul et al., 2018); Brazil (Santos et al., 2018); USA (Wei et al., 2018); USA (Zeng and Cai, 2014); China (Luo et al., 2008b); India (Abeysingha et al., 2015); China (Luan et al., 2018)
	Coupling or comparing SWAT with other models (MODFLOW, MODSIM, HYDRUS, etc.)	Using results of other models enhanced SWAT parametrization and simulations; increasing calibration parameters improved the coupled model's reliability; coupled SWAT-	Iran (Ashraf Vaghefi, et al., 2017); Jordan (Rahbeh et al., 2019); China (Zhang et al., 2016); USA (Sophocleous

Scope	Example application	Significant results	Country (Citation)
		MODFLOW simulated a complex water system, successfully.	and Perkins, 2000); USA (Aliyari et al., 2019)
Hydrologic impacts of demand	Preparing input data for a groundwater management plan.	SWAT results and field surveys were used to quantify surface water, aquifer recharge rate and water table fluctuations.	India (Perrin et al., 2012)
	Assessing surface water and	A model with managed reservoirs reproduced the distribution of river	China (Sun and Ren, 2013)
	Simulating water supply for different demands; analyzing the effects of simplifications and uncertainties; calculating "water provisions" in an ungauged basin.	Identified blue water scarcity sources and groundwater stressed areas; uncertainty sources included hydrological features, heterogeneity, conflicts of water-food-energy resources, and environmental flows.	Canada (Faramarzi et al., 2017); East Africa (Notter et al., 2012)
	Investigating the impacts of engineering structures, large dams, and land use	Major decline in available water occurred after building dams due to increased ET and infiltration, and water diversion for irrigation.	Iraq and Turkey (Jones et al., 2008)
Groundwater depletion mitigation	Evaluating options to improve groundwater	Proof-of-concept for stopping groundwater depletion with reduced	China (Hu et al., 2010)
	Evaluating impacts of agriculture water management on groundwater recharge; estimating natural and manmade recharges.	Water harvesting improved groundwater recharge while increasing ET and soil moisture; location of the structures was important; ET was the dominant hydrologic flux.	India (Garg and Wani, 2013)
	Optimizing irrigation for an important food production region with groundwater overexploitation problems	Identified optimal irrigation schedules based on crop yield and water productivity; quantified water conservation potential; determined trade-offs between limiting groundwater withdrawal to revive the	China (Sun and Ren, 2014); USA (Gayley, 2013); China (Zhang et al., 2018)

Scope	Example application	Significant results	Country (Citation)
	Modeling water use in different crop rotations in an area with declining groundwater table due	Reasonable simulation of irrigation water use and crop yield, except for cotton; adjusted crop database and auto-irrigation parameters.	USA (Marek et al., 2017)
Climate change impact assessment	Assessing climate change impacts on plant growth, hydrologic processes, limited water resources, and water balance; blue and green water resources and wheat yield in a benchmark river basin.	Scenarios of increased CO_2 and temperature decreased average ET and increased surface runoff, interflow, and streamflow; earlier plant growth changed timing of water demand and streamflow; water availability and related parameters (runoff ratio, recharge, etc.) decreased in most climate scenarios, mostly in agricultural parts or arid regions, albeit slightly in some cases; larger floods projected for some regions.	USA (Van Liew and Garbrecht, 2003); USA (Ficklin et al., 2009); Jordan (Hammouri et al., 2017); India (Reshmidevi et al., 2018); Italy (Ronco et al., 2017); Iran (Ashraf Vaghefi, et al., 2014); India, (Sahana and Timbadiya, 2020); Spain (Haro-Monteagudo et al., 2020); Canada Masud et al., 2018 & 2019)
	Simulating groundwater recharge, crop yield, and water productivity for different climates	Recharge increased with increased average rainfall; detected increased yield for most crops.	Pakistan (Awan and Ismaeel, 2014); China (Niu et al., 2018)
	Studying climate change impacts on irrigated and dryland crops using modified SWAT-MAD.	Agricultural ET, irrigation water, and crop yield fell at different rates with increased CO_2 emission; crop yield decline was mainly from reduced maturity period due to higher	USA (Chen et al., 2019a)
Coupled changes: climate, land use, and demand	Projecting future water availability and groundwater storage	Climate change may significantly reduce runoff, increasing water stress; all water budget components declined but ET.	Mexico (Molina-Navarro et al., 2016); Mongolia (Jordan et al., 2018); Iran (Andaryani et al., 2019a&b)
	Quantifying drivers of irrigation demand and developing water management plan	Quantified precise irrigation demand; climate change, planting scale and pattern had greatest impact on demand; total water demand increased even under efficient irrigation methods.	China (Zou et al., 2018)

Scope	Example application	Significant results	Country (Citation)
Adaptive agricultural water and land management	Studying the impacts and applicability of water conservation approaches and water harvesting systems; evaluating auto-irrigation function when simulating ET, water use, and crop	On-farm methods saved more water; water harvesting reliability was low and location-dependent; pressurized irrigation did not increase water storage or total flow due to reduced return flows and groundwater table decline; intra-annual variability of ET and groundwater recharge are related to irrigation, especially in dry years;	USA (Santhi et al., 2005); South Africa (Andersson et al.,2009); Tunisia (Ouessar et al., 2009); Iran (Ahmadzadeh et al., 2016); Greece (Panagopoulos et al., 2014); USA (Ahn et al., 2018); USA (Marek et al.,
	Assessing impacts of upstream water use.	Irrigating rain-fed farms has a larger impact on flow reduction than rainwater harvesting.	Iran (Masih et al., 2011)

Notable SWAT applications focusing on water quality issues and a combination of water quantity and quality issues are summarized in Tables 2.2 and 2.3, respectively. While modeling watershed hydrology processes is a precursor to applying SWAT for analyzing water quality problems, Table 2.2 provides example SWAT applications that focused on water quality simulations as the primary objective of the study. Water quality analysis applications were predominantly conducted to investigate the impacts of baseline water management and hydrologic budget analysis (Santhi et al., 2001& 2006; Luo et al., 2008a; Özcan et al., 2017), as well as water quality implications of future climate and land use scenarios (Records et al., 2014; Nguyen et al., 2017; Ba et al., 2020). On the national level, SWAT has been used as the backend model for web-based decision support tools such as Hydrologic and Water Quality System (HAWQS) to examine potential impacts of climate change on water quality (Srinivasan, 2019). Besides these themes, potential vulnerabilities to increased demand and climate change have been investigated using combined water quantity and quality applications of SWAT (Bouraoui et al., 2005; Setegn, et al., 2010; Zettam et al., 2017) with the ultimate goal of guiding watershed management. Typical water quality concerns included sediment and nutrients (Santhi et al., 2001 & 2006; Özcan et al., 2017), pesticides (Luo et al., 2008a), and daily nutrient transport patterns (Nguyen et al., 2017).

Table 2.2. SWAT applications focusing on water quality in arid/semi-arid agricultural settings.

Scope	Example application	Significant results	Country (Citation)
Baseline water management and hydrologic budget analysis	Evaluating different options to control pollution from dairy farm manure	Simulated flow, sediment, and nutrients to assess permitted discharge volume for wastewater treatment plants and population growth with fixed crop acreage; water quality can be improved while maintaining status quo economic condition.	USA (Santhi et al., 2001)
	Evaluating BMPs to manage non-point source pollution and sediment transport	Identified effective BMPs for sediment and nutrient loading. Management operations performed better at farm level than watershed scale. Erosion control reduced nitrogen	USA (Santhi et al., 2006)
	Simulating streamflow, sediment loads, and spatiotemporal distribution of common pesticide loads; simulating nitrate leaching in a	Obtained better streamflow results when irrigation source was outside the sub-basin; streamflow was most sensitive to runoff curve number (CN); pesticide load transfer was related to surface runoff and pesticide application; streamflow simulation errors cascaded to pesticide simulation; adjusting	USA (Luo et al., 2008a); Iran (Akhavan et al., 2010)
	Assessing the impact of irrigation return flows on nitrate loads	Estimated monthly and annual streamflow and nitrate concentration for subbasins.	Spain (Comín et al., 2014)
	Finding an effective BMP set to manage lake eutrophication	Selected a combination of fertilizer reduction, slope modification ("terracing"), and soil conservation ("no tillage"); detected no significant sediment and nutrients loads reduction.	Turkey (Özcan et al., 2017)
Coupled changes: climate, land use, and demand	Studying downstream impacts of prolonged drought and nutrient loads from upstream livestock grazing areas	Quantified nutrient loads and possibility of algal growth under current condition and combined future land use and climate change scenarios; Estimated current and future amounts of phosphate, nitrate and Chlorophyll-a	Australia (Nguyen, et al., 2017)
	Simulating non-point source pollution under different climate and agricultural management scenarios	Reduced streamflow would result in decreased irrigation water use and increased total nitrogen and phosphorus loads in drainage canals.	China (Ba et al., 2020)

Table 2.3. Studies examining both water quantity and quality in arid/semi-arid agricultural regions.

Scope	Example application	Significant results	Country (Citation)
Baseline water management and hydrologic budget analysis	Studying the impact of heavy irrigation on return flows and watershed water quality, especially diffuse phosphorous (P) pollution	SWAT-IRRIG improved irrigation simulations; selected BMPs based on farm profitability and surface water quality included optimum irrigation to decrease irrigation return flow, conservation tillage to reduce total suspended sediments, and reduced phosphorous application to decrease total phosphorous loads.	Spain (Dechmi et al., 2012; Dechmi and Skhiri, 2013)
	Investigating the impacts of soil and water conservation structures on water quantity and quality (sediment)	Quantified water balance using rainfall and irrigation data as well as model results; contour ridges (simulated as potholes) decreased runoff, river discharge, and sediment yield, while increasing groundwater recharge significantly (i.e., 50%)	Tunisia (Abouabdillah, et al., 2014)
	Modeling river water quantity and quality as one of Adelaide's drinking water sources	Calibrated a model of quantity and quality of the river flow; multi-site calibration was preferred for sediment and nutrient load while single-site calibration was appropriate for flow calibration.	Australia (Shrestha et al., 2016)
	Assessing the impact of new dam construction and land use change on drinking groundwater	Coupled SWAT-MODFLOW-MT3DMS quantified the concentration response to the changes and projected increasing salinity in drinking wells.	Iran (Ehtiat et. al., 2018)
	Assessing the ability of modified SWAT-AG in modeling agricultural watersheds with shallow groundwater tables	Successful simulation of soil water content, water table changes, salt movement in soil, crop growth, and water usage.	China (Xiong, et al., 2019)
Impacts of demand	Evaluating SWAT performance in predicting quantity and quality of water under different water resources management scenarios	Flow simulation was satisfactory but, overall, the simulation was not accurate due to a lack of rainfall data and reservoir operation information; The model predicted that increase in irrigated area would not deteriorate the water quality for drinking purposes.	Tunisia (Bouraoui et al., 2005)
Climate change impact assessment	Examining the deterioration of Lake Tana due to poor management and droughts.	Estimated water balance components for four rivers in a basin; groundwater was the major contributor to the basin's water yield.	Ethiopia (Setegn, et al., 2010)

Scope	Example application	Significant results	Country (Citation)
Coupled changes: climate, land use/cover, and demand	Evaluating the impact of climate change and human activities on hydrology and sediment yield.	DEM resolutions and delineation thresholds did not impact streamflow simulations, but the difference between sediment transport results was significant.	China (Li et al., 2013)
	Using SWAT, MODFLOW, and MT3DMS models to model groundwater, stream-aquifer interaction, and nitrate concentration.	Scenario-based modeling captured the impact of land use changes on recharge, pumping, and groundwater level; nitrate concentration in groundwater increased in all scenarios.	Spain (Pulido-Velazquez et al., 2015)
	Assessing the impact of reservoirs on water resources and sediment yield; estimating surface water components, and addressing the impacts of demand pressures and prolonged dry seasons	Estimated the contribution of each water resource; surface runoff and lateral flow contributed more to the flow; estimated average annual sediment load; reservoirs detained a large amount of water and sediment.	Algeria (Zettam et al., 2017)

The growing number of SWAT applications over the last 20 years have contributed to better understanding of various long-standing and trending agricultural water sustainability challenges under different drivers of change and associated implications for water and food security and environmental quality (e.g., possibility of algal growth). Papers that examined the impact of demand increase, climate change or different management operations, mainly, pointed to the possibility of declining water resources and deteriorating water quality such as increasing salinity issues in the future (e.g. Masih et al., 2011; Molina-Navarro et al., 2016; Hammouri et al., 2017; Nguyen, et al., 2017; Jordan et al., 2018; Zou et al., 2018; Masud et al., 2018&2019). In most cases, model-based analysis of water management practices (e.g., BMPs) showed positive impact on water quantity and quality, especially for on-farm methods such as long-term fallowing, dryland farming, early plant growth, conservation tillage, and reduced phosphorous application (e.g. Santhi et al., 2005&2006; Ficklin et al., 2009; Dechmi and Skhiri, 2013; Garg and Wani, 2013; Chen et al., 2017 & 2018a&b). Other methods such as crop replacement or increasing canal conveyance efficiency had less impact on water conservation (Santhi et al., 2005). The simulated management scenarios did not always render promising results (Özcan et al., 2017). For example, saving irrigation water led to decreased crop yield (Hu et al., 2010) or pressurized irrigation methods, despite increasing crop productivity, did not result in saving water for downstream lake (Ahmadzadeh, et al., 2016).

4. Modeling Challenges, Solutions, and Performance Evaluation

A number of challenges to simulate arid/semi-arid watersheds with highly regulated water resources systems prompted analysists to use a number of innovative approaches and practical techniques to accomplish their objectives (Table 2.4). The main reported modeling challenges are lack of data (Perrin et al., 2012; Faramarzi et al., 2017; Chen et al., 2017 & 2018a), poor data quality (Marek et al., 2017; Chen et al., 2017 & 2018a), concerns about simulation accuracy (Setegn, et al., 2010; Faramarzi et al., 2017; Marek et al., 2017), and technical limitations of the existing versions of the model (Santhi et al., 2005 & 2006; Perrin et al., 2012; Sun and Ren, 2014; Wu et al., 2016; Marek et al., 2017; Chen et al., 2017 & 2018a; Wei et al., 2018) despite numerous advancements of the model code in the last two decades.

Data issues are a classic challenge in watershed modeling applications. Data availability and quality are especially important for arid/semi-arid agricultural watersheds, which experience extreme hydrologic events (e.g., droughts and flash floods) and human impacts. Successful application of SWAT in such settings requires detailed information about management operations such as irrigation, fertilizer application, cultivation, harvest, and other agricultural operations (e.g., tillage), as well as good information about watershed attributes (curve number (CN), soil hydraulic conductivity, etc.). In a number of applications, SWAT's performance was improved through augmenting data availability by combining data from different sources with SWAT's existing databases (Van Liew and Garbrecht, 2003; Perrin, et al., 2012; Molina-Navarro et al., 2016; Yu et al., 2011; Bressiani, et al., 2015). SWAT's capability to fill missing data using weather generator, auto-irrigation, and auto-fertilization functions are frequently used to cope with data unavailability issues (Zeng and Cai, 2014; Aouissi et al., 2016; Faramarzi et al., 2017; Rahbeh et al., 2019). The main issue with using auto-irrigation and auto-fertilization is that these functions may not represent on-the-ground operations, significantly simplifying the actual conditions. The uncertainty of using auto-irrigation and auto-fertilization functions instead of actual fertilization or irrigation practices can be reduced by verifying the results against available field data (e.g. Masud et al., 2018; Ahn et al., 2018).

It is also common to use supplemental tools to estimate missing data and evaluate model performance (Luo et al., 2008a; Perrin, et al., 2012; Awan and Ismaeel, 2014; Nguyen, et al., 2017; Ehtiat et. al., 2018; Qiu et al., 2019; Aliyari et al., 2019), cross-examine data from different sources (Marek et al., 2017; Chen et al., 2017 & 2018a), or manipulate built-in databases and parameters to improve simulation of certain parameters (e.g., ET) in drylands (e.g., Marek et al., 2017). In some studies, modelers traded off the accuracy of simulation of some parameters for simplicity of application when those inferior results did not affect the major aim of the study (Setegn, et al., 2010; Perrin, et al., 2012; Marek et al., 2017).

Since SWAT is open source, an active community of model developers have continuously contributed to expanding the model's capabilities and improving process representations. This has been done by developing modular codes, tools, and algorithms, including model improvements to better represent agricultural operations in arid/semi-arid regions (Ouessar et al., 2009; Notter et al., 2012; Dechmi and Skhiri, 2013; Wei et al., 2018; Zhang et al., 2018). Examples of specific technical developments to improve SWAT performance in arid/semi-arid irrigated agricultural settings include adding crop rotation simulation capability (Marek et al., 2017), developing an algorithm to simulate managed allowed depletion (MAD) irrigation in SWAT's auto-irrigation function (Chen et al., 2018a), using the modified plant growth module of winter wheat to estimate crop yields (Sun and Ren, 2014), and SWAT-Salt to model the fate and transport of major salt ions which is a major concern in irrigated croplands using surface water or groundwater sources that are rich in total dissolved solids (Bailey et al., 2019). Furthermore, coupling SWAT with other models has allowed taking advantage of the strengths of different models. Notably, developing integration frameworks for linking SWAT with MODFLOW (Guzman et al., 2015a) or coupling them (Bailey et al., 2016) has facilitated the simulation of groundwater characteristics and surface water-groundwater dynamics in arid/semi-arid agricultural regions (e.g., Ehtiat et al., 2018).

Table 2.4. Example challenges of applying SWAT to arid/semi-arid agricultural watersheds and applied solutions.

Challenge	Solution	Example(s)
Unavailable or incomplete data	Using supplemental data sources and methods to estimate missing data	Estimating missing rainfall data from closest gauges using inverse distance weighting (Van Liew and Garbrecht, 2003); using meteorological data from the same station (Chen et al., 2017 & 2018a) or nearby stations (Perrin et al., 2012); calibrating aquifer recharge using field studies (Perrin et al., 2012); combining data from sparse rain gages with radar data (Yu et al., 2011); using linear regression to fill missing data (Molina-Navarro et al., 2016); approximating daily data from monthly averages (Jones et al., 2008); estimating groundwater pumping data from annual irrigated crop acreages (Zeng and Cai, 2014)
	Using SWAT to fill missing data	Applying auto-irrigation and auto-fertilization functions (Jordan et al., 2018, Chen et al., 2017 & 2018a; Özcan et al., 2017; Faramarzi et al., 2017; Ashraf Vaghefi, et al., 2017); Filling missing weather data using WXGEN weather generator (Aouissi et al., 2016)
	Using supplemental tools to estimate missing data or evaluate model performance	Estimating groundwater recharge for model calibration using a separate watershed scale groundwater balance model (Perrin et al., 2012); using Darcy's law to estimate lateral groundwater flow between subbasins and across the watershed (Perrin et al., 2012); estimating missing monthly sediment loads using USGS' ESTIMATOR program (Luo et al., 2008a); comparing SWAT-simulated ET values with the results of calibrated surface energy balance algorithm (SEBAL) (Awan and Ismaeel, 2014); using ET data from MODIS for calibration (Qiu et al., 2019)
Data quality	Cross-examination, quality assurance/control, and combining data	Checking climate data against comparable climate data, as well as lysimeter data (Marek et al., 2017; Chen et al., 2017 and 2018a); calibrating NOAA's Climate Forecast System Reanalysis (CFSR) precipitation based on local rainfall data and combining CFSR with local rain gauge data (Bressiani et al., 2015)
Inaccurate results*	Choosing methods that improve results	Muskingum routing method produced more accurate time to peak compared to variable storage coefficient method (Van Liew and Garbrecht, 2003)
	Using existing capabilities innovatively, practical techniques, or better data	Snow fall temperature adjustments improved calibration (Jones et al., 2008); applying additional auto-irrigation with zero water stress threshold during winter wheat's dormancy (Marek et al., 2017); separating subbasins with glaciers for spatially distributed monthly glacial contribution to streamflow, defining elevation bands and detailed snow parameters, and using location map and calibrating geo-spatial parameters to simulate potholes and lakes (Faramarzi et al., 2017);
	Manipulating inputs	Changing annual crop parameters in SWAT database to improve ET results (Marek et al., 2017)
	Trading off accuracy for simplicity of application; accepting results if inaccuracy is not critical	Using Hargreaves ET calculation method based on temperature due to lack of wind and radiation data despite potentially larger errors in areas with significant wind speed (Setegn et al., 2010); results for some crops (e.g., cotton, sunflower) are not as accurate as others, possibly due to default plant parameters (Marek et al., 2016); accepting mediocre cotton yield results (due to not representing certain management operations) (Marek et al., 2017)

Challenge	Solution	Example(s)
Technical limitations	Simplifying assumptions	Static croplands due to inability to capture the variations of irrigated areas (Santhi et al., 2005)
	Developing modular codes, tools, and algorithms	Accounting for ecosystem service in the form of water provision (Notter et al., 2012); adding crop rotation simulation capability to SWAT's source code (Marek et al., 2017); developing an algorithm to simulate managed allowed depletion (MAD) irrigation in SWAT's auto-irrigation function (Chen et al., 2018a); using a modified plant growth module to estimate winter wheat yields (Sun and Ren, 2014); calculating seepage from earthen irrigation canals (Wei et al., 2018); setting individual HRUs for each farm (Wei et al., 2018); modifying the shallow groundwater module to simulate aquifer depletion (Zhang et al., 2018); developing a module to simulate salt ion fate and transport in agricultural watersheds (Bailey et al., 2019)
	Updating built-in databases	Correcting plant growth parameters (including observed LAI_{max}) for each year to adjust crop yield parameters (Chen et al., 2017)
	Using existing capabilities innovatively, applying practical modeling techniques, or using soft data	Using maximum cultivated land along with adjustments in daily irrigation water use based on historical records to account for changes in irrigated areas (Perrin et al., 2012); using daily irrigation operation in a farm with small runoff coefficient to simulate rice paddy fields (Perrin, et al., 2012); simulating large dams, small dams, and contour ridges, respectively, as reservoirs, ponds, and potholes that are filled with water and increase aquifer percolation (Abouabdillah et al., 2014); simulating surface and pressurized irrigation systems by adjusting irrigation operation parameters (Ahmadzadeh et al., 2016); using field based estimates as soft data to calibrate irrigation
	Using supplemental models and data	Applying SALMO model to simulate nutrients inside a reservoir (Nguyen et al., 2017); using results of RiverWare for reservoir operation (Qiu et al., 2019); using remote sensing data to estimate groundwater withdrawal for irrigation (Cheema et al., 2014)
	Coupling SWAT with other models	Developing coupled SWAT-MODFLOW models to capture surface water-groundwater dynamics (Ehtiat et al., 2018; Luo and Sophocleous, 2011); Coupled SWAT-MODSIM to estimate water productivity of wheat and maize with dynamic irrigation requirements (Ashraf Vaghefi, et al., 2017); applying pumped groundwater in MODFLOW to SWAT HRUs, combining surface water and groundwater irrigation in SWAT's auto-irrigation function, and applying MODFLOW-PSB for numerous groundwater sources and sinks (Aliyari et al., 2019)

* Theoretical method does not fully represent the actual condition or simulation algorithms affect results.

SWAT uses numerous parameters to simulate different hydrologic processes within watersheds. Some of these parameters are related to physical characteristics such as soil type, crop type, climate, etc. (Neitsch et al., 2011). The selection of sensitive parameters and determination of possible range of change is critical for calibrating the model. Modelers have used different ways to calibrate SWAT, including attempting a single parameter value, a range of parameter values, or changing default value of model parameters within an interval. The most common parameters extracted from the reviewed papers are summarized in Table 2.5. The parameters were broadly grouped under surface runoff, ET, soil water, and groundwater based on parameter definitions and their effect. An extensive table of the parameters reported in the reviewed literature is available in the appendix 1. Tables 2.5 and S1 provide useful suggestions about parameter values that can inform the calibration process. However, it should be emphasized that the list of parameters and the general range of calibrated parameters in these two tables are merely based on what has been reported in the literature. The sensitive parameters and their range for a particular SWAT application in an arid/semi-arid irrigated agricultural watershed should be selected based on the characteristics of the watershed, regional data, and modeling objectives. Modelers should use caution when defining the range of parameter values and they should examine the final values of calibrated parameters to ensure that parameter values are physically possible based on the theoretical definition, and they are reasonable considering the watershed characteristics.

It is recommended that parameter definitions and values be closely compared with those published in SWAT's theoretical documentation to avoid errors of oversight. In some instances, differences between the model interface and documentation can create confusion for SWAT users. For example, a value between 0-100 should be used for auto-irrigation efficiency (IRR_EFF) according to SWAT documentation but the model interface takes numbers between 0-1. Although this may appear to be a trivial discrepancy, it can become a source of error if modelers do not fully examine the theoretical underpinnings of irrigation representation in SWAT to use reasonable parameter values. A common error when using auto-irrigation is caused when the irrigation trigger is selected as "soil water content". According to SWAT documentation, the parameter value determining the start of auto-irrigation (i.e., AUTO_WSTRS) should be between 0-1, if the threshold is defined by “plant water demand”, which refers to the allowable fraction of potential plant growth before model triggers irrigation. However, when the threshold is based on “soil water content” the AUTO _WSTRS parameter value is the amount of soil water below field capacity in mmH2O. Yet, the model interface’s pop-up message for AUTO _WSTRS only states that this parameter should be between 0-1, despite the fact that modelers should use much larger values of soil water content if the objective is to simulate actual irrigation conditions in arid/semi-arid regions where soil water content may drop many millimeters below field capacity between irrigation applications. The plant available water below field capacity, a parameter which is used in determining irrigation depth through scientific irrigation scheduling, could range from 40 mmH2O per meter of crop root zone in coarse sand to 180 mmH2O in clay loam (Evett et al., 2008). In addition, except for drip irrigation systems, which account for only 10% of irrigated area within the U.S. (USDA, 2019), other types of irrigation systems cannot physically apply such a small amount of water. Further, if unchecked, unreasonable parameter values may be obtained by automatic calibration (e.g., SWAT-CUP). In one application, the calibrated Manning’s roughness coefficient (n) for tributary channels was reported to be 5.54 (Rivas-Tabares et al., 2019), which is significantly larger than the largest Manning’s number in TR-55 (0.8 for sheet flow over dense underbrush (TR-55, 1986)) and other well-known references (e.g., Chow, 1959).

Table 2.6 summarizes common calibration components and model performances broadly classified as poor, moderate, and good based on widely used goodness-of-fit factors. Common calibration methods include manual calibration (Jones et al., 2008; Reshmidevi et al., 2018; Ahn et al., 2018; Fallatah et al., 2019; Epelde et al., 2016), using SUFI-2 algorithm provided by SWAT-CUP (Abbaspour et al., 2011 & 2015) or dynamically dimensioned search (DDS; Tolson and Shoemaker, 2007) for automatic calibration and uncertainty analysis (Abbaspour et al., 2009; Masih et al., 2011; Ashraf Vaghefi, et al., 2017; Becker et al., 2019; Aliyari et al., 2019), and a combination of these approaches (e.g., Ficklin et al., 2013).

The majority (~ 80%) of the reviewed SWAT applications in arid regions calibrated the model only for streamflow and used this parameter for model performance evaluation. SWAT has also been calibrated for a combination of hydrologic components besides streamflow (e.g., ET, sediment, and nutrients) based on the aim of the study (Santhi et al., 2005; Perrin et al., 2012; Pulido-Velazquez et al., 2015; Ahmadzadeh et al., 2016; Jordan et al., 2018). Faramarzi et al. (2017) verified the model results for ET and groundwater recharge by calibrating it for streamflow and crop yield to simulate the regional watershed hydrology. Pulido-Velazquez et al. (2015) calibrated SWAT for streamflow, groundwater recharge, crop yield, and nitrate leaching. They used previous studies (i.e.

Table 2.5. Commonly used SWAT model parameters, initial parameter values, and calibrated values in the reviewed publications (see note below).

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Example Papers[c]
Surface runoff	**CN2:** SCS curve number for moisture condition II	35–98	35-98 (-35% – 32%)	Chen et al. (2011); Ficklin et al. (2013); Ahn et al. (2018); Reshmidevi et al. (2018)
	SURLAG: Surface runoff lag coefficient (days)	4	0.001–15	Chen et al. (2011); Reshmidevi and Kumar (2014); Dechmi et al. (2012); Aliyari et al. (2019)
	CH_N2: Manning's n value for the main channel	0.008–0.5	0–0.2 (-32%–30%)	Jones et al. (2008); Reshmidevi and Kumar (2014); Fallatah et al. (2019)
	CH_K2: Effective hydraulic conductivity in main channel (mm/h)	-0.01–500*	0–406	Jones et al. (2008); Akhavan et al. (2010); Ficklin et al. (2013); Reshmidevi and Kumar (2014); Abeysingha et al. (2015); Reshmidevi et al. (2018)
ET	**EPCO:** Plant uptake compensation factor	0.01–1	0–1 (39%–99%)	Akhavan et al. (2010); Chen et al. (2011); Abeysingha et al. (2015); Reshmidevi et al. (2018)
	ESCO: Soil evaporation compensation coefficient	0.01–1	0–1 (23%–55%)	Chen et al. (2011); Dechmi et al. (2012); Ficklin et al. (2013); Ahn et al. (2018); Reshmidevi et al. (2018)
Soil water	**SOL_AWC:** Soil available water capacity ($mmH_2O/mmSoil$)	0–1*	0– 0.91 (-50%–62%) (default + 0.01)	Jones et al. (2008); Chen et al. (2011); Reshmidevi and Kumar (2014); Abeysingha et al. (2015); Ahn et al. (2018); Reshmidevi et al. (2018)
	SOL_K: Saturated hydraulic conductivity (mm/hr)	0–2000*	0.13–180 (-50%–62%)	Akhavan et al. (2010); Chen et al. (2011); Ficklin et al. (2013); Reshmidevi and Kumar (2014); Ahn et al. (2018)
Groundwater	**GW_DELAY:** Groundwater delay time (days)	0–500*	0 – 365	Abbaspour et al. (2007); Jones et al. (2008); Dechmi et al. (2012); Fallatah et al. (2019)
	GWQMN: Threshold depth of water in shallow aquifer for return flow to occur (mmH_2O)	0–5000*	0 – 4772 (default +1002.25)	Jones et al. (2008); Reshmidevi and Kumar (2014); Abeysingha et al. (2015); Epelde et al. (2016); Ahn et al. (2018); Aliyari et al. (2019); Andaryani, et al. (2019b); Bressiani et al. (2015); Fallatah et al. (2019); Delavar et al. (2020)
	ALPHA_BF: Base flow recession factor (1/days)	0.1–1	0.001–1	Jones et al. (2008); Reshmidevi et al. (2018); Fallatah et al. (2019)
	REVAPMN: Threshold water level in shallow aquifer for "revap" (mm)	0–8000*	0.65–2000	Jones et al. (2008); Akhavan et al. (2010); Reshmidevi and Kumar (2014); Abeysingha et al. (2015); Ahn et al. (2018); Aliyari et al. (2019); Andaryani, et al. (2019b)
	GW_REVAP: Groundwater "revap" coefficient	0.02–0.2	0.02–0.4	Jones et al. (2008); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Ba et al. (2020)

SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Example Papers[c]
RCHRG_DP: Deep aquifer percolation fraction	0–1	0–0.972	Dechmi et al. (2012); Reshmidevi et al. (2018); Aliyari et al. (2019); Andaryani, et al. (2019b)

[a] Initial value is based on the range of default parameter values in SWAT documentation. In cases where a default value was unavailable (marked with an asterisk), the range is based on the lowest and highest values of initial attempts among all applications.

[b] Relative change indicates the range over which the parameter values were varied.

[c] A full list of papers is provided in Table S1 in Supplementary Material.

NOTE: The list of parameters, initial ranges, and the range of calibrated parameter values are given to provide an idea about initiating model parametrization and calibration. Model parametrization and calibration should be performed based on region-specific data (if available) and characteristics of the watershed. Readers are referred to Table S1 in Supplementary Material for a full list of parameter values reported in the literature in different parts of the world.

Table 2.6- Summary of common calibration descriptors, components, and goodness-of-fit factors used to evaluate simulations.

Descriptor	Component	Goodness-of-fit factor* NSE value/range		R-squared value/range		PBIAS (%) value/range		Citation
		Reported	Recommended	Reported	Recommended	Reported	Recommended	
Poor: Unsatisfactory	Streamflow	-11.30-0.22	≤0.50	-	-	-	≥±25	Setegn et al. (2010); Tarawneh et al. (2016)
	ET	0.42	≤0.50	-	-	-	-	Marek et al. (2017)
	Crop yield	-4.40-(-0.11)	≤0.50	-	-	-	-	Luo et al. (2008b)
Moderate: Adequate, acceptable	ET	0.40	-	0.27	-	-1.50-37.90	-	Van Liew and Garbrecht (2003)
	Nutrients	-0.20-0.64	-	-	-	-	-	Özcan et al. (2017)
Good: Fairly well, good, satisfactory, well, very good; above satisfactory	Streamflow	0.20-0.99	0.50-1.00	0.20-0.99	-	1.30-19.00	<±10 - < ±25	Santhi et al. (2001&2006); Van Liew and Garbrecht (2003); Luo et al. (2008a); Jones et al. (2008); Andersson et al. (2009); Abbaspour et al. (2009); Ficklin et al. (2009); Setegn et al. (2010); Dechmi and Skhiri (2013); Zeng and Cai (2014); Abeysingha et al. (2015); Bressiani et al. (2015); Ahmadzadeh et al. (2016); Shrestha et al. (2016); Tarawneh et al. (2016); Brouziyne et al. (2018); Faramarzi et al. (2017); Nguyen, et al. (2017); Wei et al. (2018); Ahn et al. (2018); Santos et al. (2018); Reshmidevi et al. (2018); Luan et al. (2018); Ashraf Vaghefi, et al. (2017); Rahbeh et al. (2019); Aliyari et al. (2019)
	Sediment	0.75	0.50-1.00	-	-	19.10	<±15 - < ±55	Luo et al. (2008a); Özcan et al. (2017); Santhi et al. (2001); Dechmi and Skhiri (2013)
	ET	0.67-0.85	0.50-1.00	0.85	-	-	-	Luo et al. (2008b); Marek et al. (2016&2017); Chen et al. (2017 & 2018a); Awan and Ismaeel (2014); Ahmadzadeh et al. (2016); Ahn et al. (2018); Melaku and Wang (2019)
	Nutrients	0.36-0.80	0.50-1.00	-	-	4.70-71.40	<±25 - < ±70	Luo et al. (2008a); Santhi et al. (2001); Dechmi and Skhiri (2013); Shrestha et al. (2016); Özcan et al. (2017); Nguyen, et al. (2017)
	Crop yield	0.99	0.50-1.00	0.95	-	1.30	-	Andersson et al. (2009); Abbaspour et al. (2009); Dechmi and Skhiri (2013); Ahmadzadeh et al. (2016); Chen et al. (2017& 2018a); Faramarzi et al. (2017); Ashraf Vaghefi, et al. (2017)
	Groundwater	0.70	0.50-1.00	0.86	-	-	-	Ahmadzadeh et al. (2016); Melaku and Wang (2019)

*NSE: Nash-Sutcliffe efficiency, R-squared: coefficient of determination, PBIAS: percent bias; Reported range is based on the lowest and highest values among all applications and recommended range is based on guidelines in Moriasi et al. (2007).

soft data) to evaluate simulated groundwater recharge rate, stream-aquifer interactions, and nitrate leaching, and calibrated the model for irrigation water and crop yield based on crop surveys and experimental data (Pulido-Velazquez et al., 2015).

Marek et al. (2016) concluded that ET simulated by SWAT for irrigated crops in an arid watershed was reasonable, although using the default crop growth model and default values for parameters controlling plant behavior in some cases like cotton and sunflower could introduce inaccuracies (generally underestimation). In another study, SWAT was calibrated for recharge based on a groundwater balance equation due to the lack of continuous flow time series in seasonal rivers (Perrin et al., 2012). Jones et al. (2008) applied a step by step manual calibration procedure to model the differences in flow regime and watershed characteristics of Tigris-Euphrates River system in mountainous and plain parts. They first adjusted snowpack and snowmelt parameters to account for the snowmelt-runoff regime of the river flow. In the next step, they calibrated soil water and groundwater parameters for high and low flow conditions in downstream gauges, and finally adjusted channel routing parameters. Ignoring the snowmelt and frozen soils may weaken the model’s ability to simulate low flows in areas where these processes occur (Zhang et al., 2016).

In an effort to facilitate objective model evaluation, Moriasi et al. (2007 and 2015) summarized a number of quantitative goodness-of-fit factors (e.g., Nash-Sutcliffe efficiency (NSE) and percent bias (PBIAS)) and offered guidelines for systematic watershed simulation assessment based on a comprehensive literature survey. It is interesting to note how modelers interpret the goodness-of-fit factor values using a variety of verbal descriptors to demonstrate simulation quality. For example, a model calibration can be deemed “good” over a wide range of NSE values for streamflow simulations (0.20-0.99) described as “fairly well”, “very good”, and “above satisfactory” (Table 2.6). This finding is not unique to models of irrigated agricultural watersheds as it can be seen elsewhere as well (Douglas-Mankin et al., 2010; Tuppad et al., 2011; Krysanova and White, 2015).

5. Discussion

Capturing the adaptive nature of agricultural practices in arid/semi-arid regions to cope with drastic surface water variability is a formidable modeling challenge (Niraula et al., 2012) that involves tradeoffs between data requirement, calibration effort, and model performance. As such, simulating arid/semi-arid irrigated agricultural watersheds with SWAT requires innovative approaches that utilize multi-component model calibration, account for irrigation, and report current limitations to guide future model advancements.

The Need for Multi-Component Calibration. As a model that provides numerous parameters to simulate a variety of biophysical processes in watersheds, estimating appropriate/realistic parameter values to build SWAT models is generally difficult due to equifinality or non-unique parameter values, meaning that different sets of parameter values may produce equally good results for a particular water budget component (Khatami et al., 2019). In heavily irrigated agricultural lands, all the major water budget components should be quantified and interpreted with a particular attention to irrigation and land management.

Multi-component calibration and validation of major hydrologic components can improve the reliability of results or pinpoint areas where field data are most needed. Deliberate calibration of components such as streamflow, ET, and groundwater recharge based on "hard" and "soft" data and knowledge of the watershed hydrology can help account for the water budget impacts of agricultural management decisions in arid and semi-arid climates (Arnold et al., 2015). Despite a satisfactory streamflow calibration (NSE=0.61-0.91), Acero Triana et al. (2019) recalibrated SWAT based on both groundwater recharge and streamflow to avoid coupled SWAT-MODFLOW model instability caused by excessive zonal recharge simulated by SWAT in some parts of the basin. Although NSE values of SWAT simulated streamflow dropped from 0.64 to 0.54, the multi-component calibration was necessary to ensure SWAT-MODFLOW simulations matched groundwater heads, as well as measured streamflow (Acero Triana et al., 2019).

Based on our review, the majority of models of irrigated agricultural watersheds are typically calibrated and validated for streamflow without checking the model's reliability in reproducing other components, a finding that is consistent with other reviews of SWAT to simulate watershed hydrology in general (Wellen et al., 2015). Only a very small fraction (5%) of the applications calibrated SWAT for more than two water quantity or quality components. While model calibration for streamflow only is often practical and time saving, neglecting other important natural or anthropogenic hydrologic components can undermine realistic regional water budget analyses in irrigated agricultural areas in arid/semi-arid regions. In these areas, agricultural evapotranspiration, soil water content, groundwater recharge, and return flows are actively managed through irrigation to maximize crop production. Representation of these processes and model calibration issues in irrigated agricultural settings need further investigation to guide agricultural water management at the spatial scales smaller than course regional water budget analyses.

The argument in favor of multi-component calibration does not mean that serendipitous outcomes based on streamflow calibration are impossible. For example, in one application, SWAT simulated biomass well although the model was calibrated to capture peak flows (Jordan et al., 2018). However, caution should be used in evaluating water budget components generated with SWAT models of arid/semi-arid irrigated agricultural watersheds that are calibrated based on streamflow alone. A good streamflow calibration does not necessarily render realistic results when evaluating other important, managed components of the water budget. Thus, additional effort to complete a multi-component calibration is recommended when quantifying hydrologic fluxes that govern water availability in managed systems such as irrigated agricultural watersheds in dry regions.

The lack of sufficient observational data for ET and groundwater recharge pose a great challenge for multi-component calibration to quantify the water budget of irrigated agricultural systems in arid/semi-arid climates (Masud et al., 2018 & 2019). The ability of SWAT to simulate watershed processes using built-in databases is a reason for popularity of the model use in data-scarce regions (e.g., Aouissi et al., 2016). Literature values and parameter estimates based on expert judgments can provide useful soft data for use along with observational records to facilitate multi-component calibration of SWAT. Abbaspour et al. (2009) suggest a combination of streamflow and crop yield as a more reliable representation for the main water budget components than only using streamflow because crop yield represents ET as well as nutrient uptake. The combination of reasonable streamflow and ET results should theoretically translate into improved soil moisture and GW recharge simulations. Leveraging global databases, remote sensing, or models to fill the data gaps can improve the data sets required for more accurate model set up and calibration (Luo et al., 2008a; Githui et al., 2012; Awan and Ismaeel, 2014; Reshmidevi et al., 2018; Bressiani et al., 2015; Qiu et al., 2019; Becker et al., 2019).

Accounting for Irrigation. The importance of irrigation and associated processes (e.g., return flow) that affect water budget calculations for arid/semi-arid regions has been documented (Kannan et al., 2011; Githui et al., 2012). In arid regions with insignificant rainfall, crop ET and groundwater recharge are typically directly related to irrigation. It has been shown that incorporating irrigation using groundwater changes streamflow pattern (Zeng and Cai, 2014) and including irrigation return flows can improve model calibration (Kannan et al., 2011). In another application, recharge was found to be higher in irrigated perennial pastures compared to non-irrigated areas (e.g., Githui et al., 2012).

Often, lack of detailed information on agricultural operations (irrigation, planting, fertilizing, etc.) necessitates simplifying the model, which requires additional checks (Sinnathamby et al., 2017; Masud et al., 2018 & 2019). SWAT's auto-irrigation function is commonly used to simulate irrigation based on plant water demand or heat units or soil water content which might be quite different from what happens in reality (Luo et al., 2008a; Ficklin et al., 2009; Kannan et al., 2011; Bressiani et al., 2015; Faramarzi et al., 2017; Marek et al., 2017; Chen et al., 2017 & 2018a; Jordan et al, 2018; Ahn et al., 2018). Inevitably, the auto-irrigation function introduces some uncertainties by over-estimating surface water withdrawal in areas where surface water and groundwater are conjunctively used for irrigation (Ahn et al., 2018). It is essential to verify the simulated irrigation against available observed or soft data (e.g., monthly or daily irrigation) or calibrate crop ET as a surrogate for irrigation (e.g., Faramarzi et al., 2017) to ensure reasonable consistency between simulated and actual conditions.

Reporting Model Limitations, Sensitivity, and Uncertainty. While watershed modeling inherently involves some level of subjectivity regarding parametrization decisions based on circumstantial considerations (e.g., purpose, time, cost, setting, and data availability), objective evaluation of model performance in simulating the hydrological fluxes is an indispensable modeling activity that is sometimes overlooked. There appears to be a general lenience to interpret model performance as "good" (Table 2.6) with minimal scrutiny of model performance and limitations. Details of irrigation simulation, the most important agricultural water management activity, are often not discussed in many applications (e.g., Wagner et al., 2012; Gebremicael et al., 2013; Epelde et al., 2016; Fallatah et al., 2019). Likewise, there is very limited coverage of regional relevance of model parameter values and associated uncertainties in the growing body of literature on SWAT applications in arid/semi-arid irrigated agricultural watersheds. Of the 102 reviewed applications, only 5 explicitly reflected on the concerns about the adequacy of simulated regional hydrologic fluxes, and used both streamflow and crop yield (surrogate for ET) in an attempt to produce regionally meaningful results (Faramarzi et al., 2017; Abbaspour et al., 2009; Ahn et al., 2018; Akhavan et al., 2010; Acero Triana et al., 2019). Articulating modeling assumptions, simplifications, and possible errors (e.g., Masud et al., 2018) contribute to insightful model applications by other users. Reporting limitations (e.g., data availability, technical capabilities, and model performance) explicitly can help put the watershed modeling results in the appropriate context. It can encourage efforts to address the data challenges by developing much needed monitoring programs and improving SWAT processes/algorithms to better quantify different components of the water budget in arid/semi-arid agricultural watersheds.

Several factors can impact the calibration and model reliability besides model capabilities, data issues and modeler's knowledge of regional natural or managed hydrologic characteristics. The combination of data issues, multitude of interactive biophysical processes, and equifinality makes parameter estimation of highly managed irrigated watersheds very difficult. Arnold et al. (2012) offered the most sensitive parameters in SWAT for different water quantity and quality components. Yuan et al. (2015) identified the most sensitive parameters for runoff simulation, base flow, and sediment and nutrient transport. Neglecting "important processes", the choice of objective function and optimization algorithms when using automated calibration, and model conditionality are other factors that affect model reliability (Guzman et al., 2015b; Abbaspour et al., 2018). Different objective functions and optimization algorithms might calibrate and validate the model well regardless of the reasonable range of the parameters (Abbaspour et al., 2018). Sensitivity and uncertainty analysis are recommended for hydrological models as exploratory and diagnostic tools to support calibration efforts and ensure credible results (Abbaspour et al., 2015 & 2018).

Remaining Challenges and Ideas for Future development and Applications. Over the last twenty years, SWAT has continually evolved to accommodate the need to simulate diverse natural and managed watershed processes in irrigated lands. Nonetheless, a number of remaining challenges should be addressed to expand the applicability of

SWAT to irrigated agricultural settings in arid/semi-arid regions to capture management uncertainties during the transition from wet to dry years (Table 2.7). Adaptive agricultural water and land management decisions in these areas are closely related to surface water variability and groundwater sustainability. The extent and magnitude of water scarcity and associated pumping costs and economic value of crops affect agricultural water management decisions such as inter-annual changes in pumping, irrigation schedule (frequency and amount) and method (surface (gravity), sprinkler, and/or drip irrigation), cropping pattern, and in extreme cases land retirement. Advancements such as conjunctive use of surface water and groundwater, explicit simulation of different irrigation systems, and dynamic land use would significantly enhance the flexibility and applicability of the model for arid/semi-arid irrigated agricultural lands. The conjunctive use of surface water and groundwater resources, a common drought adaptation measure, and effectiveness of irrigation technologies (e.g., drip) cannot be simulated directly by the current versions of SWAT. Further, the reviewed SWAT applications typically used static land use/cover conditions during long-term hydrologic simulations, which does not capture hydrologic impacts of drought-adaptive agricultural practices despite their significance (Ahn et al., 2018). Recent developments to include dynamic land use data is a notable progress that requires testing worldwide (Moriasi et al., 2019).

Future advancements can expand the crop database and improve auto-irrigation (Table 2.7). SWAT's crop database can be expanded through collaborations with agronomists to develop parameter sets for crops that are cultivated in arid/semi-arid regions (e.g., apricot, pecan, pistachio, pomegranate, etc.). Applying auto-irrigation scheduled by date and soil water content threshold in the current versions of SWAT can lead to continued irrigation of crops even after the harvest (Chen et al., 2017). As long as there is enough water in the source (reach, aquifer, or other watersheds), the auto-irrigation function keeps irrigating the fields until soil water content reaches the specified water stress threshold below field capacity. This issue can be addressed by providing options in the auto-irrigation module to stop irrigation based on the crop maturity and harvest time. The problem of continuous irrigation is not the case for setting auto-irrigation based on heat units, likely because conditions prompting irrigation will no longer prevail once the heat units for crop maturity are met.

Our review of the applications of SWAT in arid/semi-arid irrigated agricultural watersheds reveals strict dominance of the model's use to better understand water quantity aspects of water management. While this is to be expected given the reality of water scarcity and associated challenges for agricultural production in these regions, the capabilities of SWAT to model water quality have been underutilized. SWAT can be improved with respect to simulation of water quality aspects of irrigated agriculture in arid/semi-arid regions. Representation of salinity issues of irrigated agriculture can be advanced by providing capabilities to account for soil salinity and water salinity stress on crop growth and yield in SWAT-Salt, the salinity module of SWAT (Bailey et al., 2019). There is also a need for improved modeling of the fate and transport of pesticides, especially for the prevailing low streamflow conditions in arid/semi-arid regions (Table 2.7). SWAT+, which is the revised version of the model aims to improve the model structure for easier code development and better spatial representation of the watershed features such as interaction of rivers and landscape (Bieger et al., 2017). With mounting concerns about reaching the limits of good quality water resources in many regions (Gleick and Palaniappan, 2010; de Graaf et al., 2019), using SWAT to examine water quality for various combinations of agricultural land and water management will be an important area of future model applications.

Table 2.7. Remaining challenges and potential solutions for applying SWAT to irrigated agricultural settings in arid/semi-arid climates.

Remaining Challenge	**Solution**
Modeling adaptive agricultural water management	Updating the model source code to: (1) simulate conjunctive use of water from different sources for irrigation, including surface water, shallow groundwater, and deep groundwater; (2) simulate different irrigation systems (surface (gravity), drip, sprinkler, and subsurface irrigation)
Modeling adaptive agricultural land management	Updating the model to simulate dynamic land use to represent changes in cropping pattern ***
Expanding the plant (i.e., crop) growth database*	Developing parameter sets for crops that are currently not included in the crop database such as nuts (pecan, pistachio), fruits (apricot, pomegranate, cherry), cucurbits (pumpkin, squash, zucchini)
Improving auto-irrigation function	Providing options to stop auto-irrigation post-harvest or at the end of the growing season
Modeling the effects of soil and water salinity	Updating the model to account for soil salinity and water salinity stress on crop growth and yield
Modeling the fate and transport of pesticides**	Improving the original code to better simulate the fate and transport of pesticides, especially for low flows and account for the effect of drift in pesticide application

*Users can add any plants to the model database. However, including the characteristics of common crops in the model database will facilitate the model's application and reduces the possibility of input errors.

**See Wang et al. (2019) for more information.

*** See Moriasi et al. (2019) for more information.

6. Conclusions

This paper provided a review of SWAT applications in irrigated agricultural watersheds in arid/semi-arid climates in the last two decades. The applications fall into three broad categories listed as follows in the order of prevalence: (1) water quantity analysis, (2) a combination of water quantity and quality issues, and (3) water quality analysis (only a few). The main modeling challenges are lack of data, poor data quality, concerns about simulation accuracy, and technical limitations of the existing versions of the model. Researchers have used a number of innovative approaches and practical techniques to deal with the modeling challenges, including augmenting data availability by combining data from different sources with those provided in the existing SWAT databases, using supplemental tools to estimate missing data and evaluate model performance, trading off the accuracy of simulation of some parameters for simplicity of application where those inferior results did not affect the major aim of the study, and developing modular codes, tools, and algorithms.

Simulation of physical characteristics of agricultural watersheds in arid and semi-arid climates requires insightful model parametrization, model setup, and calibration using soft data along with available field measurements (i.e., hard data). While a wide array of existing and emerging capabilities make SWAT the watershed model of choice in different settings, fine-tuning SWAT to model key hydrologic attributes (e.g., streamflow, ET, and groundwater recharge) of arid/semi-arid irrigated agricultural watersheds remains time consuming and challenging. We synthesized SWAT parametrizations for heavily irrigated arid/semi-arid agricultural areas to inform model set-up and calibration in future modeling efforts. It is essential that users carefully examine what the model can or cannot provide in relation to the objectives of the study based on practical understanding and theoretical underpinnings of simulating irrigation to avoid potential errors, especially when using auto-irrigation function and auto-calibration tools. Reporting modeling limitations explicitly can help put the watershed simulation results in appropriate context. Future advancements such as conjunctive use of surface water and groundwater, dynamic annual land use, explicit capabilities to model irrigation management interventions, and simulation of salinity impacts on crop growth would significantly enhance the flexibility and performance of the model for addressing water and food security questions in the context of arid/semi-arid irrigated agricultural areas.

CHAPTER III

CLIMATE CHANGE IMPACTS ON WATER AVAILABILITY IN A SEMI-ARID, AGRICULTURE-DOMINATED BASIN IN THE US SOUTHWEST

1. Introduction

Many areas around the world face water sustainability challenges tied to variability of renewable water and growing water demand due to population growth and higher standards of living (Döll et al., 2012; Wada et al., 2014; AghaKouchak et al., 2015; Grafton et al., 2017). Overexploitation of limited, non-renewable water resources to cope with water shortages in arid/semi-arid regions makes these regions particularly vulnerable to severe water stress under plausible hotter and drier conditions in the future (Castle et al., 2014; Ward et al., 2019). In the U.S., rising aridity is generally observed in the southwest (Cayan et al., 2010; Seager et al., 2013; Cook et al., 2015) and it is expected to become more severe in future decades, reducing headwater snowpack and watershed soil moisture, increasing evapotranspiration (ET), and altering the magnitude and timing of streamflow (Garfin et al., 2013; Dettinger et al., 2015). Understanding the implications of these hydroclimatic changes is essential for adaptive water resources planning and management in drought-prone basins in the southwestern U.S., including the Rio Grande Basin.

Water in the upper Rio Grande Basin is shared between the three states of Colorado, New Mexico, and Texas based on the 1938 Rio Grande Compact (RGC 1938). In addition, the 1906 treaty between the U.S. and Mexico governs surface water deliveries of an annual total of about 74 million cubic meters (MCM) (60,000 acre-feet) to northern Chihuahua, Mexico in a normal year (IBWC 1906). The decreasing snowpack in the Rio Grande headwaters in Colorado is already evident in historical data (Elias et al., 2015; Chavarria and Gutzler 2018) with a significant corresponding decline in streamflow associated with rising temperature in the headwaters (Llewellyn and Vaddey 2013; Udall and Overpeck 2017; Lehner et al., 2017). The river, the main surface water source in the middle Rio Grande region, is fully allocated and net groundwater storage is declining (Sheng 2013; Fuchs et al., 2018). Agricultural activities in this region are predominantly concentrated along the main stem of the Rio Grande where surface water and groundwater are conjunctively used to sustain irrigation. Although domestic water demands are primarily met by groundwater resources (McCoy and Shomaker 2017), growing water shortages can increase the competition between urban and agricultural water users in the future. The ecological functions of the Rio Grande are also at risk because of the difficulty of providing environmental flows in this heavily managed, fully appropriated water system (Lane et al., 2015; Blythe and Schmidt 2018).

Stakeholder groups (e.g., agricultural, urban, and environmental) in the middle section of the Rio Grande Basin have been alarmed by the prospect of adverse impacts of climate change on regional water availability. This paper provides a thorough assessment of water availability for irrigated agriculture, the largest single water user in the New Mexico-Texas portion of the basin, under plausible surface water projections throughout the 21st century. The climate impact assessment framework is comprised of three components: (1) climate-based Rio Grande flow projections at the upstream boundary of the study watershed derived from bias-corrected intrabasin climate projections (i.e., temperature and precipitation) provided by the U.S. Bureau of Reclamation (USBR 2016); (2) a calibrated spatially distributed watershed hydrology model developed using the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998); and (3) a relationship between reservoir releases and groundwater withdrawal to represent the conjunctive use of surface water and groundwater for irrigation. We evaluate the impacts of surface water conditions on different components of the surface water budget, as well as groundwater storage. Sustainability of irrigated agriculture in this water-scarce region will increasingly depend on preparing to use slightly saline to marginal quality groundwater due to mounting pressure on the already-strained fresh groundwater to cope with diminishing river flows.

2. Materials and Methods

2.1. Study Area

The study watershed occupies about 6000 km^2 in the middle section of the Rio Grande Basin (Fig. 3.1) with approximately 400 km^2 of agricultural lands. The region is arid/semi-arid with an average annual precipitation of approximately 270 mm and maximum and minimum mean daily temperatures of 33°C and -7°C, respectively. Rio Grande water is stored in the Elephant Butte reservoir (completion: 1916, capacity: 2,713.6 MCM (2.2 million acre-feet)) for irrigation and hydropower generation. Elephant Butte reservoir releases are regulated by Caballo reservoir with a capacity of 424.3 MCM (343,990 acre-feet) located 40 kilometers (25 miles) downstream. In normal years, water is released from the Caballo regulatory reservoir from March to September to meet irrigation demands. Two upstream US Geological Survey (USGS) gauging stations (08358300 and 08358400) record inflow to the Elephant Butte reservoir and two downstream gauging stations record releases from Elephant Butte (08361000) and Caballo (08362500) reservoirs. USGS gauge at El Paso (08364000) measures flow at the watershed outlet.

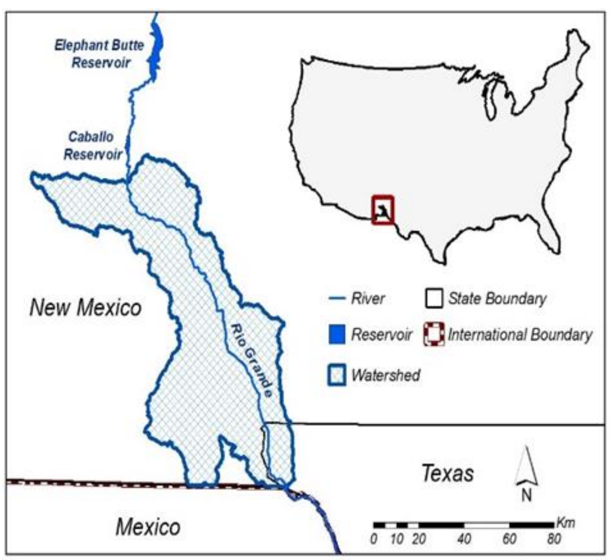


Figure 3.1. Study watershed in the New Mexico-Texas portion of the Rio Grande Basin.

The Mesilla groundwater basin (Mesilla Basin), the main groundwater resource in the watershed, is used in conjunction with reservoir releases to support irrigated agriculture. The area is known for pecan production, a major cash crop in the Elephant Butte Irrigation District (EBID). Three main diversion dams and five main diversion canals distribute water among irrigated lands. The historical variation of croplands shows significant drops in the acreages of different crops during drought periods except high-value perennial pecan. For example, drastically reduced reservoir releases during the 2011-2013 drought mostly affected cotton, corn, alfalfa, and other crops while pecan orchards remained relatively unaffected (Fig. 3.2). The acreages of crops do not decline at the same rate as the reduced reservoir releases because extensive groundwater pumping from Mesilla Basin compensates for surface water shortages (Fig. 2). The groundwater quality varies from fresh water in the deep zone to more saline in the shallower zones and towards the south. Estimates of fresh groundwater storage vary significantly (Sheng 2013), ranging up to 123 billion cubic meters (BCM) (Wilson et al., 1981). Hawley and Kennedy (2004) estimated the volume of recoverable fresh to slightly saline groundwater (i.e., Total Dissolved Solids (TDS) < 3000 mg/L) storage in the Mesilla Basin to be about 55.5 BCM. Overexploitation of fresh groundwater has also caused intrusion or upwelling of brackish water, deteriorating the quality of water in the aquifer (Ashworth and Hopkins 1995; Sheng 2013).

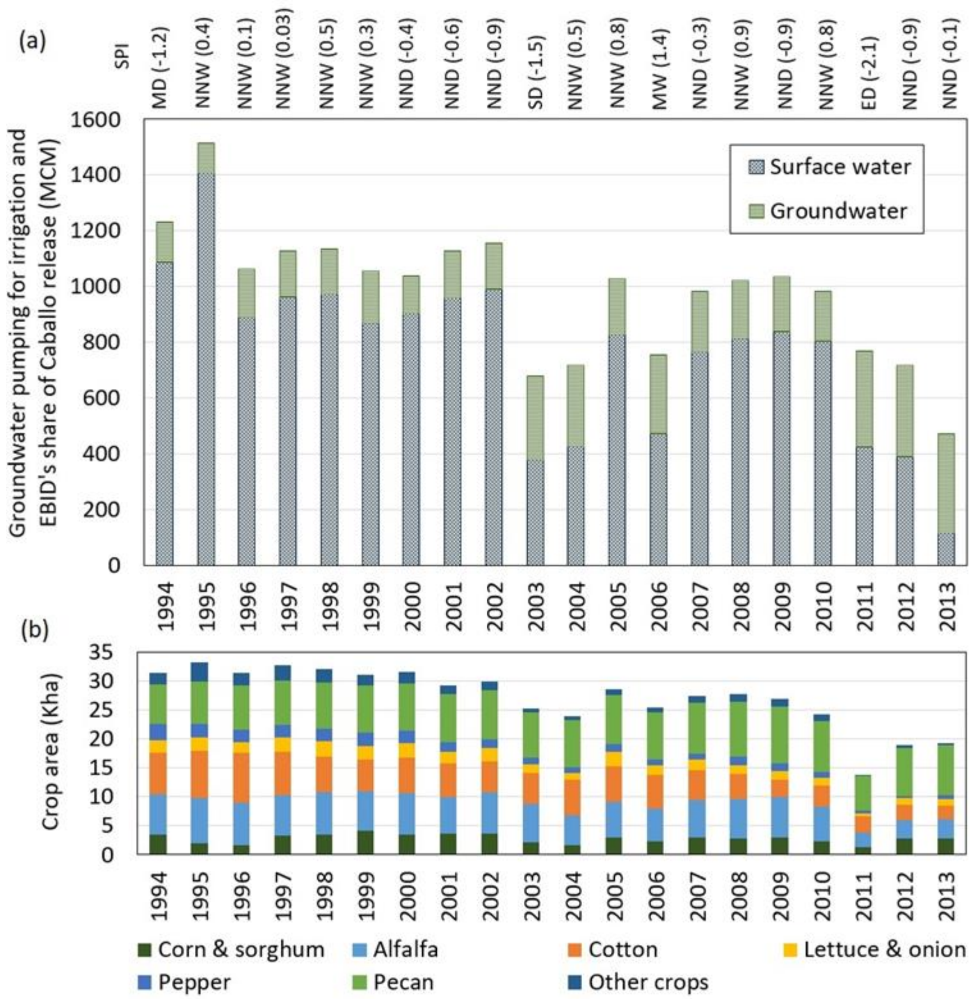


Figure 3.2. Water withdrawal and irrigated crop production in the study area: (a) conjunctive use of surface water and groundwater during wet and dry years characterized by standardized precipitation index (SPI; McKee et al., 1993) using PRISM rainfall data (Dally et al., 2008): extremely dry (ED: -2.00 or less), severely dry (SD: -1.50 to -1.99), moderately dry (MD: -1.00 to -1.49), near normal dry (NND: -0.99 to 0.00), near normal wet (NNW: 0.00 to 0.99), moderately wet (MW: 1.00 to 1.49), very wet (VW: 1.500 to 1.99), extremely wet (EW: 2.00 and more); and (b) variation of crop acreages in response to renewable water availability.

2.2. Climate Change Impact Assessment Framework

We used projected Rio Grande flows to calibrate a SWAT model of the study area to evaluate the impacts of future climate conditions on surface water and groundwater resources, taking into account the conjunctive use of water from these sources for irrigation (Fig. 3.3). The components of the climate change impact assessment framework are discussed in this section.

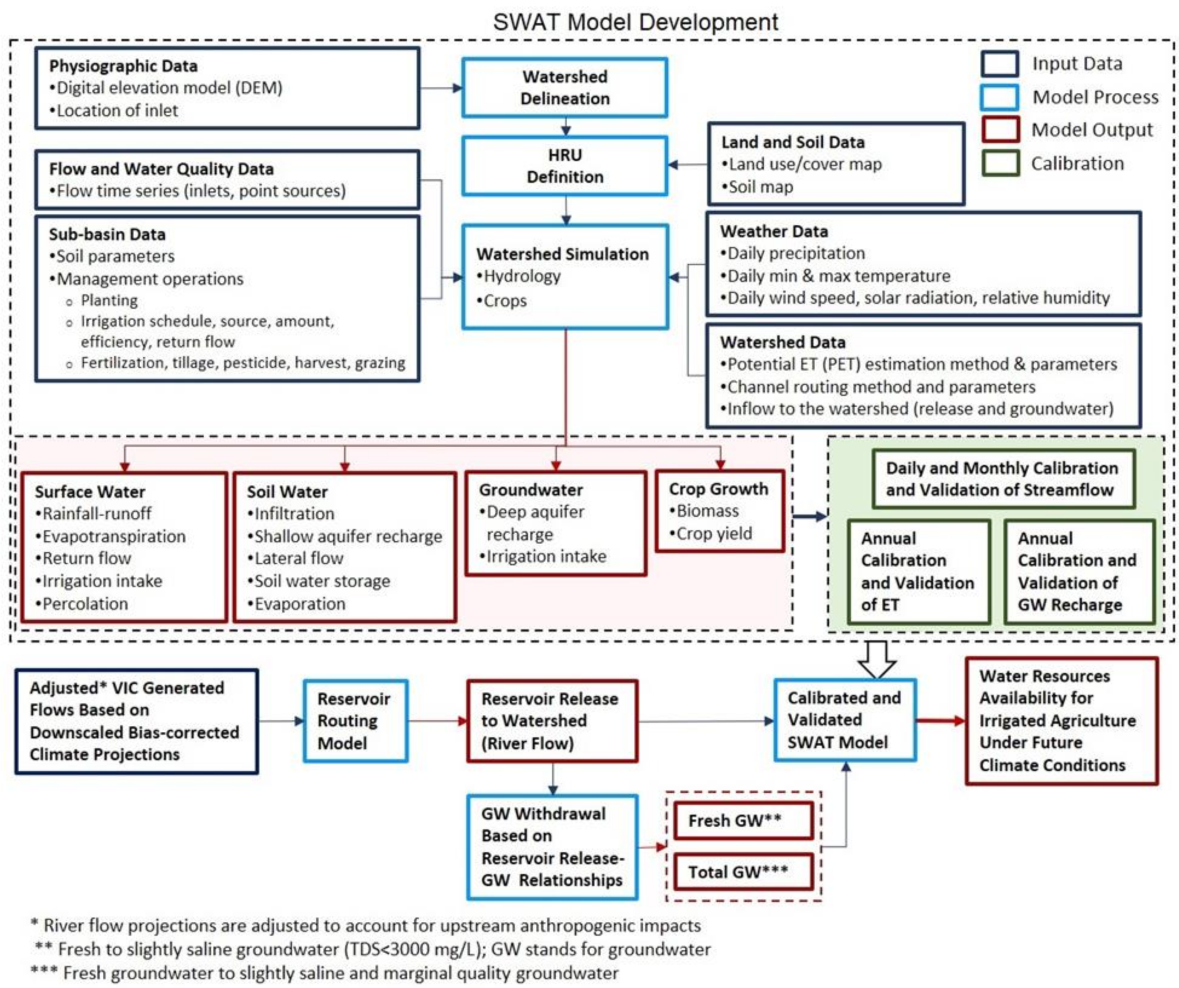


Figure 3.3. A general schematic of the climate impact assessment framework.

Climate-based Surface Water Projections. Global climate models (GCMs) have been used to generate 97 different streamflow projections on the main stem of the Rio Grande (USBR 2016) using the variable infiltration capacity (VIC) rainfall-runoff model (Liang et al., 1994 and 1996). These GCM-based projections describe natural river flows, with no simulation of human impairments upstream that would affect the flows into Elephant Butte Reservoir. To account for upstream developments, Townsend and Gutzler (2020) developed a statistical normalization procedure that parameterizes upstream water manipulation by calculating constants that force the first and second moments of model-simulated annual flows for a 50-year historical period at the San Marcial gauge just upstream of Elephant Butte Reservoir to match the equivalent moments of observed flows during the same period. The parameterization constants are then applied to projected naturalized flows to obtain projected flows that account for upstream management. The effect of this normalization procedure is to reduce simulated natural flows into Elephant Butte Reservoir during the historical period by 70-75%, a reduction that closely matches the naturalization of observed flows estimated by Blythe and Schmidt (2018).

The 97 normalized Rio Grande flow projections (2020-2099) cover a variety of flow conditions as can be seen in the exceedance probability plots of the projections and the observed historical flow at San Marcial (Fig. 3.4). The majority of projections have a median flow that is 20-60% lower than the historical median flow, indicating increasing future surface water scarcity. A few scenarios include smaller flows in the early years and larger flows toward the end of the century (e.g., bcc-csm1-1_rcp26 and bcc-csm1-1_rcp45). Four projections were selected to represent Rio Grande flow scenarios (Table

1), namely Dry1 (access1-0_rcp85), Dry 2 (hadgem2-es_rcp85), Wet1 (fio-esm_rcp45), and Wet2 (cnrm-cm5_rcp85). In addition, at the request of agricultural water stakeholders, a no reservoir release scenario (NR) was also simulated, which represents the most extreme case of future surface water scarcity for downstream irrigation. The differences of monthly flows in the four selected streamflow scenarios relative to the average historical Rio Grande flows are shown in Fig. 3.5 to offer a visual comparison of the relatively dry and wet projections. Dry 1 scenario has the largest number of drier-than-average months while the Wet 2 scenario has largest number of wetter-than-average months. The two other projected scenarios, i.e., Dry 2 and Wet 1, respectively, represent moderately dry and wet conditions that are consistent with the observational record. All the selected scenarios indicate declining streamflows based on the Mann-Kendall test (Z-values range between -2.74 to -6.27).

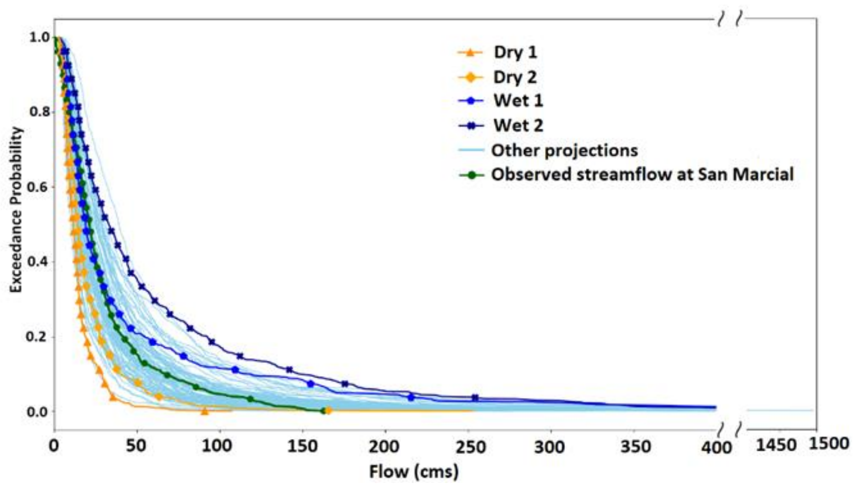


Figure 3.4. Exceedance probability plots for monthly streamflow projections and observed monthly historical flow rates (1994-2013) recorded at the USGS San Marcial gauge. The four climate-based flow scenarios selected for impact assessment include

Dry1 (access1-0_rcp85), Dry 2 (hadgem2-es_rcp85), Wet1 (fio-esm_rcp45), and Wet2 (cnrm-cm5_rcp85).

Table 3.1. Selected climate-based monthly streamflow projections (up to 2099).

Scenario	Projection*	Source	MK**	Mean annual flow at San Marcial (cms)	No. of years with mean annual flow > historical
Dry1	ACCESS1-0_RCP85	Australian Community Climate and Earth System Simulator	-5.39	12.55	1
Dry2	HADGEM2-ES_RCP85	Coupled Earth system model By Met Office Hadley Center, U.K.	-4.23	18.70	12
Wet1	FIO-ESM_RCP45	First Institute of Oceanography-Earth System Model (FIO-ESM), China	-2.74	44.15	27
Wet2	CNRM-CM5_RCP85	Earth system model by Centre National de Recherches Meteorologiques, France	-3.39	61.83	42
NR	-	No release from upstream reservoir	-	-	0

* RCP stands for Representative Concentration Pathway.es of emissions and mitigation pathways. RCP 45 is an intermediate greenhouse gas emission mitigation pathway in which radiative forcing is stabilized at approximately 4.5 W/m after 2100. RCP 85 is a high GHG emission pathway with radiative forcing exceeding 8.5 W m-2 by 2100 and continuing to rise (Flato et al., 2013).
** Mann-Kendall (MK) non-parametric trend test (Mann, 1945; Kendall, 1975).

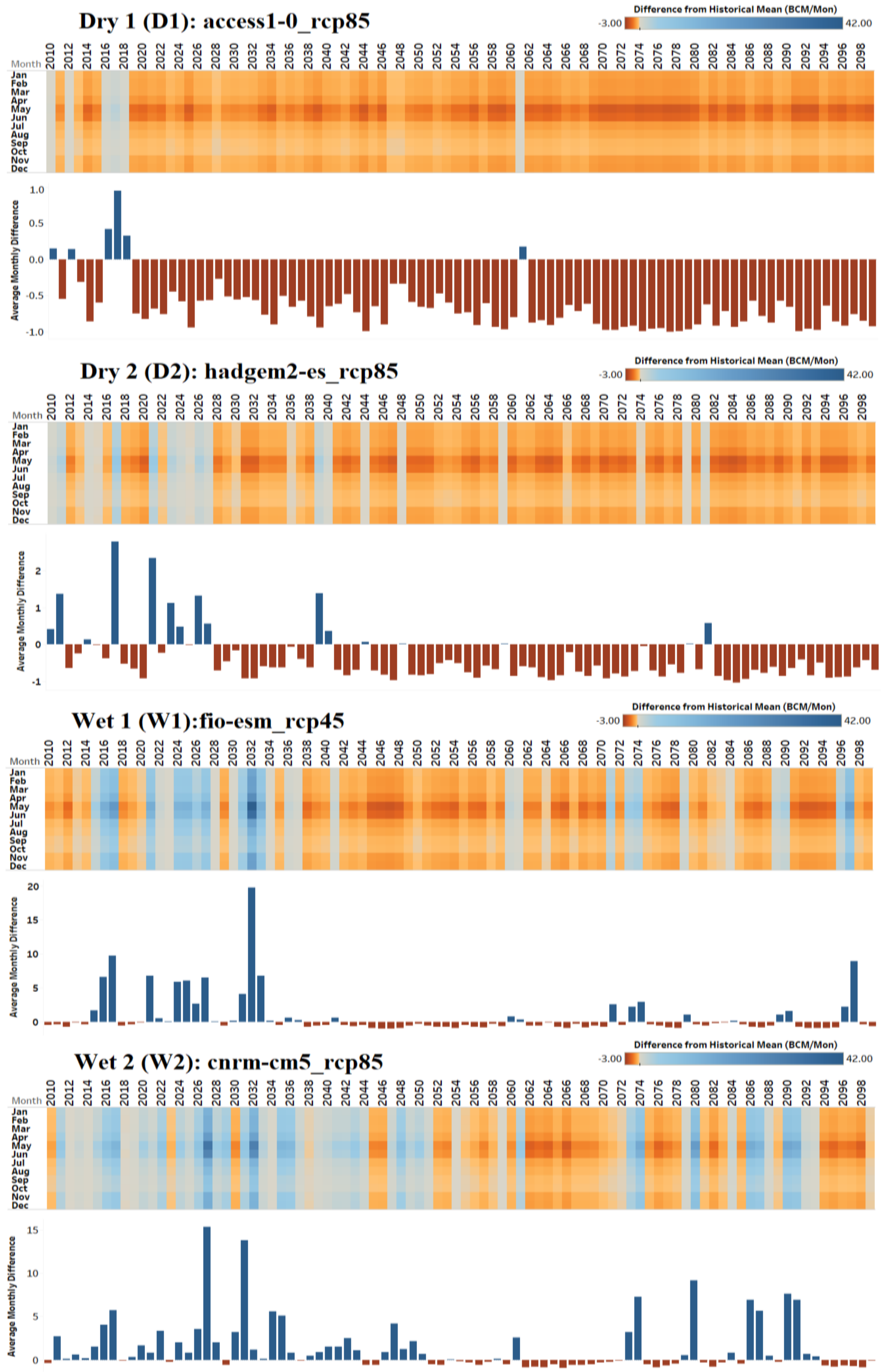


Figure 3.5. Visualization of projected Rio Grande volumetric flows representing dry (i.e., Dry 1 and Dry 2) and wet (Wet 1 and Wet 2) futures relative to the average observed historical flows at San Marcial gauge.

The projected streamflows were routed through the Elephant Butte-Caballo reservoir system to establish upstream flow boundary condition for watershed analysis under different flow scenarios. A simple reservoir model was developed based on the water balance and downstream demand (annual average of about 974.5 MCM (790,000 acre-feet) for full allocation) to determine monthly releases. The reservoir operation model accounts for elevation-volume-area relations and measured reservoir evaporation (USBR, personal communication). In reality, releases from Elephant Butte are based on water elevations in Caballo reservoir while Caballo reservoir releases water based on downstream demands and volume of available water in the two reservoirs. However, for simplicity, the two reservoirs were simulated as a combined system that stores and regulates the inflow into the study watershed.

Watershed Hydrology Model. We used SWAT, a public-domain semi-distributed, continuous-time watershed hydrology model (Arnold et al., 1998) to represent watershed processes and quantify different components of the water budget. SWAT accounts for the impacts of water and land management practices in the water balance calculations and simulates relationships between crop yield and soil moisture, which makes it a useful tool for agricultural watershed studies (Van Liew and Garbrecht 2003; Abbaspour et al., 2007; Ficklin et al., 2009; Schierhorn et al., 2014; Abbaspour et al., 2015; Ahn et al., 2018). The model is widely used to simulate arid/semi-arid irrigated agricultural watersheds around the world to facilitate diverse water resources investigations (Samimi et al., 2020), including many climate change impact assessment studies (Abbaspour et al., 2009; Tang et al., 2013; Ashraf Vaghefi et al., 2014; Hammouri et al., 2017; Li and Jin 2017; Nguyen et al., 2017; Reshmidevi et al., 2018). SWAT divides sub-basins into smaller hydrological response units (HRUs) based on terrain slope, land use, and soil characteristics across the watershed (Fig. 3.3). Water quantity and quality are simulated based on the water balance in each HRU and then routed along channel network in the sub-basins and the watershed. The crop growth is modeled using the plant growth module and related databases (Neitsch et al., 2011).

We used 10 ×10 m digital elevation models (DEM), 2011 land use/cover data (NLCD 2011), and a combination of STATSSGO and SURGO soil maps to delineate 10 sub-basins and 7,175 HRUs in the study watershed. The NLCD land use layer for 2011, an exceptional drought year based on SPI (Fig.3.2), was used to represent adaptive land management to cope with declining surface water availability in the future. Weather data (e.g., precipitation, temperature, and humidity), runoff curve numbers, plant growth characteristics, and agricultural management operations (e.g., irrigation, fertilization, pesticides, tillage, etc.) are available in various editable built-in databases that allow capturing the specific conditions of different applications through model calibration (Arnold et al., 2012).

Characterization of streamflow, ET, and groundwater recharge is essential for regional water availability assessments in irrigated agricultural watersheds. We calibrated the SWAT model for all three components (i.e., multi-component calibration). The lack of sufficient observational data for ET and groundwater recharge poses a challenge for quantifying these water budget components. We adopted a “hard” and “soft” data approach (Arnold et al., 2015) using various measured data sets (i.e., hard data) such as streamflow, precipitation, temperature, and land use/cover along with a combination of literature values and expert judgements (i.e., soft data). For example, we used annual and monthly ET rates measured on selected pecan orchards in New Mexico for calibrating pecan ET (Sammis et al., 2004; Samani et al., 2009, 2011 & 2013) along with water requirements for other crops estimated by a CROPWAT model based on information in FAO Bulletin 56 (Smith, 1992; Allen et al., 1998).

Agricultural management information includes planting, irrigation, and harvest, which are available to varying extents from field operation reports and literature (Abdul-Jabbar et al., 1983; Sammis et al., 2004; Wang et al., 2007; USDA 2010; Ahadi et al., 2013). In the absence of recent measurements of recharge rates, literature values and expert opinions were used as first estimates of average groundwater recharge amounts (e.g., Sheng 2013). We used SWAT's auto-irrigation function since details of irrigation schedule for several crops were unavailable. To account for the conjunctive use of surface water and groundwater, estimated monthly groundwater pumping was lumped with monthly reservoir releases and introduced to the model as total available water for irrigation. A combination of manual calibration and automated SWAT-CUP SUFI2 calibration (Abbaspour, 2013) was applied for parameter estimations and sensitivity/uncertainty analysis to obtain satisfactory model calibration at monthly and daily scales (see Section 3.1). The performance of the SWAT model during the calibration and validation stages were determined using the NSE, r-squared, and PBIAS goodness-of-fit factors (Moriasi et al., 2007).

Conjunctive Use of Surface Water and Groundwater. The annual groundwater pumping data for different purposes (agriculture, urban, industry) from 1961 to 2004 (Papadopulos and Associates 2007), including 13,148 agricultural groundwater wells were used to characterize the conjunctive use of surface water and groundwater. For irrigation wells, each year was divided into growing season (March to October) and non-growing season (November to February). Farmers usually pump groundwater to make up for the surface water shortage for irrigation during the growing season (Fuchs et al., 2018), which creates an inverse relation between Caballo reservoir releases and groundwater withdrawal (Fig. 3.6). The simulated growing-season groundwater pumping during the 1961-2004 period using the release-pumping regression equation matches the historical groundwater withdrawal. Since no trend is detectable for the pumping rates during the non-growing season, the maximum of historical pumping at each well during this time period was assigned as future pumping rate for the well. Though conservative, this assumption does not lead to significant overestimation of groundwater withdrawal because agricultural groundwater is predominantly withdrawn during the growing season. For the rare extremely wet conditions, historical minimum groundwater pumping rates were used. This piecewise approximation of groundwater pumping as a function of reservoir release improves estimates of groundwater withdrawals when reservoir releases exceed 1,200 MCM per year (Fig. 3.6).

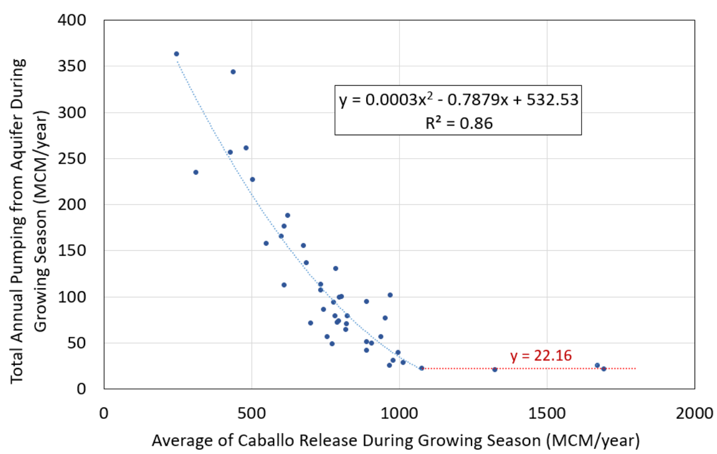


Figure 3.6. Regression relationship between total annual groundwater pumping and releases from Caballo reservoir during the growing season.

The reservoir release-groundwater withdrawal relationships were used to project groundwater withdrawals into the future using the scenario-based reservoir releases. A lumped groundwater balance model was set up to evaluate the potential impacts of the selected climate-based surface water projections on long-term groundwater availability. The groundwater balance accounts for scenario-based SWAT-generated recharge and corresponding projected groundwater withdrawals for agricultural and urban purposes (i.e., EBID and the City of Las Cruces, New Mexico). Two scenarios of conjunctive use of surface water and groundwater were simulated: (1) River + FGW: Rio Grande water (i.e., releases from Caballo reservoir) used along with fresh to slightly saline groundwater (TDS <3000 mg/L); and (2) River + GW: Rio Grande water used along with fresh to slightly saline and marginal quality groundwater (TDS>3000 mg/L). We used an estimate of recoverable fresh to slightly saline groundwater storage in the Mesilla Basin (about 55.5 BCM) by Hawley and Kennedy (2004) to examine the reliability of agricultural water availability under these two conjunctive use scenarios and projected reservoir releases. Once fresh to slightly saline groundwater storage is depleted, agricultural groundwater pumping is assumed to be provided from marginal quality groundwater storage in the Mesilla Basin.

3. Results

3.1. SWAT Calibration and Validation

An initial calibration was performed focusing on reproducing monthly and daily flows for the time period of 1994-1999. Common goodness-of-fit factors (NSE = 0.73, r-squared = 0.95, and PBIAS = -15%) indicated satisfactory initial model calibration (Moriasi et al.,

2007) using a time period that includes both historical low and high flow conditions. The model was then calibrated manually for ET and groundwater recharge, consecutively, while the impacts of parameter adjustments on the overall model results were closely checked to ensure reasonable simulated values for all three water budget components. Sensitive parameters for each component were selected based on manual investigations and literature review. The parameter values obtained from manual calibration were then compared with SWAT-CUP SUFI2 algorithm results for streamflow to further improve the calibration (NSE = 0.84, r-squared = 0.96, and PBIAS = 6.2%). The model performed comparably well during the validation period (NSE = 0.74, r-squared = 0.90, and PBIAS = 0.61%). Parameter values were fine-tuned separately for agricultural and non-agricultural lands to account for the impact of irrigation and larger infiltration rates in agricultural lands. The initial and final values of key calibrated parameters are summarized in Table 3.2.

Table 3.2- Calibration parameters in the multi-component SUFI-aided calibration.

Parameters	Definition	Initial Range	Final Estimate
ALPHA_BF	Base flow recession constant (days)	0.1-1	0.9
GWQMN	Return flow threshold depth (mm)	0-5,000	1,000
IRR_EFF	Irrigation efficiency	0-1	varies based on reports
AUTO_WSTRS	Water stress to trigger irrigation	0-field capacity	0.9
SOL_AWC	Available soil water capacity (mm/mm)	varies	varies (0.04-0.1-0.8)
EPCO	Plant uptake compensation factor	0.01-1	0.85
ESCO	Soil evaporation compensation factor	0.01-1	0.8
GW_REVAP	Groundwater “revap” coefficient	0.02-0.2	Ag.: 0.1; non-Ag.: 0.02
SOL_K	Soil saturated hydraulic conductivity	varies	varies (0-1,523 in different layers)
GW_delay	Groundwater delay time (days)	31	Ag.: 35; non-Ag.: 300
CN2	Curve number condition 2	35-98	varies (40-75)
IRR_ASQ	Surface runoff ratio	0-1	0.3
LAI_INIT	Initial leaf area index	varies	4

Figure 3.7 shows the simulated flows compared with observed Rio Grande flows at El Paso station. The streamflow is governed by upstream dam releases and rainfall in the area was practically insignificant in terms of runoff contribution during the droughts of 2006 and 2012–2013. Validation results confirmed that the calibrated model captured the seasonality of the outflow hydrograph during the simulation period. The model overestimated peak flows and some low flows, especially towards the end of the simulation period. The model also captured the spatial distribution of ET and groundwater recharge, which are larger along the main stem of the Rio Grande due to

irrigation and river channel seepage losses (Figure 3.8). Comparing the simulated ET of pecan and alfalfa with measured values in the study area shows that the multi-component calibrated model simulations are close to the observed ET values in the same period. Aquifer recharge generated by the model was also compared with available literature values and technical reports as “soft data” (Conover 1954; Sheng 2013; Ahn et al., 2018) (Fig. 3.9). Based on these performance evaluations, the watershed model was deemed suitable for climate impact assessments.

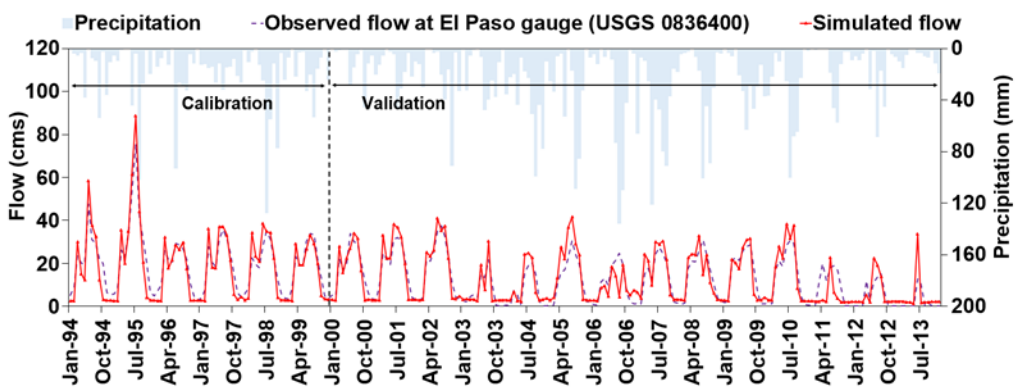


Figure 3.7. Comparison of observed streamflow with SWAT simulations.

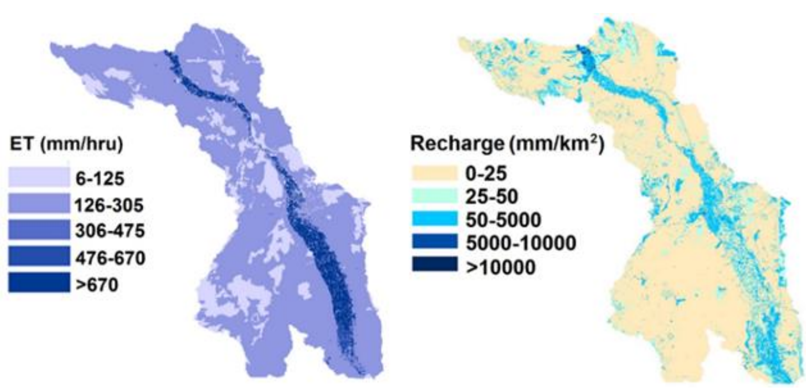


Figure 3.8. Spatial distribution of simulated ET and groundwater recharge in the study area.

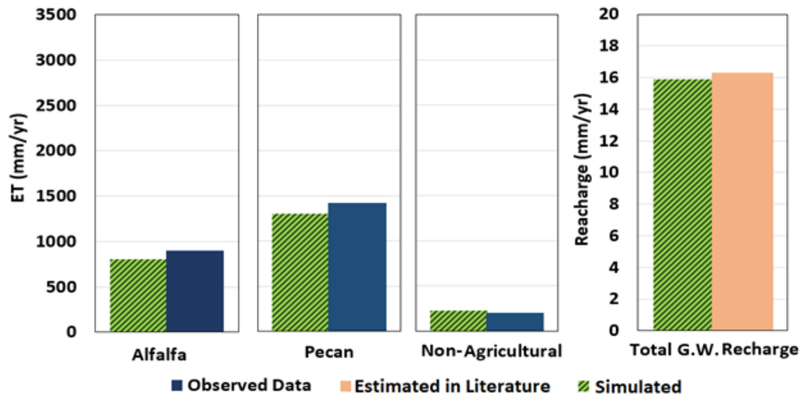


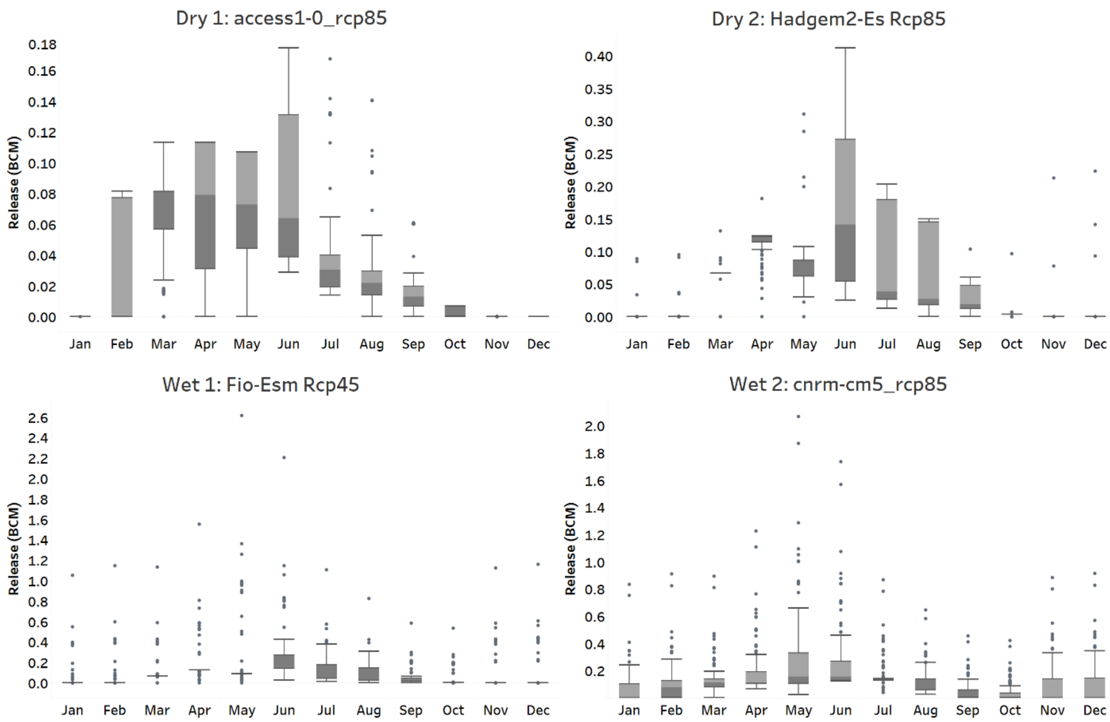
Figure 3.9. ET and groundwater recharge calibration compared with measured ET (Sammis et al., 2004 & 2013) and estimated recharge values in the Rincon Valley of EBID (Ahn et al., 2018).

3.2. Future States of Elephant Butte-Caballo Reservoir System

The monthly ranges of reservoir system release and storage for each streamflow scenario are shown in Fig. 10. As expected, dry scenarios resulted in lower monthly reservoir releases (i.e., up to 0.17 BCM for Dry 1 and 0.41 BCM for Dry 2) compared to wet scenarios (i.e., up to 0.42 BCM for Wet 1 and 0.66 BCM for Wet 2, excluding outliers). All scenarios include periods of nearly no release even during the irrigation season. The reservoir system never reaches full capacity under the extreme Dry1 scenario (the largest storage is about 2.8 BCM) and it rarely fills up under Dry 2 scenario. The prospect of a full reservoir system in the future is also dim under Wet 1 scenario whereas an extremely wet future (Wet 2 scenario) can potentially fill up the reservoirs relatively frequently. The storage in the reservoir system is disproportionately affected during dry conditions due to continuous evaporation. For example, an average 58% decrease in monthly inflow to EB reservoir under Dry 1 would reduce reservoir system storage by about 87% in the future

(Table 3.3). As reported in Table 3, the reservoir storage will frequently drop below 10% full under dry scenarios and it will be less than 50% full the majority of the time even under a plausible relatively wet projected future (Wet 1).

a)



b)

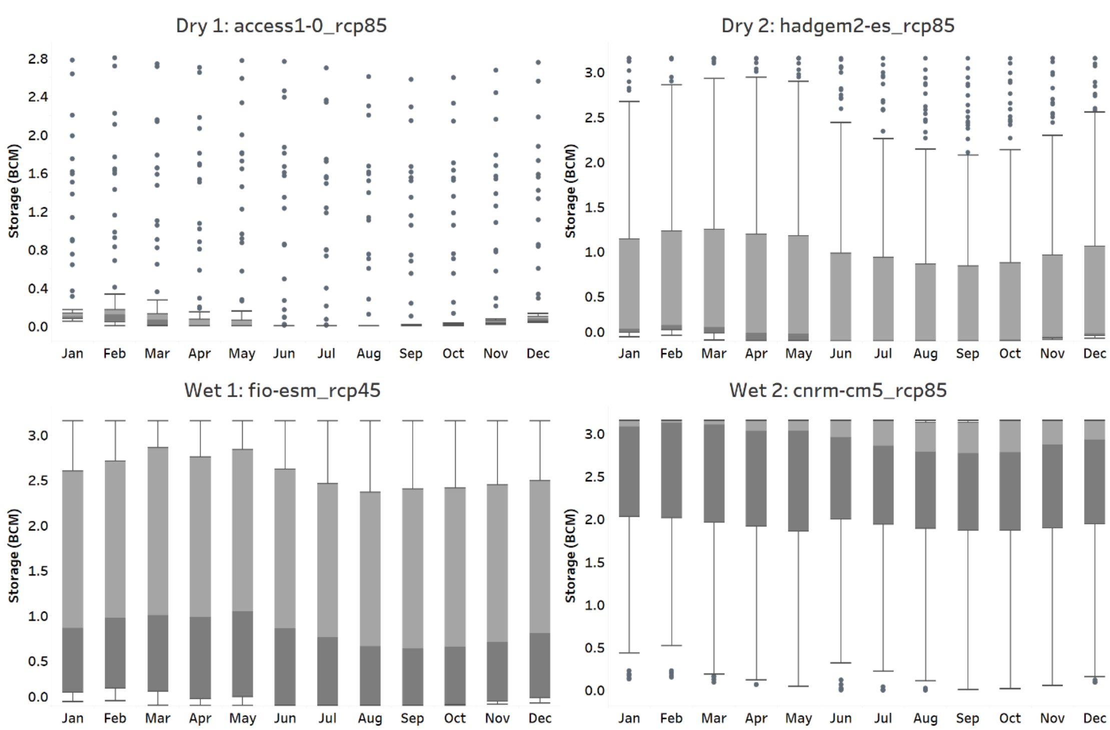


Figure 3.10. Ranges of Elephant Butte-Caballo reservoir system release (a) and storage (b) under selected climate-based flow scenarios through year 2099.

3.3. Impacts on Agricultural Water Availability

Table 3.3 summarizes the average annual values of major water budget components simulated under baseline and future projections. The baseline simulation uses historical releases and NOAA weather data (precipitation and temperature) from four weather stations inside and around the study area from 1993 to 2013 (with one year warm-up period). Future precipitation and temperature conditions are based on hadgem2-es model rcp 8.5 projections. Irrigation is drastically reduced under the doomsday no release (NR) condition, which means severe agricultural water shortage. Many pecan orchards will not survive such conditions in the long-run as suggested by the radical decline of pecan yield (Table 3.3). Although the average historical inflow to the watershed is comparable to the Dry1 scenario, most water budget components are smaller in the latter, showing the adverse impact of higher temperature and lower precipitation in the headwaters in future. The Dry1 and Dry2 scenarios generated similar results because of the role groundwater plays in alleviating agricultural water scarcity. However, the average annual irrigation is slightly smaller when only fresh to slightly saline groundwater is used to supplement river water, which causes a proportionate decline in the pecan yield (Table 3.3). The largest values of water budget components were obtained using the extreme wet (Wet 2) scenario which is least expected based on historical hydro-climatic trends.

Table 3.3. Simulated average annual values of major water budget components for different projected scenarios (2022-2099).

Scenario	Reservoir storage (% of time) <50 % full	Reservoir storage (% of time) <10 % full	Water source	Flow (m^3) In	Flow (m^3) Out	Deep GW recharge (mm)	Base flow (mm)	Irrigation (mm)	ET (mm)	Soil moisture (mm)	Pecan yield*** (ton/ha)
Baseline	100	38	River+ GW*	25	13.3	78	16.4	539	635	10.5	1.08
NR	-	-		2	2.8	54	7	255	343	15	0.19
Dry1	98	87	River+ GW	25.2	12.3	68.8	12	589	626	11.2	0.98
			River+ FGW**	19	9.3	62.7	10	505	561	11.3	0.93
Dry2	78	69	River+ GW	25.2	12.3	68.8	12	589	626	11.2	0.98
			River+ FGW	23.5	13.2	64	11	525	577	11	0.95
Wet1	62	36	River+ GW	51	38	72.3	14	605	635	11.2	0.98
			River + FGW	48	36	69.4	13	574	612	11	0.97
Wet2	21	8	River + GW	68	53	80.3	19	639	653.5	11.1	0.99
			River + FGW	66	52.6	79.6	18	633	649	12	0.99

*GW= Fresh groundwater to slightly saline (Total Dissolved Solids (TDS)<3000 mg/L) and marginal quality groundwater (TDS>3000 mg/L)

** FGW= Fresh to slightly saline groundwater (TDS<3000 mg/L)

*** Average pecan yield for the period 2022-2099.

A drier future will increase pressure on good quality groundwater to offset the impact of reduced surface water availability (Fig. 3.11), likely depleting it in the second half of the 21st century. This is indicated in the declining reliability of agricultural water supply when only fresh to slightly saline groundwater is used for irrigation during the 2060-2099 period (Table 3.4). Reliability is defined as the probability that water demands are fully met (McMahon et al., 2006). The results show that Dry1 and Dry2 scenarios would possibly result in depleting 80% of the fresh groundwater storage by 2060, which bears critical implications for irrigated agriculture. Fresh groundwater storage will last longer (e.g., up to 2070) under a moderately wet scenario (Wet 1) whereas extreme wet future conditions (Wet 2), the least likely scenario, would prevent the depletion before the end of 21st century. The reliability of meeting agricultural water demand declines in the second half of the 21st century under all the simulated future water availability conditions (Table 3.4). River water alone does not meet the agricultural water demand all the time even under Wet 2 scenario, which shows that agricultural water demand has significantly outgrown renewable water availability. In the absence of agricultural water management improvements to prolong fresh groundwater availability, agricultural producers should prepare to use marginal quality groundwater in the future to mitigate potential impacts of fresh groundwater depletion.

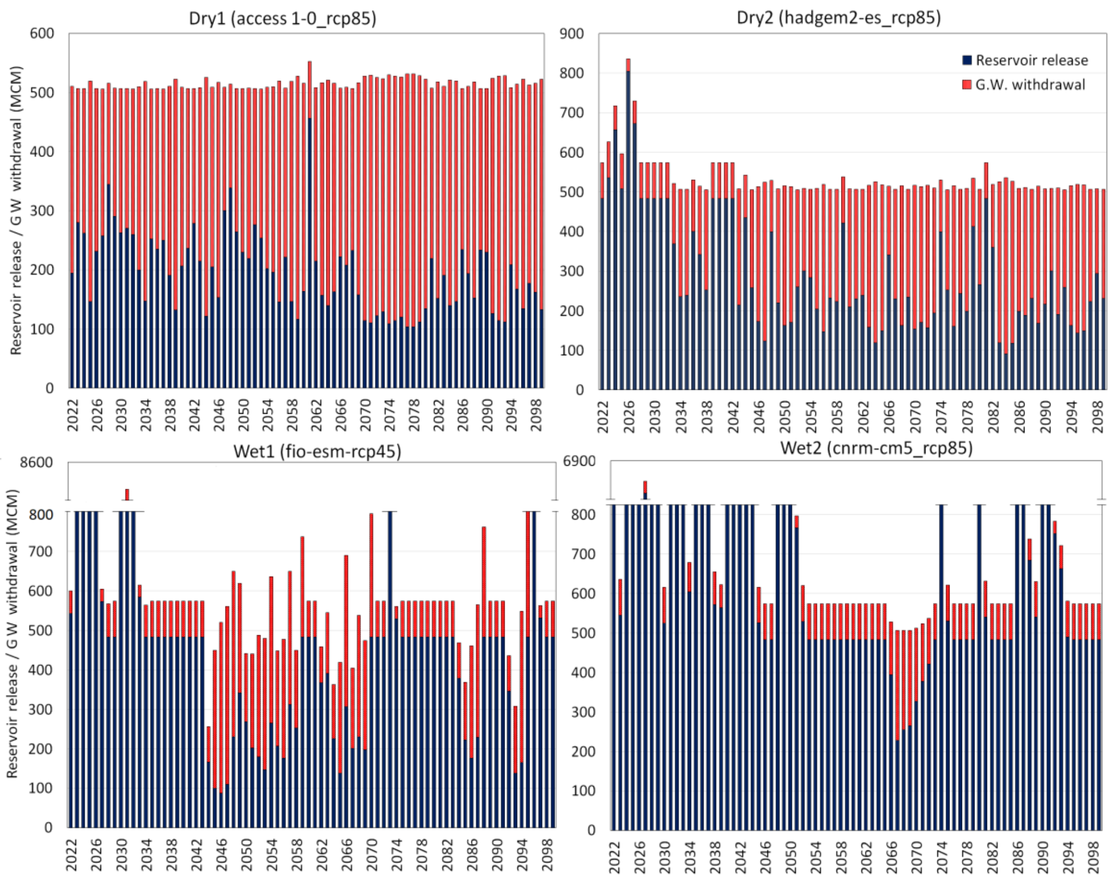


Figure 3. 11. Conjunctive use of surface water and groundwater for the selected scenarios.

Table 3.4. Reliability of water resources in different time periods under future scenarios

Scenario	**Water source**	**Reliability* (%)**	
		2020-2060	**2060-2099**
Dry1	Surface water and fresh to slightly saline groundwater	49	17
	Surface water and fresh to marginal quality groundwater	49	50
Dry2	Surface water and fresh to slightly saline groundwater	54	18
	Surface water and fresh to marginal quality groundwater	54	50
Wet1	Surface water and fresh to slightly saline groundwater	62	38
	Surface water and fresh to marginal quality groundwater	62	57
Wet2	Surface water and fresh to slightly saline groundwater	75	63
	Surface water and fresh to marginal quality groundwater	75	63

* Reliability is defined as the probability that water demands are fully met (McMahon et al., 2006).

Figure 3.12 illustrates average annual agricultural ET as an indicator of crop production, contrasting baseline ET with simulated ET. Baseline ET is included to provide a basis for comparing the variability and magnitude of ET under Dry 1 and Wet 2 scenarios. The dry-scenario ET results are shown for two cases, namely (i) when only river water and fresh to slightly saline groundwater (FGW) are available for irrigation, i.e., Dry1 (River+FGW), and (ii) when river water is used in conjunction with both fresh to slightly saline and marginal quality groundwater, i.e., Dry 1 (River+GW). The significant drop in ET in Dry1 (River+FGW) in the late 2050's demonstrates the severe vulnerability of irrigated agriculture when fresh to slightly saline groundwater is depleted. If marginal quality groundwater can be used effectively for irrigation, it will be possible to maintain full water allocation reliability at about 50%. However, using marginal quality groundwater in the long run would decrease crop productivity and adversely impact soil salinity and texture, which were not accounted for in the present assessment.

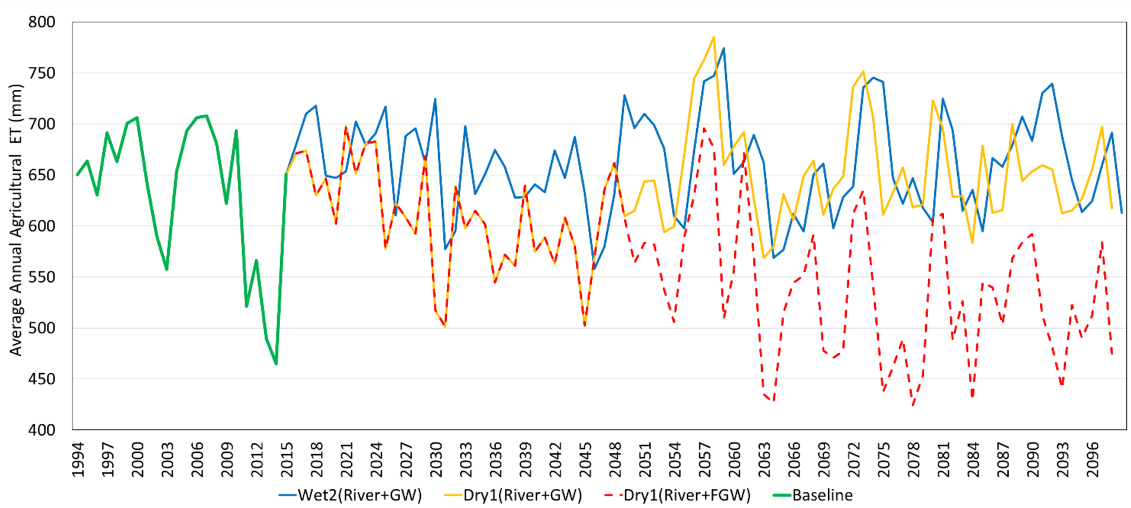


Figure 3.12. Simulated Evapotranspiration for Baseline, Wet2 and Dry 1 with all available water resources and Dry1 with surface water and fresh groundwater.

4. Discussion

The wide range of managed streamflow projections developed based on 97 downscaled bias-corrected GCM products indicates significant uncertainty in future water availability in the region. It is essential to account for upstream impacts on flows as a primary input for assessing potential impacts of future climate conditions in heavily regulated arid/semi-arid basins (e.g., Townsend and Gutzler 2020), and select flow projections that are regionally relevant based on the realities of how flow conditions have changed historically. The historical Rio Grande flows in the study area (i.e., San Marcial and El Paso gauges) display an overall declining trend related to a combination of climate conditions and upstream management practices (Fig. 3.13). The declining trend underscores the importance of preparing for scenarios of reduced surface water availability under hotter and drier conditions in the future. This is particularly important for evaluating long-term availability of fresh groundwater and sustainability of irrigated agriculture.

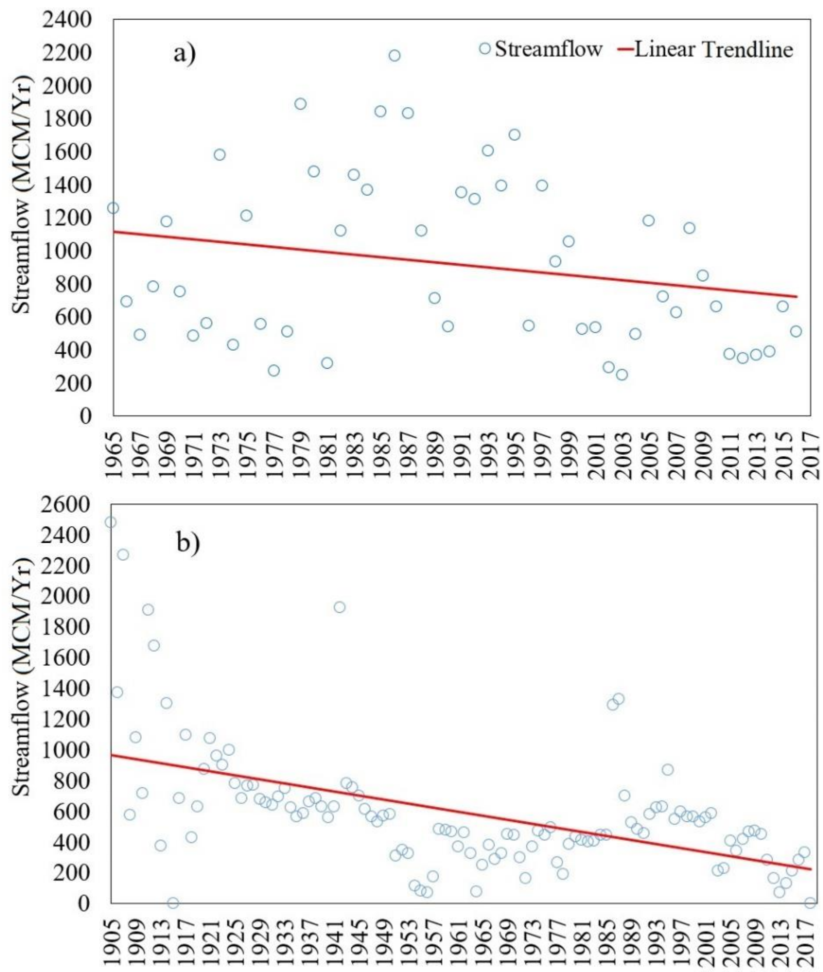


Figure 3.13. Historical annual variability of Rio Grande flow at San Marcial gauge (USGS 08358300) immediately upstream of the watershed (a) and at watershed outlet at El Paso gauge (USGS 08364000).

The results should be interpreted in light of a few caveats related to the watershed modeling component of the climate impact assessment framework. Calibration of highly managed water systems using governing hydrologic parameters is generally challenging, especially when detailed management operations data are unavailable (Abbaspour 2013).

A good streamflow calibration does not necessarily translate into equally good results for other managed components (e.g., ET and groundwater recharge) of the water budget in arid irrigated areas. Thus, the multi-component calibration strategy applied in the current analysis was necessary to provide a realistic characterization of the water budget components in the region to inform adaptive management of regional water resources. Other caveats include limited capability for detailed simulation of pecan trees such as impacts of irrigation water shortage in different time periods on plant survival and yield. A static crop mix and acreage was assumed in the model based on recent land use maps (NLCD 2011), which does not capture dynamic land use change in response to water availability during wet and dry periods and crop market value. Thus, the reported implications of future climate conditions are conservative in that they are based on water demands corresponding to agricultural lands during the exceptional drought in 2011. Due to higher agricultural activity in average and wetter than average years, which requires more irrigation, the impacts of diminished river flow in the future may be even more severe.

It is necessary to improve agricultural water management with the ultimate goal of reducing net water consumption in the region. While water storage in the upstream reservoirs and increasing groundwater withdrawal can mitigate the negative impacts of future droughts, the dominant agricultural water management approach for high-value crops is unsustainable. The modeling results show that agricultural activities will increasingly rely on groundwater in the future because the dwindling surface water will make it difficult to provide full river water allocation to EBID in most years. Based on the range of available estimates of good quality groundwater storage in the Mesilla Basin, maintaining the region's agricultural production is only possible at the expense of depleting fresh groundwater within the 21st century and transitioning to using marginal quality groundwater. The transition to using marginal quality groundwater for irrigation will create a set of new challenges, including increasing energy cost of pumping and groundwater desalination, which may weaken the economic attractiveness of irrigated agriculture.

The future availability of irrigation water in the middle section of the Rio Grande will depend on the cooperation of all users to develop an integrated regional water plan to manage the declining resources. The Elephant Butte-Caballo reservoir system will become a much less reliable water source in the future. There is a critical need to better understand groundwater availability in the region to inform short-term tactical agricultural water management decisions in light of long-term water sustainability considerations. Specifically, it is important to update the estimates of fresh and brackish groundwater storages based on hydrogeological assessments to develop robust models of the aquifer while accounting for mixing of fresh and saline groundwater as result of increased pumping. It is time to build consensus about possible regional water management improvements needed and take action to prolong fresh groundwater availability in the middle section of the Rio Grande.

5. Conclusions

We applied a stakeholder-driven climate impact assessment framework consisting of projected monthly Rio Grande flows at San Marcial gauge, a spatially distributed watershed hydrology model, and a simple model of conjunctive management of surface water and groundwater to support irrigated agriculture. The calibrated and validated SWAT model reproduced the major components of the water balance budget (e.g., streamflow, ET, and groundwater recharge) in the arid/semi-arid agricultural watershed with a heavily managed river system to support irrigation. The results suggest that the region will likely become more groundwater-dependent in the future as the reliability of the upstream Elephant Butte-Caballo reservoir system declines. Sustaining irrigated agriculture in the long run will require adopting more efficient irrigation methods with the ultimate goal of reducing net agricultural water consumption in the region. In the absence of improved agricultural water management practices, it is highly likely that maintaining the region’s agricultural production will lead to fresh groundwater depletion within the 21st century. As such, the region should prepare to cope with the challenges of transitioning to using marginal quality groundwater for irrigation (e.g., increasing energy cost of pumping and groundwater desalination). It is essential to build consensus among stakeholders about possible regional water management improvements and take timely actions to protect fresh groundwater availability in the region.

CHAPTER IV

ADAPTIVE AGRICULTURAL WATER MANAGEMENT TO COPE WITH WARM-DRY FUTURE IN THE US DESERT SOUTHWEST

1. Introduction

Increasing risks of water shortage and deteriorating water quality, especially in arid/semi-arid regions, raises concerns about water resources management strategies to secure future food production and ensure watershed sustainability (Wallace, 2000; English et al., 2002; Qadir et al., 2003; Jury and Vaux 2005; Ward and Pulido-Velazquez 2008; Brinegar and Ward 2009; Al-Ghobari and Dewidar 2018; USDA, n.d.). Applicability of the water resources management practices depends on the watershed conditions (topography, access to water resources, etc.), economic and social aspects that affect the cost of improving and/or shifting away from existing methods. The social and environmental impacts of the new water conservation methods should not be overlooked as in some cases these practices may produce counter-intuitive results leading to more water consumption (e.g., Ward and Pulido-Velazquez 2008).

In 2012, irrigated agriculture covered nearly 8% of the U.S. farmlands and rangelands, consuming about 80% of the water resources (USDA, n.d.). Most of the irrigated lands are located in the western states with arid/semi-arid climate. Increasing aridity in the southwestern US (Garfin et al. 2013; Dettinger et al. 2015) would impact the access of the agriculture sector to water with acceptable quantity and quality. Water conservation practices and increasing the resilience of the agricultural sector support food security and economy, especially in the face of uncertainties related to water-shortages (Ganjegunte and Clark 2017; English et al., 2002). Adaptive irrigation practices such as deficit irrigation, partial root zone drying, mulching, and crop pattern change facilitate coping with growing water scarcity (Nouri et al., 2019; Eberbach et al., 2011; Sadras, 2009). Likewise, advanced irrigation approaches such as surface and sub-surface drip and sprinkler irrigation and micro irrigation along with modern technology such as remote sensing, soil moisture monitoring, etc. to schedule irrigation and minimize the water losses have produced promising results around the world (Koech and Langat 2018; Li et al., 2007; Ganjegunte and Clark 2017).

The main objective of this paper is to analyze the impacts of different agricultural water management interventions on future water availability in an arid/semi-arid region with limited surface water and fresh groundwater resources for irrigation. Adaptive agricultural water management approaches like irrigation scheduling, deficit irrigation, and land use management do not require major changes in infrastructure and are already practiced to some extent by farmers as a general response to water shortages (Skaggs and

Samani 2005). Other methods such as drip irrigation would require fundamental changes in irrigation infrastructure, creating a heavier economic burden. Substituting current high-value commodity crops with drought-tolerant cash crops such as pistachio and pomegranate that are compatible to the climate of New Mexico is another approach that has generally been applied as a drought adaptation strategy in arid regions (Herrera, 1991; Wang et al., 2015).

The study area in the middle Rio Grande basin is an example of an arid/semi-arid irrigated agricultural watershed facing water quantity and quality concerns due to demand growth and extreme climate-related variability of renewable water (Elias et al., 2015; Chavarria and Gutzler 2018, Samimi et al., in review). The groundwater resources are in this region are declining due to increasing withdrawal (Sheng 2013; Fuchs et al. 2018). Rio Grande flow projections at San Marcial up to year 2100 demonstrate great uncertainty in future surface water conditions (Townsend and Gutzler 2020), which affect future states of the EB-C reservoir system and groundwater sustainability (Samimi, et al., in review). Analysis of 97 climate projections shows that the majority of the river flow projections indicate drier conditions compared to the historical record. Even “wet” future projections would also experience major droughts, resulting in more pressure on groundwater resources (See section 3.3 in Chapter III).

It is highly likely that fresh to slightly saline groundwater (TDS < 3000 mg/L) in the middle section of the Rio Grande will be depleted in the second half of the 21st century under warm-dry scenarios. The agricultural sector is vulnerable to fresh groundwater depletion, which can cause economic losses associated with diminishing crop production. To cope with this plausible scenario, it is necessary to investigate feasible water saving strategies to prolong the life of the fresh to slightly saline groundwater resources. Alternatively, irrigated agriculture in this region should prepare to use marginal quality groundwater and mitigate the impacts of irrigation with saline water including yield loss, soil salinization, soil degradation, etc. Using more irrigation water to leach out salt from the root zone, diluting the saline water with available fresh water, switching to drip irrigation, on-farm desalinization plants, and growing more salt-tolerant crops are example strategies to deal with the impacts of salinity. Such measures are costly and energy demanding and might not be always efficient given the watershed conditions, implementation challenges and maintenance requirements (Miyamoto, 2006).

Pecan is the highest-value crop in the study area, which is most vulnerable to water shortages (Miyamoto et al., 1995; Miyamoto and Storey 1995). The region has witnessed a 25% increase in the area of pecan farms from 1994 to 2013 because of high profitability of this crop. In the past, producers have typically decreased the acreage of other crops or stopped growing them altogether, especially alfalfa and cotton, to save water for pecan farms during droughts. The efficiency of current irrigation methods for pecan, cotton, and alfalfa in the study area is estimated to range between 60 to 90 percent (Skaggs and Samani 2005; Ahadi et al., 2013). In particular, flood-irrigation of pecan farms in southern New Mexico leads to significant water losses because irrigation schedules typically do not account for crop water demand in different growth stages (Skaggs and Samani 2005; Samani and Skaggs 2008). Scheduling the time and amount of irrigation events according the plant’s water demand will increase the flood irrigation efficiency. Irrigation scheduling based on soil water content measurements and soil moisture sensors will also increase the water consumption efficiency, creating opportunities to save more water (Ganjegunte and Clark 2017; Kalisek et al., 2011).

Agricultural water conservation methods mainly focus on increasing the water productivity through reducing the irrigation water consumption with minimum negative impact on crop yield. This can be obtained by increasing irrigation efficiency through reducing the water loss during conveyance from the source to the farm (e.g., channel lining), on-farm water losses (e.g., drip irrigation, sprinkler irrigation, mulching), and irrigation scheduling based on monitoring ET or soil moisture content to minimize water application when irrigation is not needed. Water savings are also possible during the periods of crop growth when the plant is less sensitive to water stress (e.g., deficit irrigation, partial root-zone drying). Other options to reduce irrigation include breeding drought tolerant crops (Condon et al., 2004), growing drought adaptive crops, and leveling the farm ground to improve water distribution (Knutson et al., 1998; Thompson et al., 2009; Perry, 2011; Mir et al., 2012; Li et al., 2013; Ganjegunte and Clark 2017). Further, using treated wastewater or marginal quality saline water can reduce reliance on fresh groundwater (Knutson et al., 1998).

This paper contributes to climate-informed adaptation of agricultural water management in an arid/semi-arid agricultural watershed where heavily irrigated croplands face the risk of increasing water shortages due to possible warm-dry future climate conditions. The objectives of the paper are two-fold: 1) simulate a series of agricultural water adaptation scenarios using a multi-component calibrated SWAT model; and 2) evaluate the water conservation potential of each scenario, as well as opportunities for agricultural water savings using a combination of the analyzed interventions. Water conservation potential is defined in this study as the percentage of reduction in irrigation water applied by the model based on the user-defined scenarios of deficit irrigation. The implications of various intervention options (e.g., irrigation, changing current cropping pattern, and growing alternative high-value crops) to sustain irrigated agriculture are discussed using the middle Rio Grande in the arid US-Mexico border region as a case study. Results of this study inform model-based evaluation of agricultural water management interventions in hydroclimatically similar areas to adapt to growing risks of water shortages due to plausible warm-dry conditions in the future.

2. Methods and Materials

2.1. Study Area

The study area is the New Mexico-Texas portion (watershed area: ~ 6000 km^2; agricultural area: ~ 400 km^2) of the Rio Grande basin (Fig. 3.1). The region is classified as arid/semi-arid with an average annual precipitation of approximately 270 mm (less than one-third of global average) and average maximum and minimum daily temperatures of 42 °C and -23 °C, respectively (absolute min is -28°C and absolute max is 45°C from different weather stations). The soil types in the farmlands are very various, the larger portion of pecan farms are covered with clay loam and loam but pecan orchards in EBID vary between all types of soil from sand to clay (Miyamoto and Storey 1995).

The Rio Grande streamflow is regulated at the Elephant Butte (EB) and Caballo reservoirs. The EB reservoir (completion: 1916, Capacity: > 2.2 million acre-feet) stores water for irrigation and hydro-power production (USBR, n.d.). Caballo Reservoir with a capacity of 343,990 acre-feet is located 25 miles downstream of the EB Dam to regulate the releases from the main reservoir. “Water discharged from the EB Power plant during winter power generation is impounded at Caballo Dam for irrigation use during the summer.” (USBR, n.d.). Two gauges, USGS 08358300 Rio Grande conveyance channel at San Marcial and USGS 08358400 Rio Grande Floodway at San Marcial measure inflow to the EB reservoir. The reservoirs’ releases are recorded by USGS gauges 08361000 Rio Grande below EB and 08362500 Rio Grande below Caballo. The USGS gauge 08364000 Rio Grande at El Paso measures the outflow from the watershed.

The main irrigated agricultural activities occur within Elephant Butte Irrigation District (EBID) located downstream of the Caballo reservoir. Three diversion dams, Mesilla, Leasburg, and Percha, and five main canals distribute water among > 90,000 acres of irrigated lands. Alfalfa and pecan are major crops, covering about 50% of the cultivated area. Figure 3.2 shows the historical changes in crop pattern in the EBID and compares it with the water availability in the watershed. The major drought periods in 2003-2004 and 2011-2012 caused decline in all crops especially alfalfa, pepper, corn, cotton, and vegetables. The surface water availability for agriculture depends on upstream reservoir releases. In normal years, water is released from Caballo reservoir from March to September to meet the irrigation water demands in the EBID.

To compensate for surface water shortages during the irrigation season, farmers pump groundwater from the Mesilla basin, the main aquifer in the region (Sheng, 2013). The annual groundwater withdrawal data were obtained from observational records and a piecewise linear approximation of groundwater withdrawal based on releases from the Caballo reservoir (Samimi et al., in review). The monthly distribution is estimated based on monthly releases and monthly water table measurements available from USGS (e.g.,

USGS 321745106492101 MBOWN-29 - 23S.01E.22.241A (LC-2A)). A constant daily withdrawal is assumed in each month. These estimations introduce uncertainty in the SWAT model results, which will be reduced through a model calibration process.

Increasing salinity in water resources is a major problem in arid/semi-arid regions (Williams, 1999). The surface water and groundwater salinity data from 2014 to 2016 in the study area demonstrate the availability of fresh surface water (TDS<1000 mg/L) in the river channel during the reservoir release period (Ma et al., 2019). Samples collected from wells along the main stem of the river indicate fresh to slightly saline groundwater with TDS values ranging between 300 to 2000 mg/L (Ma, et al., 2019). Sources of salinity in the Rio Grande are mainly upstream river flow which provides the majority of salt ions, natural river bed material, and saline groundwater intrusion (Wurbs, 2002; Hogan et al., 2007; Szynkiewicz et al., 2011 and 2014; Yuan and Mayer, 2012). As fresh water availability declines, there is mounting concern about increasing salinity in groundwater and river water.

Traditional flood irrigation (basin irrigation) is commonly practiced in the EBID. The on-farm irrigation efficiency in several EBID farms has been estimated between 60%-83% (Samani and Skaggs 2005; Ahadi et al., 2013). The high efficiencies are attributed to deficit irrigation and high water consumption of pecan. However, studies have also shown that some fields within the irrigation district over-irrigate while others fail to meet their water requirements (Samani and Skaggs 2005). Agricultural producers are concerned about the prospect of reduced future water availability, especially the sustainability of irrigated pecan production using current agricultural water management approaches (Hargrove and Heyman, 2020).

2.2. Simulating Irrigation with SWAT

SWAT is a semi-distributed model that simulates watershed hydrology using the water balance equation (Arnold et al., 1998). The watershed is first divided into hydrological response units (HRU) based on similar land use/land cover type, soil characteristics, and slope in each subbasin. The water balance in each HRU is calculated based on input information including weather data, elevation, land use/land cover, soil, management practices (irrigation, fertilization, harvest, etc.), and plant growth information. The model's built-in databases provide input data including weather data, land use, and plant growth (Neitsch et al., 2011). SWAT has been widely applied in arid/semi-arid areas with irrigated agriculture to simulate the impacts of changes in climate and agricultural management on the water budget components (Samimi et al., 2020).

SWAT has two options to simulate irrigation. The first option is manual irrigation based on user-defined irrigation schedule (i.e., time and amount of water), as well as irrigation efficiency. When detailed information about irrigation schedule is unavailable, users can select the auto-irrigation function to allow the model to simulate the irrigation timing and amount based on default or user-defined parameter values. The model assumes irrigation continues until soil water content reaches the field capacity (Neitsch et al., 2011). The model allows the user to define the start of auto-irrigation on a specific day and month or based on the amount of crop heat units.

When a specific date is set for auto-irrigation, the model triggers irrigation events based on a pre-defined water stress threshold. Two types of water stress thresholds can be defined, i.e., plant water demand or soil water content. For the plant water demand threshold, the model monitors the plant growth and triggers irrigation once growth falls below the threshold. For soil water content, a pre-defined soil water deficit compared to field capacity is used as the threshold to initiate irrigation. We selected the specific date and soil water content threshold for auto-irrigation. The auto-irrigation function in SWAT model continues irrigation even after the harvest season (Akhavan et al., 2010; Samimi et al., 2020). Thus, we specified an extreme water stress threshold at the end of the irrigation season to stop irrigation after harvest.

The soil water deficit threshold for auto-irrigation is defined using the available soil water concept. The total available water content (AWC) in the soil is the amount of water available to plant, which is calculated as the difference between the field capacity and wilting point. Field capacity is the maximum amount of water that stays in the soil against gravity. The wilting point is the minimum threshold of soil water content accessible to the plant. These values depend on the soil type. Plants cannot uptake all the AWC easily (FAO 22). The readily available water (RAW) in the soil is the portion of the total available water that can be easily used by plants without any water stress. The readily available water varies in crops between 0.3-0.7 of AWC. Lower RAW values are typically used for dry and hot climates (FAO 22). RAW has been estimated to be 0.45-0.50 for pecan, 0.65 for cotton, 0.55 for oat and alfalfa, and 0.30 for onion and vegetables (FAO 22; Kallestad et al., 2008). The RAW for each crop in the study area was calculated based on soil AWC from SSURGO map and effective rooting depth of plants, where root density is 80% and maximum water uptake occurs (USDA, 1997).

The auto-irrigation parameters were calibrated separately for each crop. The water stress threshold for soil moisture deficit was calculated based on the soil and crop characteristics. Based on the SSURGO soil map, the average AWC for the majority of farmlands is 0.13 - 0.14. The water stress threshold (AUTO_WSTRS) for soil moisture content was calculated for the AWC of 0.13, crop effective rooting, and RAW coefficient of 30-50% as recommended for each crop (FAO 22; Kallestad et al., 2008). The amount of water application for each irrigation event (IRR_MAX) was set based on the general information on irrigation applications in the region (Example: 4 acre-feet per acre for pecan).

3. Intervention Scenarios

Several agricultural water management interventions are reported in the literature to improve irrigation efficiency and crop water use efficiency (e.g., Heaton et al., 1982; English et al., 2002; Sadras, 2009; Eberbach et al., 2011; Chai et al., 2016; Ganjegunte and Clark 2017). The intervention scenarios are examined to identify opportunities to conserve water to sustain irrigated agriculture, in general, and high-value pecan crops, in particular. The interventions were grouped into two main categories of irrigation and cropping change, which were analyzed by simulating thematic scenarios of deficit irrigation, changing crop pattern, and growing alternative crops. The examined intervention scenarios were selected based on their practical application in the study area, taking into account past adaption approaches, and the SWAT model's ability to simulate the interventions properly.

3.1. Deficit Irrigation

Deficit irrigation is applied in water-scarce regions around the world as a way to increase water use efficiency by reducing irrigation water with minimum loss in crop yield

(Martin et al., 1989; Costa et al., 2007). It is designed based on reducing crop ET to a fraction of pan evaporation or potential crop ET. Deficit irrigation is implemented by reducing the amount of irrigation, increasing the RAW coefficient, and/or reducing the number of irrigation events, especially during less sensitive growth stages (Onder et al., 2009; Payero et al., 2009; Liu et al., 2017; Bauder et al., 2011). Crops under unregulated deficit irrigation experience certain levels of water stress throughout the irrigation season (FAO 22, Costa et al., 2007). One type of regulated deficit irrigation means that plants are stressed during specific periods of their growth cycle when they are less vulnerable to water stress (Chai et al., 2016). Regulated deficit irrigation requires knowledge of plant growth periods and related heat unites in each climate. It is more practical with trickle and drip irrigation where the timing and amount of irrigation can be easily controlled (FAO 22, Costa et al., 2007).

The effectiveness of deficit irrigation depends on climate, soil water retention potential, and plant physiology and mechanisms to cope with water stress (Aydinsakir et al., 2013; witt et al., 2020). Although some studies have reported that deficit irrigation may decrease crop productivity to some extent (Bauder et al., 2011; Djaman et al., 2020), other studies have shown increased crop quality or improved yield factors under deficit drip irrigation such as boll weights and opened boll numbers (Onder et al., 2009; Liu et al., 2017). In some cases, the yield reduction associated with deficit irrigation was negligible (Costa et al., 2007; FAO 22). In areas facing growing water scarcity and raising economic value of water, the increase in water use efficiency may justify the yield reduction (FAO 22).

Yield loss in deficit irrigation is typically estimated by the following equation (Doorenbos and Kassam 1979):

$$1 - \frac{Y_c}{Y_m} = K_y \left(1 - \frac{ET_c}{ET_m}\right) \quad (1)$$

Where ET_c and ET_m are the crop ET and potential ET of the crop (the maximum crop ET) in mm, Y_c is the yield in kg/ha, achieved with ET_c; Y_m is the maximum yield in kg/ha related to potential crop ET_c; and K_y is the yield response factor estimated through research and experiment for each crop and for different stages of crop growth.

The impact of water stress on different plants and their crop yield is varied. Alfalfa is a water demanding crop that is relatively adaptable to water stress because of its deep roots and the ability to go to dormancy during droughts (Bauder et al., 2011). The ET and yield reduction of alfalfa in whole season deficit irrigation is greater than "partial season irrigation" (Bauder et al., 2011; Djaman et al., 2020; Smeal et al., 1991). Partial season irrigation of alfalfa is normally practiced by stopping the irrigation after a cut, e.g., in some areas irrigation is stopped after the first, second, or third cut whereas in other places it may continue until the last cut (Bauder et al., 2011; Djaman et al., 2020).

Any water stress level and timing results in corn yield reduction (Payero et al., 2006; Payero et al., 2009; Yazar et al., 2009). The yield reduction and optimum time for deficit irrigation in semi-arid regions depends on many factors that vary from year to year (Payero et al., 2009). For cotton, deficit drip irrigation during the initial and final stages of cotton growth were most efficient in the Southern High Plains with 350-450 mm rainfall (Himanshu et al., 2019). Moderate water stress without decreasing irrigation events had minimum yield loss in cotton in arid climate of Central Asia (Pereira et al., 2009). In the Mediterranean, 50% of pan evaporation had the best result for deficit irrigation of cotton (Onder et al., 2009) and corn (Aydinsakir et al., 2013). Mixing deficit irrigation with other measurements like mulching to manage soil water might be more effective (Pereira et al., 2009). There is a dearth of literature on deficit irrigation of pecan orchards, although it is generally known that pecan is highly sensitive to water stress (Miyamoto et al., 1995; Miyamoto and Storey 1995).

Unregulated deficit irrigation scenarios were simulated through changing the water stress threshold and irrigation amounts for the entire irrigation season to expose crops to a certain level of water stress. Increasing the water stress threshold (soil water deficit) in SWAT does not necessarily lead to the desired increase in crop water stress. A trial and error process was applied to identify the combination of water stress threshold and irrigation amount to reach the desired level of water stress for each crop. To simulate stage-based regulated deficit irrigation scenarios the auto-irrigation periods were controlled by adding extra auto-irrigation functions with high water stress thresholds (AUTO_WSTRS=999) to stop irrigation at certain stages.

3.2. Modifying Current Crop Pattern

Agricultural producers in the study area experienced major droughts in 2003-2004 and 2011-2013. Based on historical records of crop acreage, the producers may take part of their irrigated lands out of production depending on river water availability while they rely on fresh groundwater to sustain pecan, the most vulnerable perennial crop. The changes in crop patterns in response to droughts can be seen in Figure 3.2. The major drops in the total cultivation areas are due to decrease in alfalfa, corn, peppers, cotton, and vegetables. The crop pattern scenarios were selected based on the general practices in the region such as reducing alfalfa and cotton acreages or stopping their cultivation altogether to save water (Ganjegunte and Clark 2017).

3.3. Alternative Crops

Pecan production is affected by water stress and salinity, especially Na^+ and Cl^- ion concentrations in water (Heaton et al., 1982; Miyamoto et al., 1995; Miyamoto, 2006). Water stress can impact the quality of nuts, affect plant growth, and in the long run might kill the tree. Saline water with TDS more than 700 - 1000 mg/L impacts the growth of plants and shrinks the size of leaves and nuts. Growth decline starts at EC of 2.5-3 dS/m in the soil saturation extract, while tree "die-back" starts at higher EC (6-8 dS/m) (Miyamoto, et al., 1986; Miyamoto, 2006). Adding gypsum to the soil might increase the crop's tolerance to some extent (Miyamoto, 2006).

Pistachio and pomegranate are example high-value crops that are relatively adaptive to water stress and salinity (Herrera, 1991; Holland et al., 2009). In recent years, New Mexico farmers have expressed interest in growing pistachio and pomegranate as potential alternatives to pecan (Wang et al., 2015; Carreon, 2019). Pistachio is resistant to water shortage and salinity (TDS up to 4000 ppm is reported) and is cultivated in arid regions of the world (Herrera, 1991). It has been cultivated in the US as a commercial crop since 1929 and its acreage has increased significantly, mostly in California (Herrera, 1991; Geisseler and Horwath, 2016). The climate of the study area is potentially suitable for growing pistachio trees, which need hot summers and cold winters (not colder than -9 to -12 ^oC) for ideal growth and wind for pollination. The tree starts to bear fruit after 5-10 years while the full fruit production takes up to 15 years (Herrera, 1991). Pistachio needs about 1020 mm/year or 2500 cubic meters (2 acre-feet) of water annually. Despite being a drought-adaptive crop, enough soil moisture during late winter, spring and early summer is required to produce quality crop (Herrera, 1991; Goldhamer et al., 1985; Doster et al., 2001). Deficit irrigation at certain stages of crop growth may have minimal impact on pistachio yield (Goldhamer and Beede 2004).

Pomegranate is a native plant of the Middle East, which is grown in Iran, Afghanistan, India, Mexico, Southwest US, and Latin America (Glozer and Ferguson, 2008; Çam et al., 2009; Volschenk, 2020). The crop is gaining attention is a competitive commodity crop due to its growing use in food and medicine industries (Çam et al., 2009; Lansky & Newman, 2007; Carreon, 2019). Pomegranate can be grown in different climates including tropical and subtropical, but the best quality of fruits is obtained in arid regions (Chandra et al., 2010). Pomegranate is compatible to New Mexico climate because of its resistance to droughts (Glozer and Ferguson, 2008; Aseri et al., 2008). The water demand of pomegranate is estimated about 1250-1500 mm/year (Glozer and Ferguson, 2008). Water stress of up to 50% ET in drip irrigation did not have harmful impacts on the crop growth in Iran (Parvizi et al., 2016; Parvizi et al., 2014). Subsurface and surface drip irrigation reduced water application to 53-953 mm/year based on the plant age (Aseri et al., 2017; Volschenk, 2020).

The cold resistance of pomegranate varies between different cultivars. The minimum temperature is reported between -11 oC (Glozer and Ferguson, 2008) and -15oC (Parvizi et al., 2016) while some cultivars can tolerate up to -30oC (Parvizi et al., 2016). It takes 3-5 years for a young pomegranate tree to become productive (Glozer and Ferguson, 2008). The irrigation requirement for young trees is measured at 441-456 mm/year in subsurface and surface drip irrigation systems in California (Wang et al., 2015). Salinity tolerance threshold of pomegranate is reported to be about 2650 mg/L of TDS. Plants irrigated with saline water with TDS of 4000-6000 mg/L demonstrated some vegetative growth problems (Holland et al., 2009). Table 4.1 summarizes the intervention scenarios investigated in this study. Three main scenarios of deficit irrigation, modifying the current crop pattern, and alternative crops are defined.

Table 4.1 Description of selected scenarios for irrigation water conservation to cope with dwindling river water and potential fresh groundwater depletion in 2050

Scenario	**Name**	**Description**
Baseline	Baseline	Recent historical data (1995-2013)
Baseline Projection	Baseline Projection	Current condition under projected surface water in a warm-dry climate scenario with fresh GW (2020-2098)
Deficit Irrigation	DI_alf_July	Alfalfa is not irrigated after July
	DI_alf45	Deficit irrigation of alfalfa by reducing alfalfa ET to 45% of average simulated alfalfa ET in the Baseline condition (1995-2013)
	DI_alf65	Deficit irrigation of alfalfa for 65% of average simulated alfalfa ET
	DI_cor65	Deficit irrigation of corn for 65% of average simulated corn ET
	DI_alf45cot85	Deficit irrigation of alfalfa for 45% of average simulated alfalfa ET and simulated cotton for 85% of average cotton ET
	DI_cot_July	Cotton is not irrigated after July
	DI_cot_50	Deficit irrigation of cotton for 50% of average simulated cotton ET
Modifying Current Crop Pattern	CP_pecan-4	Flood irrigated pecan orchards are increased by 4% in 2020; Young pecan trees are simulated
	CP_no-alf-2050	Alfalfa cultivation is stopped completely in 2050
	CP_50%alf-2050	Alfalfa acreage is reduced by half in 2050
	CP_no-cot-2050	Cotton cultivation is stopped completely in 2050
	CP_no-cot-50%cor-2050	Cotton cultivation is stopped completely and corn cultivation area is reduced by half in 2050
	CP_Extreme	All crops are removed after 2050 except pecan

Alternative Crops	AC_PISCH	Cotton is replaced by flood irrigated pistachio by 2030
	AC_POMG	Cotton is replaced by flood irrigated pomegranate by 2030
	AC_POMG_drip	Cotton is replaced by drip irrigated pomegranate by 2030

4. Results

4.1. Multi-Component Calibration and Validation

The SWAT Model was calibrated and validated for different water budget components as well as irrigation amounts. Since the main objective of the study is to evaluation different irrigation interventions, the model should be able to reflect the current irrigation practices and crop water consumption. To meet these conditions, the model was first calibrated and validated for the monthly observed river flow at the watershed outlet (USGS 08364000) using Sufi2 algorithm in SWAT-CUP (Abbaspour, 2015). The calibration period is 1995-2004 to cover both high and low flows in the historical period. Two years of warm-up (1993-1995) were considered to set the primary values of model parameters.

The model was then validated for the period of 2005-2013 with low streamflow during the 2011-2013 drought. Figure 4.1 shows the results of final calibration and validation. The goodness-of-fit factors to evaluate the model's performance include NSE, PBIAS, and R2 (Moriasi et al., 2007). The model shows good performance during calibration period (NSE=0.68, PBIAS=1.5% and R2=0.86). The goodness-of-fit factors for the validation period are NSE=0.7, PBIAS= -7%, and R2=0.84, which comparably good performance. The performance improves significantly during 1995-2002 (NSE=0.8, PBIAS= -4.5%, and R2=0.9), which excludes a severe drought in 2003. The model overestimates some peak flows, especially in 2003 and 2004. It also overestimates the low flows in the validation period, possibly due to overestimation of groundwater withdrawal outside irrigation season (see Section 2.2 in Chapter III).

In the next step, the model was manually calibrated for average annual irrigation and ET as well as groundwater recharge. In each step the main components (streamflow, crop ET, groundwater recharge, and applied irrigation) were cross -compared to find a realistic calibrated parameter set for the heavily irrigated watershed located in an arid/semi-arid region. Due to limited irrigation schedule data for different crops in the study area, we used a range of values based on measurements reported in the literature (Abdul-Jabbar et al., 1983; Samani et al., 2009; Samani et al., 2011; Samani et al., 2013; Samani et al., 2004; Ward et al., 2014). Table 4.2 shows the parameterization of the calibrated model.

The initial auto-irrigation settings resulted in lower average annual irrigation amounts than expected based on the literature and “soft data” for crops especially pecan and alfalfa (e.g., Abdul-Jabbar et al., 1983; Sammis et al., 2004; Samani et al., 2009, 2011 & 2013). Soft data means expert judgements (Arnold et al., 2015). In order to calibrate the irrigation, we reduced the AUTO_WSTRS depths for all crops. This might indicate that farmers either irrigate the fields before the soil water deficit reaches at least 50% of AWC or they overapply water to leach out the salt from the soil layer. The irrigation at the HRU level is not consistent; some HRUs are overirrigated while others are underirrigated based on water availability to each HRU and subbasin at each time step.

The thresholds for the HRUs with different AWC were corrected individually. Model calibration for irrigation resulted in lower values of RAW than the initial thresholds. This indicates a potential difference between the model set up and actual irrigation practices on the ground, which are mainly based on counting the days between irrigation events instead of checking the soil moisture (Ganjegunte and Clark 2017). The SWAT model, on the other hand, irrigates the HRUs based on the defined dates and soil water deficit. By comparing the irrigation results against the general information about irrigation water consumption of each crop in the region, we calibrated the SWAT auto-irrigation factors to better capture actual irrigation practices.

Table 4.2. Calibration parameters in the multi-component SUFI-aided calibration

Parameters	**Definition**	**Default Range/Value**	**Final Estimate**
ALPHA_BF	Base flow recession constant (days)	0-1	0.4
GWQMN	Return flow threshold depth (mm)	0.01-5000	1500
CANMX	Maximum canopy storage (mmH_2O)	0	1-3
OV_N	Manning's "n" value for overland flow	0.008-0.5	0.02
EPCO	Plant uptake compensation factor	0.01-1	0.9
ESCO	Soil evaporation compensation factor	0.01-1	0.8
GW_REVAP	Groundwater "revap" coefficient	0.02-0.2	0.08
CH_N2	Manning's n value for the main channels	0.008-0.5	0.03 (Rio Grande literature)
GW_delay	Groundwater delay time (days)	31	Ag.: 20; non-Ag.: 115
CN2	SCS curve number for moisture condition II	35-98	varies (40-75)
LAI_INIT	Initial leaf area index	varies	4
REVAPMN	Threshold water level in shallow aquifer for "revap" or deep percolation (mmH2O)	varies	800
RCHRG_DP	Deep aquifer percolation fraction	0-1	0.1
SURLAG	Surface runoff lag coefficient (days)	4	2-4
HVSTI	Harvest Index	varies	0.13-1.25

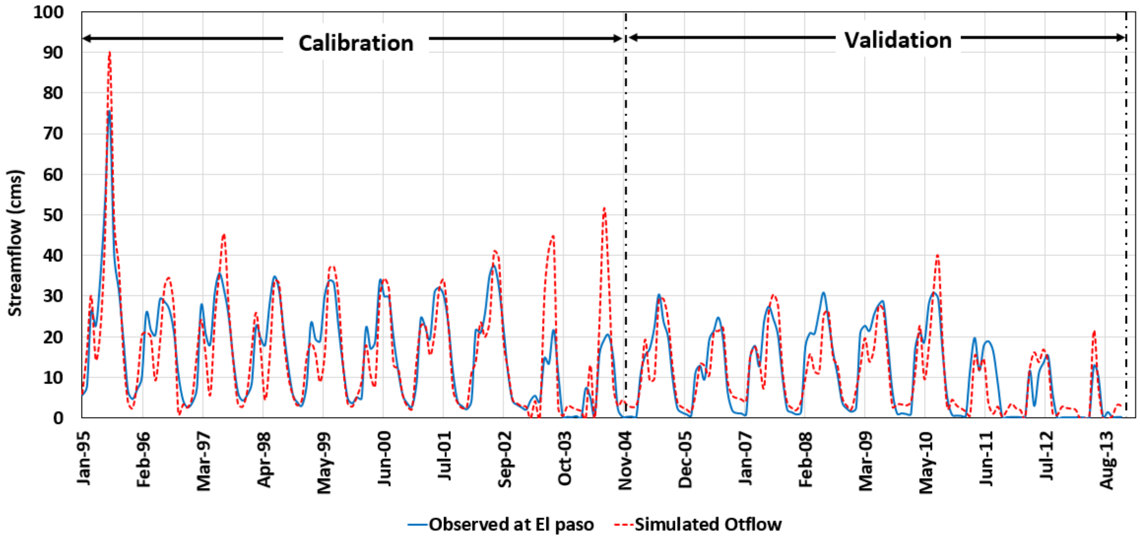


Figure 4.1. Streamflow calibration and validation for the time period 1995-2013

Calibration of the model based on ET is also essential to improve the simulation of irrigation events in SWAT. The average simulated crop ET during the irrigation season and annual groundwater recharge were also calibrated. Since groundwater recharge measurements were unavailable, we used soft data from literature as an estimation (Ahn et al., 2018). The annual average groundwater recharge is simulated at 25 mm, although other modeling applications in the study area reported groundwater recharge to be about 16 mm (Ahn et al., 2018).

Table 4.3 compares the average simulated irrigation, ET, and yield of major crops with reported values for single farms in the study area or other parts of New Mexico with similar climate (Abdul-Jabbar et al., 1983; Samani et al., 2009; Samani et al., 2011; Samani et al., 2013; Samani et al., 2004; Ward et al., 2014). It indicates that, overall, the model somewhat underirrigates alfalfa and corn. The irrigation and ET of onion matches the reported values in the literature (Kannan et al., 2011). However, despite using the maximum harvest index in SWAT (HVSTI=1.25) the simulated onion yield is significantly lower than the literature reported values.

Table 4.3. Calibration results for crop irrigation, ET, and yield.

Crop	**Reported Irrigation (mm)**	**Simulated Irrigation (mm)**	**Reported ET(mm)**	**Simulated ET (mm)**	**Average Reported Yield (tons/ha)**	**Simulated Yield (tons/ha)**
Pecan	368-2300 (Avg:1300)	224-2970 (Avg.: 1700)	825-1400	369-1460 (Avg.: 1060)	2.5	0.3-2.3
Alfalfa	900-2100	127-1713 (Avg.:983)	390-1240 (Avg. 900)	312-1140 (Avg.: 850)	19	0.7-14
Cotton	650-950	170-1920 (Avg.: 736)	650-890	370-1260 (Avg.: 947)	1.1	0.02-7
Corn	760-1300	127-930 (Avg.: 580)	685	214-1045 (Avg.: 740)	58	2-20
Pepper	1050-1400	570-1900 (Avg.: 1260)	900	614-1310 (Avg.: 1098)	5	2-16
Onion	350-1040	190-1560 (Avg.: 667)	1010	360-1055 (Avg.: 782)	55	0.02-14.5

*Avg.: Average in growing season

The monthly simulations of irrigation are comparable with field measurements. Table 4.4 compares three years of measured irrigation data from a flood-irrigated pecan orchard (Wang et al., 2007) with weighted average irrigation of pecan simulated by SWAT. It should be noted that in the referenced field experiment, the irrigation water in the orchard was supplied by two wells and the trees did not experience any water stress throughout the experiment (Wang et al., 2007). Although, irrigation data from one farm may not represent the pecan irrigation practices across the study area, the closeness of the simulated and measured pecan irrigation amounts increase the confidence in the model. The difference between the model results and observational irrigation data in 2003, a severely dry year based on standardized precipitation index (SPI: -1.5; Fig. 3.2), indicates increased groundwater withdrawal, and possibly overirrigation, to avoid adverse drought impacts.

Table 4.4. Comparison of average monthly measured and simulated irrigation amounts.

Irrigation Month*	2002		2003		2004	
	Reported Irrigation**	**Simulated Irrigation**	**Reported Irrigation****	**Simulated Irrigation**	**Reported Irrigation****	**Simulated Irrigation**
March	115	238	120.4	90	NA***	181.4
April	114.4	317.3	135.4	215	146.3	66.7
May	325.7	372	415.9	259	231.5	98.4
June	354.5	431	467.1	359	421.5	418
July	303.1	234	393.7	357	343.5	326
August	357.5	227	323.5	211	346.7	280
September	187.6	217	283.7	109	NA***+127	180
October	196.4	104.5	189.6	39	146.8	35.5
Irrigation Season	1954.2	2141	2329.3	1638	1636.3	1587

* The field was irrigated twice in May and October and three times a month from June to September.

** Measured water application in a flood-irrigated pecan orchard with no water stress throughout the experiment (Wang et al., 2007).

*** No data was reported for the irrigation events.

The monthly measurements of ET from a pecan orchard in 2003 to 2005 (Wang et al., 2007) and an alfalfa field in 2008 (Samani et al., 2013) were compared with the corresponding area-weighted average monthly ET values simulated by SWAT (Fig. 4.2 and 4.3). Both figures illustrate the variability of ET during the irrigation season. Pecan ET reaches its peak in June-July period while peak alfalfa ET occurs in June. The results are comparable given the fact that measured ET data are from a single farm whereas SWAT results are aggregated for all irrigated lands under each crop in the study area. The generally lower values of simulated pecan ET may also be attributed to slight under-irrigation of pecan in SWAT.

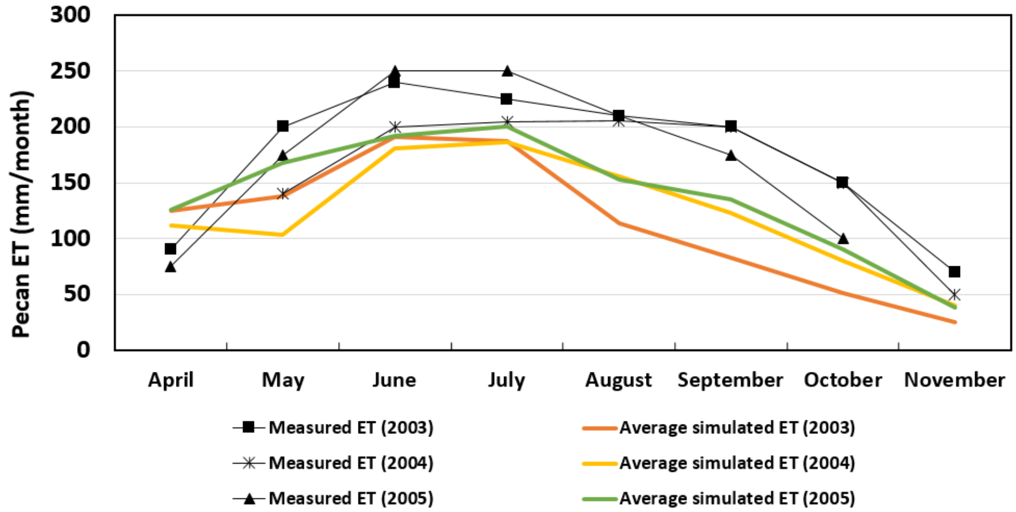


Figure 4.2. Comparison of pecan ET measurements in a sample farm (Wang et al., 2007) and average monthly simulated ET by SWAT.

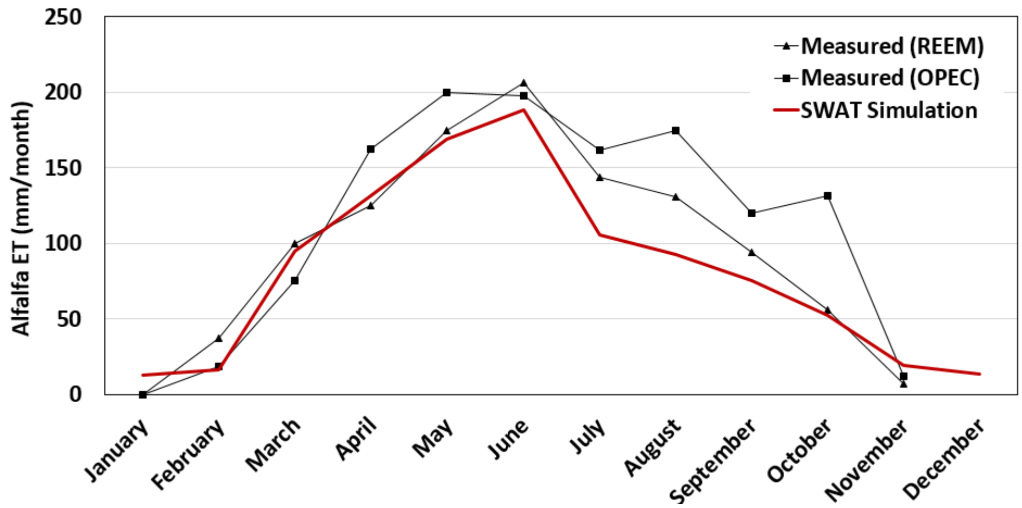


Figure 4.3. Comparison of alfalfa ET measured by OPEC (One-Propeller Eddy Covariance) tower in a sample farm, ET estimated using the Regional ET Estimation Model (REEM) for the same field (Samani et al., 2013) and area-weighted average monthly ET of alfalfa farms in the study area simulated by SWAT in 2008.

4.2. Assessment of Water Conservation Scenarios

Table 4.5 compares the total water consumption of all farms, and average irrigation of pecan, alfalfa, corn, cotton, and pepper farms during the irrigation season under different intervention scenarios. Deficit irrigation was simulated by imposing water stress to the crops throughout the irrigation season or at the end it as is common in the literature (e.g., Bauder et al., 2011; Djaman et al., 2020; Himanshu et al., 2019). In practice, the water stress through deficit irrigation is applied as a percentage of crop's potential ET or pan evaporation (Onder et al., 2009; Payero et al., 2009; Liu et al., 2017; Bauder et al., 2011) or by omitting specific irrigation events in a regulated deficit irrigation scheme. The water stress was simulated by increasing the soil water deficit threshold and reducing irrigation water in the auto-irrigation function. However, changing only one of these two parameters in the model does not necessarily produce the desired water stress level because of the SWAT's auto-irrigation algorithm and the diversity of farms. For example, increasing the soil water deficit by 50% will not directly translate into a 50% crop water stress due the presence of different soil types. Likewise, merely increasing or decreasing irrigation water (IRR_MX) by a certain amount will not provide a specific water deficit. A combination of these two parameters were set by trial and error to achieve specific levels of water stress under different scenarios.

As summarized in Table 4.5, both regulated and unregulated deficit irrigation of alfalfa result in increased water availability for pecan and other plants. The increased water availability achieved by deficit irrigation of alfalfa farms is greater as compared with deficit irrigation of cotton farms because of alfalfa's larger water demand and acreage (more than 30% of total cultivated lands) in the study area. Since many farms have already had to apply deficit irrigation to some extent to handle the past water shortages, the average irrigation season ET of each crop in the baseline case (1995-2013) was used as the basis for defining in the watershed-scale simulations. Other possible bases for water stress targets such as irrigation water or potential ET render realistic water stress levels for deficit irrigation at the regional scale.

Compared to cotton, removal of alfalfa from the crop mix had a much larger effect on increasing water availability (Table 4.5). For example, by removing alfalfa from the crop mix in 2050 (i.e., CP_no-alf-2050) due to likely depletion of fresh groundwater, pecan water availability increased up to 27% while corn and cotton would also receive about 11% and 35% more water, and watershed outflow increased by 16%. However, even the aggressive scenario of completely removing alfalfa from the crop mix after 2050 will not provide enough water to prevent crop loss during major long-term droughts in the future (Figure 4.4). Overall, scenarios of removing alfalfa in 2050 (CP_no-alf-2050) and 45% and 85% deficit irrigation, respectively, for alfalfa and cotton (DI_alf45cot85) had the largest effect on increasing pecan water availability in the study area at the expense of crop yield loss in alfalfa and cotton farms. These scenarios also increased watershed outflow, which can help increase downstream water availability, a major feature of the water conflicts between New Mexico and Texas farmers.

For scenarios of modifying crop pattern and alternative crops, it was assumed that the total area of farms remains constant and new crops substitute those that are taken out of production or whose acreage is reduced. To simulate the alternative crops, the general information (e.g., maximum root depth, maximum leaf area index) for pistachio and pomegranate plants was added to the SWAT land use database. More specific plant parameters such as radiation-use efficiency were assumed to be the same as default values for “orchards” land use in the model. Growing flood irrigated pistachio and pomegranate instead of cotton (about 9% of EBID farmlands in 2008) resulted in small to significant reduction of irrigation water availability for other crops because the water requirements of these alternative crops are comparable to the water requirement of pecan. Nonetheless, using deficit or drip irrigation for these drought-tolerant crops will reduce the negative impact on water availability in the watershed.

Table 4.5. Average watershed outflow and crop irrigation water for different scenarios during the growing season

Scenario	Outflow (MCM)	EBID Irrigation (MCM)	EBID ET (MCM)	Pecan Irr. (MCM)	Alfalfa Irr. (MCM)	Corn Irr. (MCM)	Cotton Irr. (MCM)	Pepper Irr. (MCM)
Baseline Projection	143.2	349.04	267.73	179.81	116.48	2.54	15.60	6.16
DI_alf_July	147	347.80	266.21	191.64	102.06	2.62	16.67	6.18
Change (%)	2.7	-0.36	-0.57	6.58	-12.38	3.11	6.83	0.38
DI_alf45	182	316.98	247.06	213.25	44.95	2.73	18.99	6.20
Change (%)	27	-9.19	-7.72	18.60	-61.41	7.11	21.69	0.74
DI_alf65	170	322.40	261.77	205.10	60.38	2.65	17.97	6.20
Change (%)	18.7	-7.63	-2.23	14.06	-48.16	4.04	15.18	0.72
DI_cor65	146	348.7	267	180	116.6	1.6	15.70	6.16
Change (%)	2	-2.60	0.08	1.35	-9.0	-36.1	1.8	0.3
DI_cot_July	143.7	358.6	266.1	179.4	128.5	2.5	13.7	6.1
Change (%)	0.42	0.17	-0.34	0.97	0.28	0.06	-10.93	0.08
DI_cot_50	148.4	356.64	262.12	181.63	128.86	2.55	8.85	6.15
Change (%)	3.65	-0.38	-1.83	2.20	0.56	0.25	-42.59	0.06
DI_alf45cot85	184	315.63	245.25	214.05	44.97	2.73	16.78	6.20
Change (%)	28.7	-9.57	-8.40	19.04	-61.39	7.19	7.56	0.74
CP_pecan-4	143.5	353.00	266.55	189.85	115.54	0.98	12.78	6.13
Change* (%)	0.26	1.13	-0.44	5.58	-0.80	-61.38	-18.10	-0.42
CP_no-alf-2050	165.5	341	242	228	50	3	21	6.2
Change (%)	15.6	-2.3	-9.5	27.0	-56.9	10.6	35.9	0.8
CP_50%alf-2050	150.4	348.35	256.99	204.55	86.52	2.68	18.02	6.2
Change (%)	5	-0.2	-4.0	13.8	-25.7	5.5	15.5	0.8
CP_no-cot-2050	147.4	347.62	260.92	185.62	116.33	2.41	9.00	6.07
Change (%)	2.97	-0.4	-2.5	3.2	-0.1	-5.3	-42.3	-1.5
CP_no-cot-50%cor-2050	147.6	347.6	260.5	186.0	116.4	1.9	9.0	6.07
Change (%)	3.1	-0.4	-2.7	3.4	0.0	-23.9	-42.3	-1.5
CP_Extreme	198	339.4	212.6	259	-	-	-	-
Change (%)	38	-5.2	-20.4	45.7	-	-	-	-
AC_PISCH	142.9	351.97	268.49	179.75	118.06	2.53	-	6.16
Change (%)	-0.2	-1.69	0.56	1.14	-7.87	-0.32	-	0.37
AC_POMG	142.5	344.74	271.68	164.91	113.33	2.45	8.85	6.16
Change (%)	-0.5	-3.70	1.75	-7.21	-11.56	-3.71	-42.59	0.26
AC_POMG_drip	148.2	348.17	273.70	167.25	113.93	2.47	-	6.16
Change (%)	3.5	-2.75	2.51	-5.89	-11.09	-2.92	-	0.30

*Percent change relative to baseline projection

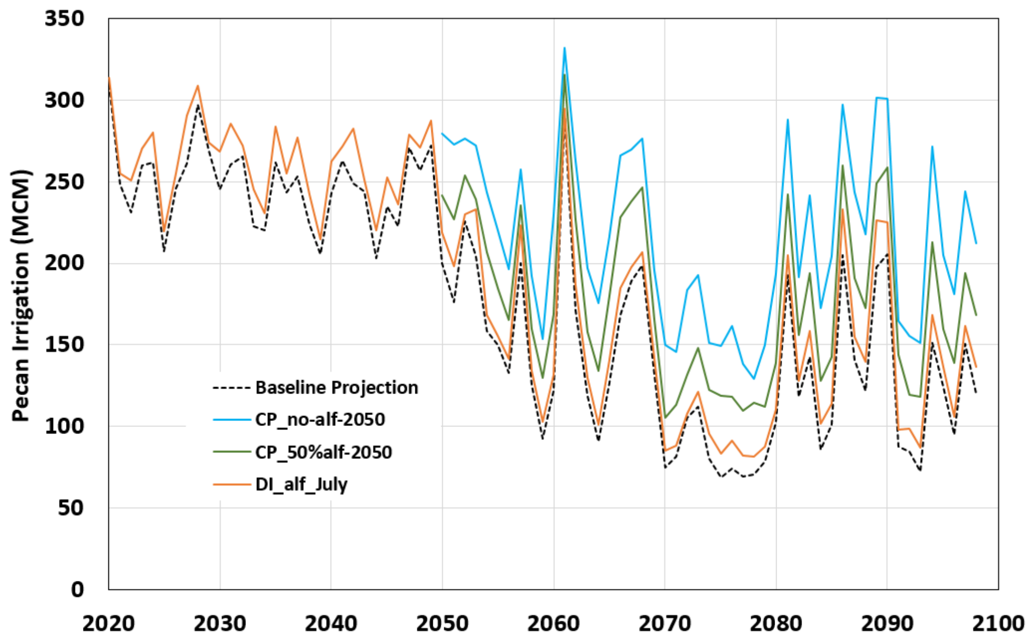


Figure 4.4. Comparing pecan irrigation water availability in different cropping and deficit irrigation interventions.

As expected, moderate whole season deficit irrigation of cotton and alfalfa saved more water than partial season deficit irrigation (Table 4.5). The pecan water availability increased by 18.6% in the case of whole season deficit irrigation of alfalfa with 45% deficit (i.e., DI_alf45 scenario) as compared to 6.6% increase as a result of partial season deficit irrigation of alfalfa (i.e., DI_alf_July scenario). However, partial season deficit irrigation of crops like alfalfa had less negative impact on the yield than the whole season water stress (Bauder et al., 2011; Djaman et al., 2020; Smeal et al., 1991).

It should be noted that SWAT distributes the water saved by irrigation interventions among all other crops based on user defined auto-irrigation parameters and water availability at the time of irrigation. Figure 4.5 shows how the amount of irrigation water saved from cotton deficit irrigation (DI_cot50) is distributed for alfalfa and pecan crops.

In reality, however, farmers can leverage these water savings to prioritize the irrigation of more valuable crops. In addition to water savings that are used by the model for irrigation of other crops, a portion of the saved water leaves the watershed as outflow (Table 4.5), which is an artifact of using the auto-irrigation function of SWAT. The largest outflow belongs to scenarios of deficit irrigation of alfalfa while other crops in some farms remained underirrigated likely due to differences in daily timing of irrigation events simulated by the auto-irrigation for different farms based on different soil types, crops, and soil moisture changes.

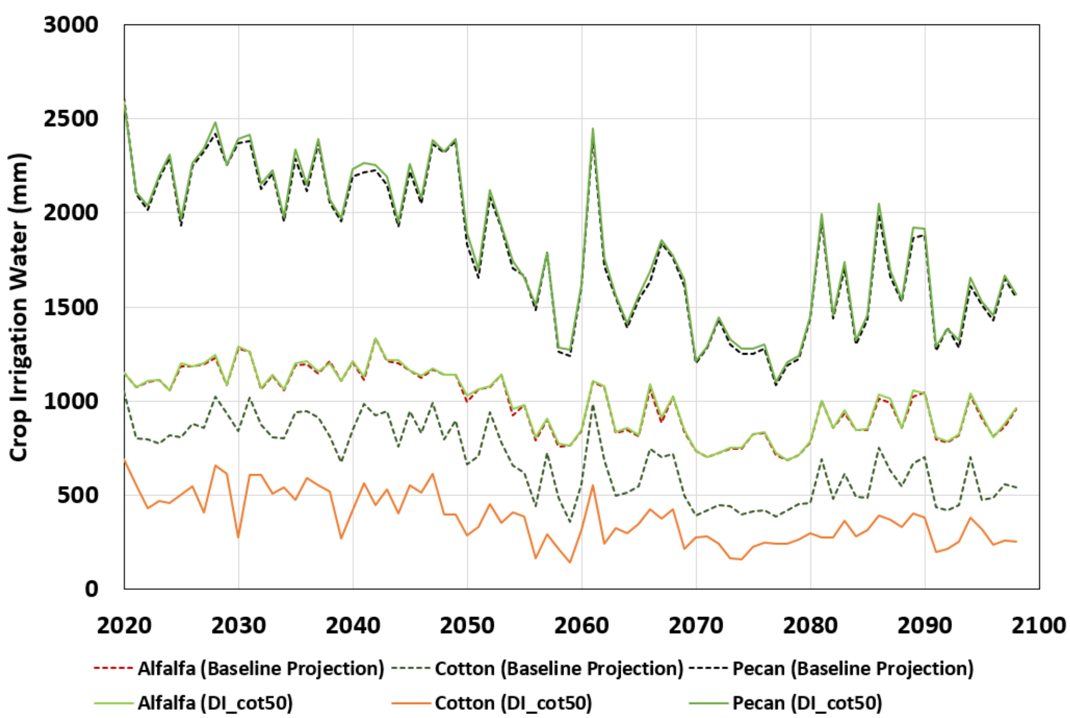


Figure 4.5. Comparing crop irrigation water distribution for pecan and alfalfa in SWAT under scenarios DI_cot50 (cotton deficit irrigation) and Baseline Projection.

Figure 4.6 compares the yield of alfalfa in deficit irrigation scenarios with the baseline projection. It illustrates the stark tradeoff between significant water conservation in alfalfa fields under all season deficit irrigation and major losses in crop productivity. Figure 4.7 shows that once the groundwater is depleted in 2050, taking an extreme measure to stop growing all other crops would save enough water to maintain the current acreage of pecan orchards. The low reservoir releases after 2050 after depletion of fresh groundwater means that the will not be enough water to grow other crops besides pecan. Unless other measures are taken to increase agricultural water supply (e.g., on-farm desalination units), the irrigated agriculture will be at risk under a warm-dry future (Figure 4.7).

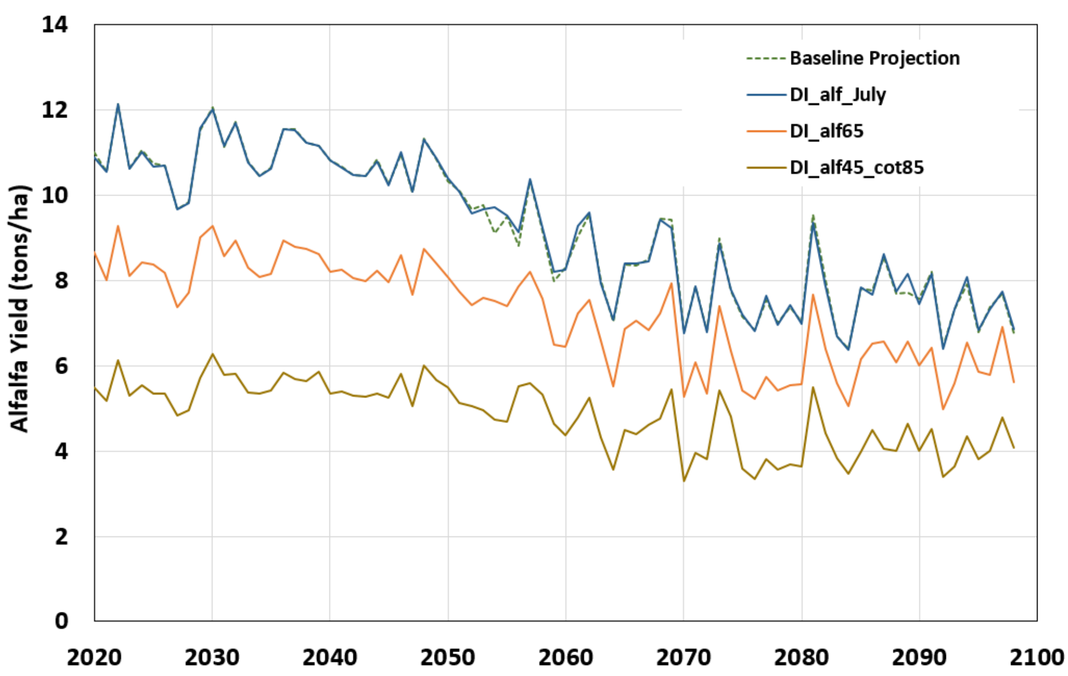


Figure 4.6. Comparing the crop yield results for alfalfa under different deficit irrigation scenarios.

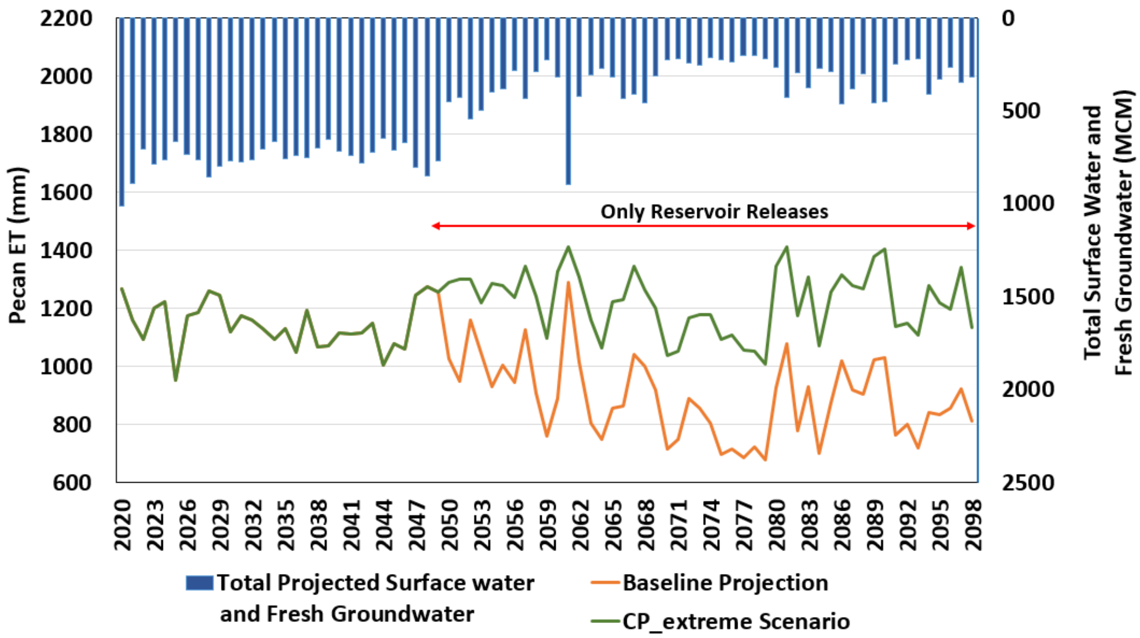


Figure 4.7. Pecan evapotranspiration in CP_Extreme scenario (i.e., removing all crops other than pecan from the mix) compared to baseline projection under warm-dry scenario with fresh groundwater availability until 2050.

5. Discussion

The middle section of the Rio Grande has reached its limit for expanding irrigated agriculture. Results from the multi-component calibrated SWAT model demonstrate that the current agricultural water use is unsustainable under a possible dry-warm climate future climate. Pecan orchards will be vulnerable to moderate to severe droughts if fresh to slightly saline groundwater storage is exhausted within the 21st century unless interventions are implemented to save water to maintain the production of the high-value pecan crops. It will be more difficult to expand the acreage of water-intensive crops in the face of dwindling agricultural water supply without significant ramifications. For example, even a slight increase in the acreage of pecan (i.e., a 4% increase in 2020) results in significant water shortage for other crops. The water availability reduction for other crops may cause excessive water deficit, resulting in major crop loss. In one scenario of pecan acreage increase, the redistribution of the fixed amount of available water to irrigate young pecan trees resulted in more than 75% water deficit for corn. These agricultural water management tradeoffs signify the need to cope with future water shortages by using marginal quality groundwater, different irrigation and cropping interventions, and enforcing market mechanisms to secure water for high-value crops based on the economic value of water.

Decreasing the acreage of pecan orchards is not a viable option due to significant economic damages associated with the loss of mature pecan trees that will be productive for several decades. Reducing the acreage or removing other crops is also challenging due to a strong sense of ownership of water (Hargrove and Heyman, 2020). Nonetheless, signs of growing water insecurity necessitate leveraging past adaptation practices to prepare for a warm-dry future. Deficit irrigation and crop pattern change have been occasionally practiced by farmers to cope with water shortages in the past. It is necessary to systematically implement these water conservation practices in a planned and controlled manner. Modeling results show that deficit irrigation and reducing the acreage of water-intensive crops like alfalfa provide modest opportunities for water saving in the study area but not enough to drastically change the vulnerability of irrigated agriculture, especially pecan farms, to future severe droughts. The results suggest that a graduate transition to a more drought-adaptive agricultural production is more effective to cope with future drought risks as opposed an abrupt response to fresh groundwater depletion around mid-21st century.

Another possible intervention to reduce the vulnerability of irrigated agriculture is graduate substitution of water-intensive annual commodity crops or high-value perennial crops with drought-adaptive alternative crops like pistachio and pomegranate, which are compatible to the climate of the study area. Flood irrigation of pistachio and pomegranate plants as alternative crops will not generate significant water savings because their reported water demand is comparable to that of pecan. An advantage of pistachio and pomegranate orchards will be their drought resilience and salinity tolerance relative to pecan, making them a potentially suitable adaptation strategy to sustain irrigated agriculture in the region using deficit irrigation. Regulated deficit irrigation, drip irrigation of the alternative crop orchards can create additional water conservation opportunities but it requires further investigations. Further, the time required for the new alternative crops to reach commercial fruiting should be considered in the decision to switch to these crops instead of growing pecan or other crops.

The irrigation management in the study area is challenged by water availability in each farm, variety of soil types, and different sizes of farms. Irrigation timing and amount depends directly on upstream reservoir releases. Farms with wells have more options in irrigating the crops properly. Deficit irrigation is forced to some farmers while others might over-irrigate (Samani and Skaggs 2005; Ganjegunte and Clark 2017). So,

Results of this model-based agricultural water management intervention analysis should be interpreted in regard to the watershed scale of the analysis and limited actual crop management data. Despite extensive efforts to calibrate the model to realistically simulate irrigation alongside streamflow, ET, and groundwater recharge, the results from the watershed-scale model are not directly applicable for the individual farms. Regulated deficit irrigation may somewhat reduce crop yields, which should be better characterized. Farm level analyses of water saving potential and likely impacts on crop yields requires detailed farm-scale modeling, and field measurements to reduce uncertainties in model setup and parametrization. Using the exact timing of the crop growth and harvest (e.g., alfalfa's number of harvests in an agricultural year) in the model will improve the simulation of regulated deficit irrigation of crops.

6. Conclusions

The water conservation potential of several irrigation interventions were analyzed in a heavily irrigated agricultural area in the middle section of the Rio Grande basin under a warm-dry climate scenario. The results show that the current agricultural practices are vulnerable to future severe droughts and risk of losing valuable pecan orchards increases by degradation of quality groundwater resources and increasing salinity. The multi-component calibrated and validated SWAT model that was especially calibrated for irrigation practices was proven to be reliable for simulating the impact of different interventions on vulnerability of agricultural activities in the watershed.

The water conservations tested in this study is limited to the SWAT ability and available data as well as the applicability of the measures regarding the stakeholders experience, existing infrastructures, and current conditions of irrigation applications in the farms. Other effective methods like drip irrigation, partial root zone drying, and irrigation scheduling based on soil moisture can be tested using other models and field experiments alongside SWAT. However, this study shows that such effective interventions cannot be used as quick responses in a short time before drought happens.

Alfalfa and cotton are the first choice of farmers to sacrifice during the drought (Chapter III). Long term regulated deficit irrigation of these crops could be more effective than current level of unregulated deficit irrigation. Detailed study of currently practiced deficit irrigation and data on crop growth stages in study area is necessary to plan for more sustainable deficit irrigation with minimum loss of crop yield. But the modeling results show that modifying current cropping pattern is somewhat helpful for regional agricultural water conservation but abrupt elimination of cotton or alfalfa when approaching the groundwater limit will not conserve significant amount of water to sustain the current crop mix. Substituting the current pattern with more tolerant crops like pomegranate and pecan would increase the resiliency of agriculture to the long-term droughts, but the irrigation water conservation will not be improved in these scenarios and might result in losing other crops like cotton and corn, unless drip or regulated deficit irrigation is applied.

Challenges of modeling in arid/semi-arid irrigated watersheds are addressed in this study. The high uncertainties are introduced due to lack of data and information about groundwater withdrawal and farming practices, multi-calibration of the model and cross referencing some parameters with available data helps to reduce some these uncertainties, for example, assuming the total available water as sum of the surface and ground water is practical for water balance calculation of the basin, but cannot be used for aquifer water table changes as our assumptions does not account for the impact of water withdrawal from the aquifer. To model the impact of groundwater withdrawal and recharge on the aquifer, a SWAT model that considers both surface and groundwater as irrigation sources along with a SWAT-MODFLOW model is required. The quality of the water resources, especially increasing salinity and more accurate estimation of fresh groundwater volume, is also an important factor and should be considered in future management plans.

More detailed studies on a farm scale are required to elaborate the positive and negative impacts of the water conservation methods on water resources, agriculture, and economy of the basin under warm and dry future. Despite the need to detailed studies, quick measures should be taken to improve the irrigation water consumption and modify the crop pattern to move towards more resiliency in the watershed. The required precautions for saline water irrigation application during major droughts is recommended. Insights from this study is applicable for similar regions around the world that are dealing with drought problems, and obstacles related to lack of field information.

CHAPTER V

SUMMARY AND CONCLUSION

1. Summary

The future of irrigated agriculture in arid/semi-arid regions like the study area in the Rio Grande basin, depends on water availability. The historical declining trend of streamflow and plausible climate projections for the region point to high possibility of a drier future that would increase the vulnerability of current agriculture condition. Modeling the watershed for the minimum crop areas in the project time period shows the high dependency of the agriculture to groundwater resources to the extent that when the groundwater with acceptable quality (TDS<3000 mg/L) declines, farmers should either take extra measures to continue with the saline groundwater or decrease their dependency to groundwater through modifying the water use efficiency.

Sustainable agriculture could ensure the water availability and food security under the increasing pressures of demand growth and climate conditions. The multi-component calibrated SWAT model shows that once the groundwater resources declined, most common practices for coping with drought like emergency crop pattern change and occasional deficit irrigation would not be effective in major droughts.

Graduate transition to a more resilient agriculture through using regulated deficit irrigation and drought adaptive crops like pistachio and pomegranate is recommended. Modern methods like drip irrigation are very effective for water use efficiency, however the need for changing infrastructures and the cost of installation and maintenance are significant obstacles for implementing them in a short time. Increasing value of water in arid/semi-arid regions justifies the investment for more complicated water and salinity management measures, however, the efficiency of such methods should be studied considering the controlling factors like climate, soil type, farm size, etc.

Multi-calibration of the model and checking it for details of irrigation activities based on available data increases the reliability of the results despite uncertainties related to lack of detailed information and measured data.

2. Conclusions

Modeling the study area with the multi-component calibrated SWAT model shows that current agriculture with the high dependency to the declining groundwater resources, is vulnerable to droughts even with the minimum farming areas during the drought in 2011. Simulating the impact of some common irrigation interventions with a multi-calibrated SWAT model that accounts for irrigation practices in detail indicated that although measures like deficit irrigation or reducing the cultivation area of water demanding crops result in levels of water conservation, taking them as emergency responses to droughts is not helpful and sustainable. Graduate transition from current condition to more resilient land use and irrigation methods improves the vulnerability of agricultural activities in the region.

Field experiments on optimum regulated deficit irrigation practices on different crops, especially pistachio and pomegranate in the study area helps to improve water application efficiency in under-irrigated farm. Soil salinity measurements to find problematic sites along with modeling the future salinization risks in soil and water resources to plan for using saline groundwater resources in farms with less salinity problems. Long-term impacts of saline water irrigation will elaborate the water resources management plans for future.

Studying the surface water- groundwater interactions is required to investigate the impact of irrigation water conservation practices on the water table. This model should be able to account for the impact of irrigation interventions on both reduction in groundwater pumping and decrease in groundwater recharge at the same time.

REFERENCES

Abbaspour, K.C., 2015. User manual for SWAT-CUP, SWAT calibration and uncertainty analysis programs. Swiss Federal Institute of Aquatic Science and Technology, Eawag, Duebendorf, Switzerland.

Abbaspour, K.C. 2013. SWAT-CUP 2012. SWAT Calibration and Uncertainty Program—A User Manual.

Abbaspour, K.C., Faramarzi, M., Ghasemi, S.S., Yang, H., 2009. Assessing the impact of climate change on water resources in Iran. Water Resour. Res. 45, 1–16. https://doi.org/10.1029/2008WR007615.

Abbaspour, K.C., 2011. User Manual for SWAT-CUP, SWAT Calibration and Uncertainty Analysis Programs; Swiss Federal Institute of Aquatic Science and Technology, Eawag: Duebendorf, Switzerland, 103.

Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. J. Hydrol. 524, 733-752.

Abbaspour, K., Vaghefi, S., Srinivasan, R., 2018. A Guideline for Successful Calibration and Uncertainty Analysis for Soil and Water Assessment: A Review of Papers from the 2016 International SWAT Conference. Water, 10.

Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., Srinivasan, R., 2007. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J. Hydrol. 333, 413-430.

Abdul-Jabbar, A.S., Sammis TW, Lugg DG, Kallsen CE, Smeal D. 1983 Water use by alfalfa, maize, and barley as influenced by available soil water. Agricultural Water Management. 6, 351–363

Abeysingha, N.S., Singh, M., Sehgal, V.K., Khanna, M., Pathak, H., Jayakody, P. and Srinivasan, R., 2015. Assessment of water yield and evapotranspiration over 1985 to 2010 in the Gomti River basin in India using the SWAT model. Current Science. 108 (1), 2202-2212.

Abouabdillah, A., White, M., Arnold, J.G., De Girolamo, A.M., Oueslati, O., Maataoui, A., Lo Porto, A., 2014. Evaluation of soil and water conservation measures in a semi-arid river basin in Tunisia using SWAT. Soil Use Manag. 30, 539-549.

Acero Triana, J.S., Chu, M.L., Guzman, J.A., Moriasi, D.N., Steiner, J.L., 2019. Beyond model metrics: The perils of calibrating hydrologic models. J. Hydrol. 578, 124032. https://doi.org/10.1016/j.jhydrol.2019.124032.

AghaKouchak, A., Feldman, D., Hoerling, M., Huxman, T., Lund, J., 2015. Water and climate: Recognize anthropogenic drought. Nature News. 524(7566), 409.

Ahadi R, Samani Z, Skaggs R. 2013 Evaluating on-farm irrigation efficiency across the watershed: A case study of New Mexico's Lower Rio Grande Basin. Agric. Water Manag. 124, 52-57.

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. Agric. Water Manag. 175, 15-28.

Ahn, S., Abudu, S., Sheng, Z., Mirchi, A., 2018. Hydrologic impacts of drought-adaptive agricultural water management in a semi-arid river basin: Case of Rincon Valley, New Mexico. Agric. Water Manag. 209, 206-218.

Akhavan, S., Abedi-Koupai, J., Mousavi, S.F., Afyuni, M., Eslamian, S.S., Abbaspour, K.C., 2010. Application of SWAT model to investigate nitrate leaching in Hamadan-Bahar Watershed, Iran. Agric. Ecosyst. Environ. 139, 675–688. https://doi.org/10.1016/j.agee.2010.10.015.

Al-Ghobari, H. M., Dewidar, A.Z., 2018. Integrating deficit irrigation into surface and subsurface drip irrigation as a strategy to save water in arid regions. Agricultural Water Management. 209. 55-61

Al-Jamal, M.S., Sammis, T.W., Ball, S., Smeal, D., 2000. Computing the crop water production function for onion. Agricultural Water Management. 46, 29–41.

Aliyari, F., Bailey, R.T., Tasdighi, A., Dozier, A., Arabi, M., Zeiler, K., 2019. Coupled SWAT-MODFLOW model for large-scale mixed agro-urban river basins. Environ. Model. Softw. 115, 200–210. https://doi.org/10.1016/j.envsoft.2019.02.014

Allen RG, Pereira LS, Raes D, Smith M, Ab W. 1998. Irrig. Drain. Pap. No. 56, FAO 300.

Amanambu, A.C., Obarein, O.A., Mossa, J., Li, L., Ayeni, S.S., Balogun, O., Oyebamiji, A. and Ochege, F.U., 2020. Groundwater System and Climate Change: Present Status and Future Considerations. Journal of Hydrology. 125163.

Ammar, M.E., Gharib, A., Islam, Z., Davies, E.G., Seneka, M. and Faramarzi, M., 2020. Future floods using hydroclimatic simulations and peaks over threshold: An alternative to nonstationary analysis inferred from trend tests. Adv. Water Resour. 136, 103463.

Andales, A., Wang, J., Sammis, T.W., Mexal, J.G., Simmons, L.J., Miller, D.R., Gutschick, V.P., 2006. A model of pecan tree growth for the management of pruning and irrigation. Agricultural Water Management. 84, 77–88.

Andaryani, S., Nourani, V., Trolle, D., Dehgani, M., Asl, A.M., 2019. Assessment of land use and climate change effects on land subsidence using a hydrological model and radar technique. J. Hydrol. 578, 124070. https://doi.org/10.1016/j.jhydrol.2019.124070.

Andaryani, S., Trolle, D., Nikjoo, M.R., Moghadam, M.H.R., Mokhtari, D., 2019. Forecasting near-future impacts of land use and climate change on the Zilbier river hydrological regime, northwestern Iran. Environ. Earth Sci. 78, 1–14. https://doi.org/10.1007/s12665-019-8193-4.

Andersson, J.C.M., Zehnder, A.J.B., Jewitt, G.P.W., Yang, H., 2009. Water availability, demand and reliability of in situ water harvesting in smallholder rain-fed agriculture in the Thukela river basin, South Africa. Hydrol. Earth Syst. Sci. 13, 2329–2347. https://doi.org/10.5194/hess-13-2329-2009

Ang, R., Oeurng, C., 2018. Simulating Streamflow in an Ungauged Catchment of Tonlesap Lake Basin in Cambodia Using Soil and Water Assessment Tool (SWAT) Model. Water Sci. 32, 89-101.

Aouissi, J., Benabdallah, S., Lili Chabaâne, Z., Cudennec, C., 2016. Evaluation of potential evapotranspiration assessment methods for hydrological modelling with SWAT—Application in data-scarce rural Tunisia. Agric. Water Manag. 174, 39-51.

Arnold JG, Kiniry JR, Srinivasan R, Williams JR, Haney EB, Neitsch SL. 2013. SWAT 2012 input/output documentation. Texas Water Resources Institute.

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., van Griensven, A., Van Liew, M.W., Kannan, N., Jha, M.K., 2012. SWAT: Model Use, Calibration, and Validation. Trans. ASABE. 55(4), 1491-1508.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: Model development. Journal of American Water Resources Association. 34(1), 73-89.

Arnold, J.G., Youssef, M.A., Yen, H., White, M.J., Sheshukov, A.Y., Sadeghi, A.M., Moriasi, D.N., Steiner, J.L., Amatya, D.M., Skaggs, R.W., Haney, E.B., Jeong, J., Arabi, M., Gowda, P.H., 2015. Hydrological Processes and Model Representation: Impact of Soft Data on Calibration. Trans. ASABE. 58, 1637-1660.

Aseri, G.K., Jain, N., Panwar, J., Rao, A. V., Meghwal, P.R., 2008. Biofertilizers improve plant growth, fruit yield, nutrition, metabolism, and rhizosphere enzyme activities of Pomegranate (Punica granatum L.) in Indian Thar Desert. Scientia Horticulturae. (Amsterdam). 117, 130–135.

Ashraf Vaghefi, S., Abbaspour, K.C., Faramarzi, M., Srinivasan, R., Arnold, J.G., 2017. Modeling crop water productivity using a coupled SWAT-MODSIM model. Water (Switzerland) 9, 1–16. https://doi.org/10.3390/w9030157

Ashworth, J. B., and Hopkins, J., 1995. Aquifers of Texas. Texas Water Development Board. Report 345.

Ashraf Vaghefi, S., Mousavi, S.J., Abbaspour, K.C., Srinivasan, R., Yang, H., 2014. Analyses of the impact of climate change on water resources components, drought and wheat yield in semiarid regions: Karkheh River Basin in Iran. Hydrol. Process. 28, 2018–2032. https://doi.org/10.1002/hyp.9747

Awan, U.K., Ismaeel, A., 2014. A new technique to map groundwater recharge in irrigated areas using a SWAT model under changing climate. J. Hydrol. 519, 1368-1382.

Ayars, J.E., Phene, C.J., Phene, R.C., Gao, S., Wang, D., Day, K.R. and Makus, D.J., 2017. Determining pomegranate water and nitrogen requirements with drip irrigation. Agricultural Water Management, 187, pp.11-23.

Aydinsakir, K., Erdal, S., Buyuktas, D., Bastug, R. and Toker, R., 2013. The influence of regular deficit irrigation applications on water use, yield, and quality components of two corn (Zea mays L.) genotypes. Agricultural water management, 128, 65-71.

Ba, W., Du, P., Liu, T., Bao, A., Chen, X., Liu, J., Qin, C., 2020. Impacts of climate change and agricultural activities on water quality in the Lower Kaidu River Basin, China. J. Geogr. Sci. 30, 164–176. https://doi.org/10.1007/s11442-020-1721-z.

Bailey, R.T., Tavakoli-Kivi, S., Wei, X., 2019. A salinity module for SWAT to simulate salt ion fate and transport at the watershed scale. Hydrol. Earth Syst. Sci. 23, 3155–3174. https://doi.org/10.5194/hess-23-3155-2019

Bailey, R.T., Wible, T.C., Arabi, M., Records, R.M. and Ditty, J., 2016. Assessing regional-scale spatio-temporal patterns of groundwater–surface water interactions using a coupled SWAT-MODFLOW model. Hydrol. Process. 30(23), 4420-4433.

Basso, B., Kendall, A.D., Hyndman, D.W., 2013. The future of agriculture over the Ogallala Aquifer: Solutions to grow crops more efficiently with limited water. Earth's Future 1(1), 39-41. doi: 10.1002/2013EF000107.

Bauder, T., Hansen, N., Lindenmeyer, B., Bauder, J., Brummer, J. 2011. Limited irrigation of alfalfa in the Great Plains and Intermountain West. Accessed on-line on March, 15, 2013.

Becker, R., Koppa, A., Schulz, S., Usman, M., aus der Beek, T., Schüth, C., 2019. Spatially distributed model calibration of a highly managed hydrological system using remote sensing-derived ET data. J. Hydrol. 577, 123944. https://doi.org/10.1016/j.jhydrol.2019.123944.

Bhantana, P., Lazarovitch, N., 2010. Evapotranspiration, crop coefficient and growth of two young pomegranate (Punica granatum L.) varieties under salt stress. Agricultural Water Management. 97, 715–722.

Bieger, K., Arnold, J.G., Rathjens, H., White, M.J., Bosch, D.D., Allen, P.M., Volk, M. and Srinivasan, R., 2017. Introduction to SWAT+, a completely restructured version of the soil and water assessment tool. JAWRA J. of the Am. Water Resou. Assoc. 53(1), 115-130.

Blythe, T.L., Schmidt, J.C. 2018. Estimating the Natural Flow Regime of Rivers with Long-Standing Development: The Northern Branch of the Rio Grande. Water Resour. Res., 54(2), 1212-1236.

Bradley Lindenmayer, R., Hansen, N.C., Brummer, J., Pritchett, J.G., 2011. Deficit irrigation of alfalfa for water-savings in the great plains and intermountain west: A review and analysis of the literature. Agronomy. J. 103, 45–50.

Bressiani, D.A., Srinivasan R., Jones, C.A., Mendiondo, E.M., 2015. Effects of spatial and temporal weather data resolutions on streamflow modeling of a semi-arid basin, Northeast Brazil. Int. J. Agric. Biol. Eng. 8(3), 125-139

Brinegar, H.R. and Ward, F.A., 2009. Basin impacts of irrigation water conservation policy. Ecological Economics, 69(2), 414-426.

Brouziyne, Y., Abouabdillah, A., Bouabid, R., Benaabidate, L., 2018. SWAT streamflow modeling for hydrological components' understanding within an agro - sylvo - pastoral watershed in Morocco. J. Mater. Environ. Sci. 9, 128-138.

Bouraoui, F., Benabdallah, S., Jrad, A., Bidoglio, G., 2005. Application of the SWAT model on the Medjerda river basin (Tunisia). Phys. Chem. Earth 30, 497–507.

Çam, M., Hişil, Y., Durmaz, G., 2009. Classification of eight pomegranate juices based on antioxidant capacity measured by four methods. Food Chemistry. 112, 721–726.

Carreon, C., 2019. La Luz pomegranate farm to produce wine and brandy. Alamogordo Daily News. Viewed October 2020, https://www.alamogordonews.com/story/news/2019/10/10/la-luz-new-mexico-pomegranate-farm-wine-vineyard-brandy-usda/3920521002/

Castle, S.L., Thomas, B.F., Reager, J.T., Rodell, M., Swenson, S.C., Famigliatti, J.S. 2014. Groundwater depletion during drought threatens future water security of the Colorado River Basin. Geophys. Res. Lett. Doi: 10.1002/2014GL061055.

Cayan, D.R., Das, T., Pierce, D.W., Barnett, T.P., Tyree, M., Gershunov. A. 2010. "Future Dryness in the Southwest US and the Hydrology of the Early 21st Century Drought." Proceedings of the National Academy of Sciences of the United States of America. 107(50): 21271-21276.

Chai, Q., Gan, Y., Zhao, C., Xu, H.L., Waskom, R.M., Niu, Y. and Siddique, K.H., 2016. Regulated deficit irrigation for crop production under drought stress. A review. Agronomy for sustainable development, 36(1), 3.

Chandra, R., Babu, K.D., Jadhav, V.T., Jaime, A. and Silva, T.D., 2010. Origin, history and domestication of pomegranate. Fruit, Vegetable and Cereal Science and Biotechnology, 2, 6.

Chavarria, S.B., Gutzler, D.S. 2018. Observed Changes in Climate and Streamflow in the Upper Rio Grande Basin. J. Am. Water Resour. Assoc. 54, 644–659. https://doi.org/10.1111/1752-1688.12640.

Cheema, M.J.M., Immerzeel, W.W., Bastiaanssen, W.G.M., 2014. Spatial quantification of groundwater abstraction in the irrigated Indus basin. Groundwater 52, 25–36. https://doi.org/10.1111/gwat.12027.

Chen, F., Crow, W.T., Starks, P.J., Moriasi, D.N., 2011. Improving hydrologic predictions of a catchment model via assimilation of surface soil moisture. Adv. Water Resour. 34, 526–536. https://doi.org/10.1016/j.advwatres.2011.01.011

Chen, Y., Marek, G., Marek, T., Brauer, D., Srinivasan, R., 2017. Assessing the Efficacy of the SWAT Auto-Irrigation Function to Simulate Irrigation, Evapotranspiration, and Crop Response to Management Strategies of the Texas High Plains. Water, 9.

Chen, Y., Marek, G., Marek, T., Moorhead, J., Heflin, K., Brauer, D., Gowda, P., Srinivasan, R., 2018a. Assessment of Alternative Agricultural Land Use Options for Extending the Availability of the Ogallala Aquifer in the Northern High Plains of Texas. Hydrol. 5(4), 53.

Chen, Y., Marek, G.W., Marek, T.H., Brauer, D.K., Srinivasan, R., 2018b. Improving SWAT auto-irrigation functions for simulating agricultural irrigation management using long-term lysimeter field data. Environ. Model. Softw. 99, 25-38.

Chen, Y., Marek, G.W., Marek, T.H., Gowda, P.H., Xue, Q., Moorhead, J.E., Brauer, D.K., Srinivasan, R., Heflin, K.R., 2019a. Multisite evaluation of an improved SWAT irrigation scheduling algorithm for corn (Zea mays L.) production in the U.S. Southern Great Plains. Environ. Model. Software. 118, 23–34. https://doi.org/10.1016/j.envsoft.2019.04.001

Chen, Y., Marek, G.W., Marek, T.H., Moorhead, J.E., Heflin, K.R., Brauer, D.K., Gowda, P.H., Srinivasan, R., 2019b. Simulating the impacts of climate change on hydrology and crop production in the Northern High Plains of Texas using an improved SWAT model. Agric. Water Manag. 221, 13–24. https://doi.org/10.1016/j.agwat.2019.04.021

Chen, Y., Marek, G.W., Marek, T.H., Xue, Q., Brauer, D.K. and Srinivasan, R., 2019. Assessing Soil and Water Assessment Tool plant stress algorithms using full and deficit irrigation treatments. Agronomy Journal, 111(3), 1266-1280.

Chenoweth, J., Hadjinicolaou, P., Bruggeman, A., Lelieveld, J., Levin, Z., Lange, M.A., Xoplaki, E., Hadjikakou, M., 2011. Impact of climate change on the water resources of the eastern Mediterranean and Middle East region: Modeled 21st century changes and implications. Water Resour. Res. 47(6).

Chow, V.T. 1959, Open-channel hydraulics: New York, McGraw-Hill, 680 p.

Comín, F.A., Sorando, R., Darwiche-Criado, N., García, M., Masip, A., 2014. A protocol to prioritize wetland restoration and creation for water quality improvement in agricultural watersheds. Ecol. Eng. 66, 10–18. https://doi.org/10.1016/j.ecoleng.2013.04.059

Condon, A.G., Richards, R.A., Rebetzke, G.J. and Farquhar, G.D., 2004. Breeding for high water-use efficiency. Journal of experimental botany, 55(407), 2447-2460.

Conover, C.S. 1954. Ground-Water Conditions in the Rincon and Mesilla Valleys and Adjacent Areas in New Mexico. Geological Survey Water-Supply Paper 1230.

Cook, B.I., Ault, T.R., Smerdon, J.E., 2015. Unprecedented 21st century drought risk in the American Southwest and Central Plains. Sci. Adv. 1(1), e1400082.

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K.R., Zeckoski, R.W., Jeong, J., Parajuli, P.B., Saraswat, D., Youssef, M.A., 2015. A Recommended Calibration and Validation Strategy for Hydrologic and Water Quality Models. Trans. ASABE. 58, 1705-1719.

Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., Pasteris, P.P. 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. International Journal of Climatology: a Journal of the Royal Meteorological Society, 28(15), 2031-2064.

Dechmi, F., Skhiri, A., 2013. Evaluation of best management practices under intensive irrigation using SWAT model. Agric. Water Manag. 123, 55-64.

Dechmi, F., Burguete, J., Skhiri, A., 2012. SWAT application in intensive irrigation systems: Model modification, calibration and validation. J. Hydrol. 470–471, 227–238. https://doi.org/10.1016/j.jhydrol.2012.08.055.

de Graaf, I.E., Gleeson, T., van Beek, L.R., Sutanudjaja, E.H. and Bierkens, M.F., 2019. Environmental flow limits to global groundwater pumping. Nature 574(7776), 90-94.

DeJonge, K.C., Andales, A.A., Ascough II, J.C. and Hansen, N.C., 2011. Modeling of full and limited irrigation scenarios for corn in a semiarid environment. Transactions of the ASABE, 54(2), 481-492.

DeJonge, K.C., Ascough II, J.C., Ahmadi, M., Andales, A.A. and Arabi, M., 2012. Global sensitivity and uncertainty analysis of a dynamic agroecosystem model under different irrigation treatments. Ecological Modelling, 231, 113-125.

Delavar, M., Morid, S., Morid, R., Farokhnia, A., Babaeian, F., Srinivasan, R., Karimi, P., 2020. Basin-wide water accounting based on modified SWAT model and WA+ framework for better policy making. J. Hydrol. 585. https://doi.org/10.1016/j.jhydrol.2020.124762.

Dettinger, M., Udall, B., Georgakakos, A., 2015. Western water and climate change. Ecol. Appl. 25(8), 2069-2093.

Djaman, K., Smeal, D., Koudahe, K., Allen, S., 2020. Hay yield and water use efficiency of alfalfa under different irrigation and fungicide regimes in a semiarid climate. Water (Switzerland), 12, 1–13.

Döll, P., Hoffmann-Dobrev, H., Portmann, F.T., Siebert, S., Eicker, A., Rodell, M., Scanlon, B.R. 2012. Impact of water withdrawals from groundwater and surface water on continental water storage variations. J. Geodyn., 59-60, 143-156. doi:10.1016/j.jog.2011.05.001

Doorenbos, J. and Kassam, A.H., 1979. Yield response to water. Irrigation and drainage paper, (33), 257.

Doster, M., Michailides, T., Goldhamer, D. and Morgan, D., 2001. Insufficient spring irrigation increases abnormal splitting of pistachio nuts. California Agriculture, 55(3), 28-31.

Douglas-Mankin, K.R., Srinivasan, R., Arnold, J.G., 2010. Soil and water assessment tool (SWAT) model: current Developments and applications. Trans. ASABE. 53(5), 1423-1431.

Du, X., Loiselle, D., Alessi, D.S. and Faramarzi, M., 2020. Hydro-climate and biogeochemical processes control watershed organic carbon inflows: Development of an in-stream organic carbon module coupled with a process-based hydrologic model. Sci. Total Environ. 718, 137281.

Eberbach, P.L., Humphreys, E. and Kukal, S.S., 2011. The effect of rice straw mulch on evapotranspiration, transpiration and soil evaporation of irrigated wheat in Punjab, India. Agricultural Water Management, 98(12), 1847-1855.

Ehtiat, M., Mousavi, S.J., Srinivasan, R., 2018. Groundwater Modeling Under Variable Operating Conditions Using SWAT, MODFLOW and MT3DMS: a Catchment Scale Approach to Water Resources Management. Water Resources Management. 32, 1631-1649.

Elias EH, Rango A, Steele CM, Mejia JF, Smith R .2015. Assessing climate change impacts on water availability of snowmelt-dominated basins of the Upper Rio Grande basin. J. Hydrol. Reg. Stud., 3, 525-546.

English, M.J., Solomon, K.H. and Hoffman, G.J., 2002. A paradigm shift in irrigation management. Journal of irrigation and drainage engineering, 128(5), 267-277.

Epelde, A.M., Antiguedad, I., Brito, D., Jauch, E., Neves, R., Garneau, C., Sauvage, S., Sánchez-Pérez, J.M., 2016. Different modelling approaches to evaluate nitrogen transport and turnover at the watershed scale. J. Hydrol. 539, 478–494. https://doi.org/10.1016/j.jhydrol.2016.05.066

Evett, S.R., Heng, L.K., Moutonnet, P. and Nguyen, M.L., 2008. Field estimation of soil water content: A practical guide to methods, instrumentation, and sensor technology. IAEA: Vienna.

Fallatah, O.A., Ahmed, M., Cardace, D., Boving, T., Akanda, A.S., 2019. Assessment of modern recharge to arid region aquifers using an integrated geophysical, geochemical, and remote sensing approach. J. Hydrol. 569, 600–611. https://doi.org/10.1016/j.jhydrol.2018.09.061

Faramarzi, M., Srinivasan, R., Iravani, M., Bladon, K.D., Abbaspour, K.C., Zehnder, A.J. and Goss, G.G., 2015. Setting up a hydrological model of Alberta: Data discrimination analyses prior to calibration. Environ. Model. Softw. 74, 48-65.

Faramarzi, M., Abbaspour, K.C., Adamowicz, W.L.V., Lu, W., Fennell, J., Zehnder, A.J.B., Goss, G.G., 2017. Uncertainty based assessment of dynamic freshwater scarcity in semi-arid watersheds of Alberta, Canada. J. Hydrol. Reg. Stud. 9, 48-68.

Ficklin, D.L., Luo, Y., Luedeling, E., Zhang, M., 2009. Climate change sensitivity assessment of a highly agricultural watershed using SWAT. J. Hydrol. 374, 16-29.

Ficklin, D.L., Luo, Y., Zhang, M., 2013. Watershed modelling of hydrology and water quality in the Sacramento River watershed, California. Hydrol. Process. 27, 236–250. https://doi.org/10.1002/hyp.9222

Flato, G., J. Marotzke, B. Abiodun, P. Braconnot, S.C. Chou, W. Collins, P. Cox, F. Driouech, S. Emori, V. Eyring, C. Forest, P. Gleckler, E. Guilyardi, C. Jakob, V. Kattsov, Reason C.   Rummukainen M. 2013. Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Food and Agriculture Organization of the United Nation. AquaCrop. Viewed October 2020, http://www.fao.org/land-water/databases-and-software/aquacrop

Frenken, K., Gillet, V., 2012. Irrigation water requirement and water withdrawal by country. Food and Agriculture Organization (FAO) of the United Nations, Rome, Italy.

Fuchs, E.H., Carroll, K.C., King, J.P. 2018. Quantifying groundwater resilience through conjunctive use for irrigated agriculture in a constrained aquifer system. J. Hydrol. 565, 747–759. https://doi.org/10.1016/j.jhydrol.2018.08.003

Ganjegunte, G., and Clark, J. 2017. Improved irrigation scheduling for freshwater conservation in the desert southwest U.S. Irrigation Science. 35, 315–326.

Garfin, G., Jardine, A., Merideth, R., Black, M. and LeRoy, S., 2013. Assessment of climate change in the southwest United States: a report prepared for the National Climate Assessment. Island press.

Garg, K.K., Wani, S.P., 2013. Opportunities to Build Groundwater Resilience in the Semi-Arid Tropics. Groundwater 51, 679–691.

Garrot, Jr., D.J., Kilby, M.W., Fangmeier, D.D., Husman Ralowicz, A.E., 1993. Production, growth, and nut quality in pecans under water stress based on the crop water stress index. Journal of the American Society for Horticultural Science. 118, 694–698. https://doi.org/10.21273/jashs.118.6.694.

Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G, 2007. The soil and water assessment tool: Historical development, applications and future research directions. Trans. ASABE. 50(4), 1211-1250.

Gayley, A., 2013. SWAT-based evapotranspirative water conservation analysis performed on irrigated croplands to determine potential regional water savings. J. Irrig. Drain. Eng. 139, 456–462. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000562

Gebremicael, T.G., Mohamed, Y.A., Betrie, G.D., van der Zaag, P., Teferi, E., 2013. Trend analysis of runoff and sediment fluxes in the Upper Blue Nile basin: A combined analysis of statistical tests, physically-based models and landuse maps. J. Hydrol. 482, 57–68. https://doi.org/10.1016/j.jhydrol.2012.12.023

Geisseler, D. and Horwath, W.R., 2016. Pistachio production in California. California Department of Food and Agriculture Fertilizer Research and Education Program (FREP).

Githui, F., Selle, B., Thayalakumaran, T., 2012. Recharge estimation using remotely sensed evapotranspiration in an irrigated catchment in southeast Australia. Hydrol. Process. 26, 1379–1389. https://doi.org/10.1002/hyp.8274.

Gleeson, T., Wada, Y., Bierkens, M.F. and Van Beek, L.P., 2012. Water balance of global aquifers revealed by groundwater footprint. Nature 488(7410), 197-200.

Gleick, P.H. and Palaniappan, M., 2010. Peak water limits to freshwater withdrawal and use. Proc. Natl. Acad. Sci. U.S.A. 107(25), 11155-11162.

Glozer, K., Ferguson, L., 2008. Pomegranate production in Afghanistan. UCDAVIS College of Agricultural & Environmental Sciences. 32.

Golcihamer, D.A., Kjelgren, R.B., Lane, J., Weinberger, G. and Menezes Jr, J., 1985. Water use requirements of pistachio trees and response to water stress.

Goldhamer, D. and Beede, R., 2004. Regulated deficit irrigation effects on yield, nut quality and water-use efficiency of mature pistachio trees. The Journal of Horticultural Science and Biotechnology, 79(4), 538-545.

Grafton RQ, Williams J, Jiang Q. 2017. Possible pathways and tensions in the food and water nexus. Earth's Futur. 5, 449–462. https://doi.org/10.1002/2016EF000506.

Grusson, Y., Sun, X., Gascoin, S., Sauvage, S., Raghavan, S., Anctil, F. and Sáchez-Pérez, J.M., 2015. Assessing the capability of the SWAT model to simulate snow, snow melt and streamflow dynamics over an alpine watershed. J. Hydrol. 531, 574-588.

Guzman, J. A., Moriasi, D.N., Gowda, P.H., Steiner, J.L., Starks, P.J., Arnold, J.G. and Srinivasan, R., 2015a. A model integration framework for linking SWAT and MODFLOW. Environ. Model. Softw. 73, 103-116.

Guzman, J.A., Shirmohammadi, A., Sadeghi, A.M., Wang, X., Chu, M.L., Jha, M.K., Parajuli, P.B., Harmel, R.D., Khare, Y.P., Hernandez, J.E., 2015b. Uncertainty Considerations in Calibration and Validation of Hydrologic and Water Quality Models. Trans. ASABE. 58, 1745-1762.

Hammouri, N., Adamowski, J., Freiwan, M., Prasher, S., 2017. Climate change impacts on surface water resources in arid and semi-arid regions: a case study in northern Jordan. Acta Geod. Geophys. 52, 141-156.

Hanson, B., Putnam, D., Snyder, R., 2007. Deficit irrigation of alfalfa as a strategy for providing water for water-short areas. Agricultural Water Management. 93, 73–80.

Hargreaves, G.H. and Samani, Z.A., 1984. Economic considerations of deficit irrigation. Journal of irrigation and Drainage engineering, 110(4), 343-358.

Haro-Monteagudo, D., Palazón, L., Beguería, S., 2020. Long-term sustainability of large water resource systems under climate change: A cascade modeling approach. J. Hydrol. 582, 124546. https://doi.org/10.1016/j.jhydrol.2020.124546

Hawley JW, Kennedy JF. 2004. Creation of a Digital Hydrogeologic Framework Model of the Mesilla Basin and Southern Jornada Del Muerto Basin. WRRI Technical Completion Report No. 332.

Heidari, A., Mayer, A., Watkins, D., 2019. Hydrologic impacts and trade-offs associated with forest-based bioenergy development practices in a snow-dominated watershed, Wisconsin, USA. J. Hydrol. 574, 421–429. https://doi.org/10.1016/j.jhydrol.2019.04.067

Heydari, N., 2014. Water productivity in agriculture: Challenges in concepts, terms and values. Irrigation and Drainage. 63, 22–28. https://doi.org/10.1002/ird.1816

Himanshu, S.K., Ale, S., Bordovsky, J. and Darapuneni, M., 2019. Evaluation of crop-growth-stage-based deficit irrigation strategies for cotton production in the Southern High Plains. Agricultural Water Management, 225, 105782.

Holland, D., Hatib, K., Bar-Ya'akov, I., 2009. Pomegranate: Botany, Horticulture, Breeding. Horticultural Reviews. John Wiley & Sons, Inc. 35, 127–192.

Hu, Y., Moiwo, J.P., Yang, Y., Han, S., Yang, Y., 2010. Agricultural water-saving and sustainable groundwater management in Shijiazhuang Irrigation District, North China Plain. J. Hydrol. 393, 219-232.

International Boundary, and Water Commission (IBWC). 1906. Convention between the United States and Mexico—Equitable distribution of the waters of the Rio Grande.

Jägermeyr, J., Pastor, A., Biemans, H. and Gerten, D., 2017. Reconciling irrigated food production with environmental flows for Sustainable Development Goals implementation. Nature Communications, 8(1), 1-9.

Jones, C., Sultan, M., Yan, E., Milewski, A., Hussein, M., Al-Dousari, A., Al-Kaisy, S., Becker, R., 2008. Hydrologic impacts of engineering projects on the Tigris-Euphrates system and its marshlands. J. Hydrol. 353, 59–75. https://doi.org/10.1016/j.jhydrol.2008.01.029

Jordan, G., Goenster-Jordan, S., Lamparter, G.J., Ulziisuren, B., Soninkishig, N., Schlecht, E., Buerkert, A., 2018. Water use in agro-pastoral livelihood systems within the Bulgan River watershed of the Altay Mountains, Western Mongolia. Agric, Ecosys. Environ. 251, 180-193.

Kalisek, D., Harris, B.L., Runyan, C., DeMouche, L. 2011. Efficient irrigation for water conservation in the Rio Grande Basin. Texas Water Resources Institute Technical Report No. 400. Texas A&M University System College Station. Texas.

Kallestad, J.C., Mexal, J.G., Sammis, T.W. and Heerema, R., 2008. Development of a simple irrigation scheduling calendar for Mesilla Valley pecan growers. HortTechnology, 18(4), 714-725.

Kannan, N., Jeong, J., Srinivasan, R., 2011. Hydrologic Modeling of a Canal-Irrigated Agricultural Watershed with Irrigation Best Management Practices: Case Study. J. Hydrol. Eng. 16, 746-757.

Kendall, M.G. 1975. Rank Correlation Methods edition 4, Charles Griffin. London, United Kingdom.

Khatami, S., Peel, M.C., Peterson, T.J. and Western, A.W., 2019. Equifinality and Flux Mapping: A new approach to model evaluation and process representation under uncertainty. Water Resour. Res. 55(11), 8922-8941.

Khokhar, T., 2017. Chart: Globally, 70% of freshwater is used for agriculture. World Bank Data Blog. Available at: https://blogs.worldbank.org/opendata/chart-globally-70-freshwater-used-agriculture (accessed August 6, 2020).

Kirchner, J.W., 2006. Getting the right answers for the right reasons: Linking measurements, analyses, and models to advance the science of hydrology. Water Resour. Res. 42, 1-5.

Kotir, J.H., 2011. Climate change and variability in Sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. Environ. Dev. Sustain. 13(3), 587-605.

Knutson, C.L., Hayes, M.J., Philipps, T., 1998. How to Reduce Drought Risk. Western Drought Coordination Council. National Drought Mitigation Center. University of Nebraska.

Koech, R., Langat, P., 2018. Improving irrigation water use efficiency: A review of advances, challenges and opportunities in the Australian context. Water (Switzerland) 10. https://doi.org/10.3390/w10121771

Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2006. World map of the Köppen-Geiger climate classification updated. Meteorologische Zeitschrift 15(3), 259-263.

Krysanova, V., White, M., 2015. Advances in water resources assessment with SWAT—an overview. Hydrol. Sci. J. 60, 771–783. https://doi.org/10.1080/02626667.2015.1029482.

Lane BA, Sandoval-Solis S, Porse EC. 2015. Environmental Flows in a Human-Dominated System: Integrated Water Management Strategies for the Rio Grande/Bravo Basin. River Res. Appl., 31(9), 1053-1065.

Lansky, E.P., Newman, R.A., 2007. Punica granatum (pomegranate) and its potential for prevention and treatment of inflammation and cancer. Journal of Ethnopharmacology. 109, 177–206. https://doi.org/10.1016/j.jep.2006.09.006

Lazare, S., Lyu, Y., Yermiyahu, U., Heler, Y., Ben-Gal, A., Holland, D., Dag, A., 2020. Optimizing nitrogen application for growth and productivity of pomegranates. Agronomy 10, 1–14. https://doi.org/10.3390/agronomy10030366

Lehner F, Wahl ER, Wood AW, Blatchford DB, Llewellyn D. 2017. Assessing recent declines in Upper Rio Grande runoff efficiency from a paleoclimate perspective. Geophys. Res. Lett., 44(9), 4124-4133.

Li, F., Liang, J., Kang, S. and Zhang, J., 2007. Benefits of alternate partial root-zone irrigation on growth, water and nitrogen use efficiencies modified by fertilization and soil water status in maize. Plant and soil, 295(1-2), 279-291.

Li, S.X., Wang, Z.H., Li, S.Q., Gao, Y.J., Tian, X.H., 2013. Effect of plastic sheet mulch, wheat straw mulch, and maize growth on water loss by evaporation in dryland areas of China. Agricultural Water Management. 116, 39–49. https://doi.org/10.1016/j.agwat.2012.10.004

Li, Q., Yu, X., Xin, Z., Sun, Y., 2013. Modeling the Effects of Climate Change and Human Activities on the Hydrological Processes in a Semiarid Watershed of Loess Plateau. J. Hydrol. Eng. 18(4). 401-412.

Li Z, Jin J. 2017. Evaluating climate change impacts on streamflow variability based on a multisite multivariate GCM downscaling method in the Jing River of China. Hydrol. Earth Syst. Sci. 21, 5531–5546. https://doi.org/10.5194/hess-21-5531-2017

Liang X, Lettenmaier DP, Wood EF, Burges SJ. 1994. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. J. Geophys. Res-Atmos., 99(D7), 14415-14428.

Liang X, Wood EF, Lettenmaier D.P. 1996. Surface soil moisture parameterization of the VIC-2L model: Evaluation and modification. Global Planet. Change, 13(1-4), 195-206.

Lindenmayer, B., Hansen, N., Crookston, M., Brummer, J., Jha, A., 2008. Strategies for Reducing Alfalfa Consumptive Water Use. Hydrology Days. 52–61.

Lioubimtseva, E., Henebry, G.M., 2009. Climate and environmental change in arid Central Asia: Impacts, vulnerability, and adaptations. J. Arid Environ. 73(11), 963-977.

Liu, H., Gao, Y., Sun, J., Wu, X., Jha, S.K., Zhang, H., Gong, X. and Li, Y., 2017. Responses of yield, water use efficiency and quality of short-season cotton to irrigation management: interactive effects of irrigation methods and deficit irrigation. Irrigation science, 35(2), 125-139.

Llewellyn D, Vaddey S. 2013. West-Wide Climate Risk Assessment: Upper Rio Grande Impact Assessment: Report. US Department of the Interior, Bureau of Reclamation, Upper Colorado Region, Albuquerque Area Office.

Luan, X., Wu, P., Sun, S., Wang, Y., Gao, X., 2018. Quantitative study of the crop production water footprint using the SWAT model. Ecol. Indic. 89, 1–10. https://doi.org/10.1016/j.ecolind.2018.01.046

Luo, Y., Sophocleous, M., 2011. Two-way coupling of unsaturated-saturated flow by integrating the SWAT and MODFLOW models with application in an irrigation district in arid region of West China. J. Arid Land 3, 164–173. https://doi.org/10.3724/SP.J.1227.2011.00164

Luo, Y., Zhang, X., Liu, X., Ficklin, D., Zhang, M., 2008a. Dynamic modeling of organophosphate pesticide load in surface water in the northern San Joaquin Valley watershed of California. Environ. Pollut. 156, 1171-81.

Luo, Y., He, C., Sophocleous, M., Yin, Z., Hongrui, R., Ouyang, Z., 2008b. Assessment of crop growth and soil water modules in SWAT2000 using extensive field experiment data in an irrigation district of the Yellow River Basin. J. Hydrol. 352, 139–156. https://doi.org/10.1016/j.jhydrol.2008.01.003

Ma, L., Garcia, S., Nyachoti, S., Hiebing, M., 2019. Major element concentrations of river water, groundwater, irrigation canals and drains, and city waste effluents from the

Middle Rio Grande Watershed Interdisciplinary Earth Data Alliance (IEDA) http://dx.doi.org/10.1594/IEDA/111231 (accessed 14 May 2019).

Mallakpour, I., Sadegh, M. and AghaKouchak, A., 2018. A new normal for streamflow in California in a warming climate: Wetter wet seasons and drier dry seasons. J. Hydrol. 567, 203-211.

Malone, R.W., Yagow, G., Baffaut, C., Gitau, M.W., Qi, Z., Amatya, D. M., Parajuli, P.B., Bonta, J.V., Green, T.R., 2015. Parameterization Guidelines and Considerations for Hydrologic Models. Trans. ASABE. 58, 1681-1703.

Mann, H.B., 1945. Nonparametric tests against trend. Econom. J. Econom. Soc. 245–259.

Marathe, R.A., Babu, K.D., Murkute, A.A., Chaudhary, D.T., 2016. Root distribution pattern of pomegranate in different soil types. Indian Journal of Horticulture. 73, 588–591. https://doi.org/10.5958/0974-0112.2017.00001.9

Marathe, R.A., Chaudhary, D.T., Shinde, Y.R., 2017. Roots density and activity of pomegranate grown in light textured soil of semi-arid region. Vegetos. 30, 48–50. https://doi.org/10.5958/2229-4473.2017.00154.9

Marek, G.W., Chen, Y., Marek, T.H., Heflin, K.R., O’Shaughnessy, S.A., Gowda, P.H., Brauer, D.K., 2020. Assessing planting date effects on seasonal water use of full- and short-season maize using SWAT in the southern Ogallala Aquifer region. Irrig. Sci. 38, 77–87. https://doi.org/10.1007/s00271-019-00653-3

Marek, G.W., Gowda, P.H., Evett, S.R., Baumhardt, R.L., Brauer, D.K., Howell, T.A., Marek, T.H., Srinivasan, R., 2016. Calibration and Validation of the SWAT Model for Predicting Daily ET Over Irrigated Crops in the Texas High Plains Using Lysimetric Data. Trans. ASABE. 59(2), 611-622

Marek, G.W., Gowda, P.H., Marek, T.H., Porter, D.O., Baumhardt, R.L., Brauer, D.K., 2017. Modeling long-term water use of irrigated cropping rotations in the Texas High Plains using SWAT. Irrig. Sci. 35, 111-123.

Martin, D., van Brocklin, J. and Wilmes, G., 1989. Operating rules for deficit irrigation management. Transactions of the ASAE, 32(4), 1207-1215.

Masih, I., Maskey, S., Uhlenbrook, S., Smakhtin, V., 2011. Impact of upstream changes in rain-fed agriculture on downstream flow in a semi-arid basin. Agric. Water Manag. 100, 36–45. https://doi.org/10.1016/j.agwat.2011.08.013

Masud, M.B., McAllister, T., Cordeiro, M.R. and Faramarzi, M., 2018. Modeling future water footprint of barley production in Alberta, Canada: Implications for water use and yields to 2064. Sci. of the Total Environ. 616, 208-222.

Masud, M.B., Wada, Y., Goss, G. and Faramarzi, M., 2019. Global implications of regional grain production through virtual water trade. Sci. of the Total Environ. 659, 807-820.

Mccoy AM, Shomaker JW. 2017. City of Las Cruces 40-Year Water Development Plan. Accessed August 2019 from http://mapserver.las-cruces.org/~/media/lcpublicwebdev2/site%20documents/article%20documents/utilities/water/lc_40yrwaterplan_2017apr--text%20only.ashx?la=en

McInerney, D., Thyer, M., Kavetski, D., Githui, F., Thayalakumaran, T., Liu, M., Kuczera, G., 2018. The Importance of Spatiotemporal Variability in Irrigation Inputs for Hydrological Modeling of Irrigated Catchments. Water Resour. Res. 54, 6792–6821. https://doi.org/10.1029/2017WR022049

McKee, T.B., Doeskin, N.J., Kieist, J. 1993. The Relationship of Drought Frequency and Duration to Time Scales. Proc. 8th Conf. on Applied Climatology, January 17-22, 1993, American Meteorological Society, Boston, Massachusetts, 179-184.

McMahon TA, Adeloye AJ, Zhou, S.L. 2006. Understanding performance measures of reservoirs. Journal of Hydrology, 324(1-4), 359-382.

Melaku, N.D., Wang, J., 2019. A modified SWAT module for estimating groundwater table at Lethbridge and Barons, Alberta, Canada. J. Hydrol. 575, 420–431. https://doi.org/10.1016/j.jhydrol.2019.05.052

Meshram, D.T., Gorantiwar, S.D., Sharma, J., Babu, K.D., 2018. Influence of organic mulches and irrigation levels on growth, yield and water use efficiency of pomegranate (Punica granatum L.). Journal of Agrometeorology. 20, 196–201.

Mikosch, N., Becker, R., Schelter, L., Berger, M., Usman, M., Finkbeiner, M., 2020. High resolution water scarcity analysis for cotton cultivation areas in Punjab, Pakistan. Ecol. Indic. 109, 105852. https://doi.org/10.1016/j.ecolind.2019.105852.

Mir, R.R., Zaman-Allah, M., Sreenivasulu, N., Trethowan, R., Varshney, R.K., 2012. Integrated genomics, physiology and breeding approaches for improving drought tolerance in crops. Theoretical and Applied Genetics. 125, 625–645. https://doi.org/10.1007/s00122-012-1904-9

Mirchi, A., Watkins Jr, D., Madani, K., 2010. Modeling for watershed planning, management, and decision making. Watersheds: management, restoration and environmental impact (Vaughn JC ed). Nova Science Publishers, Hauppauge, NY, USA.

Miyamoto, S., 2006. Diagnosis and Management of Salinity Problems in Irrigated Pecan Productions. TR-287, Texas Water Resources Institute. Texas A&M University.

Miyamoto, S., Henggeler, J. and Storey, J.B., 1995. Water management in irrigated pecan orchards in the southwestern United States. HortTechnology, 5(3), 214-218.

Miyamoto, S., Storey, J.B. 1995. Soil management in irrigated pecan orchards in the southwestern United States. HortTechnology. 219-222.

Molina-Navarro, E., Hallack-Alegría, M., Martínez-Pérez, S., Ramírez-Hernández, J., Mungaray-Moctezuma, A., Sastre-Merlín, A., 2016. Hydrological modeling and climate change impacts in an agricultural semiarid region. Case study: Guadalupe River basin, Mexico. Agric. Water Manag. 175, 29-42.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE. 50(3), 885−900.

Moriasi, D.N., Gitau, M.W., Pai, N., Daggupati, P., 2015. Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. Trans. ASABE. 58, 1763-1785.

Moriasi, D.N., Pai, N., Steiner, J.L., Gowda, P.H., Winchell, M., Rathjens, H., Starks, P.J. and Verser, J.A., 2019. SWAT-LUT: A Desktop Graphical User Interface for Updating Land Use in SWAT. JAWRA J. of the Am. Water Resou. Assoc., 55(5), 1102-1115.

Naderi, M., 2020. Assessment of water security under climate change for the large watershed of Dorudzan Dam in southern Iran. Hydrogeol. J. https://doi.org/10.1007/s10040-020-02159-1

Najarchi, M., Kaveh, F., Babazadeh, H. and Manshouri, M., 2011. Determination of the yield response factor for field crop deficit irrigation. African Journal of Agricultural Research, 6(16), 3700-3705.

Najarchi, M., Kaveh, F., Babazadeh, H. and Manshouri, M., 2011. Determination of the yield response factor for field crop deficit irrigation. African Journal of Agricultural Research, 6(16), 3700-3705.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil & Water Assessment Tool Theoretical Documentation Version 2009 (TR-406). Texas Water Resour. Inst. 1–647. https://doi.org/10.1016/j.scitotenv.2015.11.063

Nguyen, H.H., Recknagel, F., Meyer, W., Frizenschaf, J., Shrestha, M.K., 2017. Modelling the impacts of altered management practices, land use and climate changes on the water quality of the Millbrook catchment-reservoir system in South Australia. J. Environ. Manag. 202, 1-11.

Niraula, R., Kalin, L., Srivastava, P., Anderson, C.J., 2013. Identifying critical source areas of nonpoint source pollution with SWAT and GWLF. Ecol. Modell. 268, 123-133.

Niraula, R., Norman, L.M., Meixner, T., Callegary, J.B., 2012. Multi-gauge calibration for modeling the semi-arid Santa Cruz watershed in Arizona-Mexico border area using SWAT. Air Soil Water Res. 5, 41-57.

Niu, J., Liu, Q., Kang, S., Zhang, X., 2018. The response of crop water productivity to climatic variation in the upper-middle reaches of the Heihe River basin, Northwest China. J. Hydrol. 563, 909–926. https://doi.org/10.1016/j.jhydrol.2018.06.062

Notter, B., Hurni, H., Wiesmann, U., Abbaspour, K.C., 2012. Modelling water provision as an ecosystem service in a large East African river basin. Hydrol. Earth Syst. Sci. 16, 69–86. https://doi.org/10.5194/hess-16-69-2012

Nouri, H., Stokvis, B., Galindo, A., Blatchford, M. and Hoekstra, A.Y., 2019. Water scarcity alleviation through water footprint reduction in agriculture: the effect of soil mulching and drip irrigation. Science of the total environment, 653, 241-252.

Onder, D., Akiscan, Y., Onder, S. and Mert, M., 2009. Effect of different irrigation water level on cotton yield and yield components. African Journal of Biotechnology, 8(8).

Ouessar, M., Bruggeman, A., Abdelli, F., Mohtar, R.H., Gabriels, D., Cornelis, W.M., 2009. Modelling water-harvesting systems in the arid south of Tunisia using SWAT. Hydrol. Earth Syst. Sci. 13, 2003–2021.

Özcan, Z., Kentel, E., Alp, E., 2017. Evaluation of the best management practices in a semi-arid region with high agricultural activity. Agric. Water Manag. 194, 160-171.

Panagopoulos, Y., Makropoulos, C., Kossida, M., Mimikou, M., 2014. Optimal implementation of irrigation practices: Cost-effective desertification action plan for the Pinios basin. J. Water Resour. Plan. Manag. 140, 1–12. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000428

Papadopulos and Associates. 2007. Groundwater flow model for administration and management in the Lower Rio Grande Basin. New Mexico State Engineer, Santa Fe, New Mexico, USA.

Parris, K., 2011. Impact of agriculture on water pollution in OECD countries: Recent trends and future prospects. Int. J. Water Resour. D. 27(1), 33-52.

Parvizi, H., Sepaskhah, A.R., Ahmadi, S.H., 2014. Effect of drip irrigation and fertilizer regimes on fruit yields and water productivity of a pomegranate (Punica granatum (L.) cv. Rabab) orchard. Agricultural Water Management. 146, 45–56.

Parvizi, H., Sepaskhah, A.R., Ahmadi, S.H., 2016. Physiological and growth responses of pomegranate tree (Punica granatum (L.) cv. Rabab) under partial root zone drying and deficit irrigation regimes. Agricultural Water Management. 163, 146–158. https://doi.org/10.1016/j.agwat.2015.09.019

Payero, J.O., Tarkalson, D.D., Irmak, S., Davison, D. and Petersen, J.L., 2009. Effect of timing of a deficit-irrigation allocation on corn evapotranspiration, yield, water use efficiency and dry mass. Agricultural water management, 96(10), 1387-1397.

Payero, J.O., Melvin, S.R., Irmak, S. and Tarkalson, D., 2006. Yield response of corn to deficit irrigation in a semiarid climate. Agricultural water management, 84(1-2), 101-112.

Pereira, L.S., Paredes, P., Cholpankulov, E.D., Inchenkova, O.P., Teodoro, P.R. and Horst, M.G., 2009. Irrigation scheduling strategies for cotton to cope with water scarcity in the Fergana Valley, Central Asia. Agricultural Water Management, 96(5), 723-735.

Perrin, J., Ferrant, S., Massuel, S., Dewandel, B., Maréchal, J.C., Aulong, S., Ahmed, S., 2012. Assessing water availability in a semi-arid watershed of southern India using a semi-distributed model. J. Hydrol. 460-461, 143-155.

Pulido-Velazquez, M., Peña-Haro, S., García-Prats, A., Mocholi-Almudever, A.F., Henriquez-Dole, L., Macian-Sorribes, H., Lopez-Nicolas, A., 2015. Integrated assessment of the impact of climate and land use changes on groundwater quantity and quality in the Mancha Oriental system (Spain). Hydrol. Earth System Sci. 19, 1677-1693.

Qiu, J., Yang, Q., Zhang, X., Huang, M., Adam, J.C., Malek, K., 2019. Implications of water management representations for watershed hydrologic modeling in the Yakima River basin. Hydrol. Earth Syst. Sci. 23, 35–49. https://doi.org/10.5194/hess-23-35-2019

Raeisi, L.G., Morid, S., Delavar, M., Srinivasan, R., 2019. Effect and side-effect assessment of different agricultural water saving measures in an integrated framework. Agricultural Water Management. 223. https://doi.org/10.1016/j.agwat.2019.105685

Rahbeh, M., Chanasyk, D., Miller, J., 2011. Two-way calibration-validation of SWAT model for a small prairie watershed with short observed record. Can. Water Resour. J. 36, 247–270. https://doi.org/10.4296/cwrj3603884

Rahbeh, M., Srinivasan, R., Mohtar, R., 2019. Numerical and conceptual evaluation of preferential flow in Zarqa River Basin, Jordan. Ecohydrol. Hydrobiol. 19, 224–237. https://doi.org/10.1016/j.ecohyd.2019.04.001

Records, R.M., Arabi, M., Fassnacht, S.R., Duffy, W.G., Ahmadi, M., Hegewisch, K.C., 2014. Climate change and wetland loss impacts on a western river’s water quality. Hydrol. Earth Syst. Sci. 18, 4509–4527. https://doi.org/10.5194/hess-18-4509-2014

Reshmidevi, T. V., Nagesh Kumar, D., Mehrotra, R., Sharma, A., 2018. Estimation of the climate change impact on a catchment water balance using an ensemble of GCMs. J. Hydrol. 556, 1192–1204. https://doi.org/10.1016/j.jhydrol.2017.02.016

Reshmidevi, T. V., Nagesh Kumar, D., 2014. Modelling the impact of extensive irrigation on the groundwater resources. Hydrol. Process. 28, 628–639. https://doi.org/10.1002/hyp.9615

Rey, D., Holman, I.P., Knox, J.W., 2017. Developing drought resilience in irrigated agriculture in the face of increasing water scarcity. Reg. Environ. Chang. 17, 1527–1540. https://doi.org/10.1007/s10113-017-1116-6.

Rio Grande Compact (RGC). 1938. N.M. Stat. Ann. § 75-34-3 (1953), Act of May 31, 1939, Ch. 155, 53 Stat. 785.

Rivas-Tabares, D., Tarquis, A.M., Willaarts, B., De Miguel, Á., 2019. An accurate evaluation of water availability in sub-arid Mediterranean watersheds through SWAT: Cega-Eresma-Adaja. Agric. Water Manag. 212, 211–225. https://doi.org/10.1016/j.agwat.2018.09.012

Ronco, P., Zennaro, F., Torresan, S., Critto, A., Santini, M., Trabucco, A., Zollo, A.L., Galluccio, G., Marcomini, A., 2017. A risk assessment framework for irrigated agriculture under climate change. Adv. Water Resour. 110, 562–578. https://doi.org/10.1016/j.advwatres.2017.08.003

Sadras, V.O., 2009. Does partial root-zone drying improve irrigation water productivity in the field? A meta-analysis. Irrigation Science, 27(3), 183-190.

Sahana, V., Timbadiya, P. V., 2020. Spatiotemporal Variation of Water Availability under Changing Climate: Case Study of the Upper Girna Basin, India. J. Hydrol. Eng. 25, 1–18. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001890

Samani Z, Bawazir AS, Bleiweiss, M, Skaggs R, Longworth J, Tran VD, Pinon A. 2009. Using remote sensing to evaluate the spatial variability of evapotranspiration and crop coefficient in the lower Rio Grande Valley, New Mexico. Irrig. Sci. 28, 93–100.

Samani Z, Bawazir S, Skaggs R, Longworth J, Piñon A, Tran V. 2011. A simple irrigation scheduling approach for pecans. Agric. Water Manag. 98, 661–664.

Samani, Z., Sammis, T., Skaggs, R. Alkhatiri, N. Deras, J. 2005. Measuring On-Farm Irrigation Efficiency with Chloride Tracing under Deficit Irrigation. Journal of Irrigation and Drainage Engineering. 131(6), 555-559.

Samani, Z., Skaggs, R.K., 2008. The multiple personalities of water conservation. Water Policy 10, 285–294. https://doi.org/10.2166/wp.2008.154

Samani Z, Skaggs R, Longworth J. 2013. Alfalfa Water Use and Crop Coefficients across the Watershed: From Theory to Practice. J. Irrig. Drain. Eng. 139, 341–348.

Sammis TW, Mexal JG, Miller D. 2004. Evapotranspiration of flood-irrigated pecans. Agric. Water Manag. 69, 179–190.

Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan, R., Hauck, L.M., 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. J. Am. Water Resour. Assoc. 37, 1169–1188.

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. Trans. ASABE. 48(1), 137–147.

Santhi, C., Srinivasan, R., Arnold, J.G., Williams, J.R., 2006. A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. Environ. Model. Softw. 21, 1141-1157.

Santos, C.A.S., Almeida, C., Ramos, T.B., Rocha, F.A., Oliveira, R., Neves, R., 2018. Using a hierarchical approach to calibrate SWAT and predict the semi-arid hydrologic regime of northeastern Brazil. Water (Switzerland) 10. https://doi.org/10.3390/w10091137

Schierhorn, F., Faramarzi, M., Prishchepov, A.V., Koch, F.J., Müller, D., 2014. Quantifying yield gaps in wheat production in Russia. Environ. Res. Lett. 9.

Schuol, J., K. C. Abbaspour, H. Yang, R. Srinivasan and A. J. B. Zehnder. 2008. Modeling Blue and Green Water Availability in Africa. Water Resour. Res. 44, W07406, doi: 10.1029/2007WR006609.

Seager, R., Ting, M., Held, I., Kushnir, Y., Lu, J., Vecchi, G., Huang, H.P., Harnik, N., Leetmaa, A., Lau, N.C., Li, C., 2007. Model projections of an imminent transition to a more arid climate in southwestern North America. Science 316(5828), 1181-1184.

Setegn, S.G., Srinivasan, R., Melesse, A.M., Dargahi, B., 2010. SWAT model application and prediction uncertainty analysis in the Lake Tana Basin, Ethiopia. Hydrol. Process. 24, 357–367

Sheng, Z. 2013. Impacts of groundwater pumping and climate variability on groundwater availability in the Rio Grande Basin. Ecosphere 4(1), 1-25.

Shrestha, M.K., Recknagel, F., Frizenschaf, J., Meyer, W., 2016. Assessing SWAT models based on single and multi-site calibration for the simulation of flow and nutrient loads in the semi-arid Onkaparinga catchment in South Australia. Agric. Water Manag. 175, 61-71.

Singh, J., Knapp, H.V., Arnold, J.G. and Demissie, M., 2005. Hydrological modeling of the Iroquois river watershed using HSPF and SWAT 1. JAWRA J. Am. Water Resou. Assoc. 41(2), 343-360.

Singh, V.P., Woolhiser, D.A., 2002. Mathematical modeling of watershed hydrology. J. Hydrol. Eng. 7(4), 270-292.

Silberstein, R.P., Aryal, S.K., Durrant, J., Pearcey, M., Braccia, M., Charles, S.P., Boniecka, L., Hodgson, G.A., Bari, M.A., Viney, N.R., McFarlane, D.J., 2012. Climate change and runoff in south-western Australia. J. Hydrol. 475, 441-455.

Sinnathamby, S., Douglas-Mankin, K.R., Craige, C., 2017. Field-scale calibration of crop-yield parameters in the Soil and Water Assessment Tool (SWAT). Agric. Water Manag. 180, 61–69. https://doi.org/10.1016/j.agwat.2016.10.024

Skaggs, R.K., Samani, Z. 2005. Farm size, irrigation practices, and on-farm irrigation efficiency. Irrigation and Drainage. 54 (1), https://doi.org/10.1002/ird.148

Skaggs, R., Samani, Z. 2005. Irrigation Practices vs. Farm Size: Data from the Elephant Butte Irrigation District. Water Task Force Report 4. College of Agriculture and Home Economics. Cooperative Extension Service Agricultural Experiment Station.

Smeal, D., Kallsen, C.E., Sammis, T.W., 1991. Alfalfa yield as related to transpiration, growth stage and environment. Irrig. Sci. 12, 79–86. https://doi.org/10.1007/BF00190014.

Smith, M. 1992. CROPWAT: A computer program for irrigation planning and management (No. 46). Food & Agriculture Organization.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Soil Survey Geographic (SSURGO) Database for [EBID, New Mexico and Texas]. Available online. Accessed [4/20/2020].

Song, L., Zhang, J., 2012. Hydrological Response to Climate Change in Beijiang River Basin Based on the SWAT Model. Procedia Engineering 28, 241-245.

Sophocleous, M. and Perkins, S.P., 2000. Methodology and application of combined watershed and ground-water models in Kansas. J. Hydrol. 236(3-4), 185-201.

Srinivasan, R., 2019. HAWQS user guide: Version 1.1. Spatial Sciences Laboratory, Texas A&M AgriLife Research, College Station, TX https://epahawqs.tamu.edu/ (accessed August 1, 2020)

Srivastava, P., Gupta, A.K., Kalin, L., 2010. An ecologically sustainable surface water withdrawal framework for cropland irrigation: a case study in Alabama. Environ. Manage. 46, 302-13.

Sun, C., Ren, L., 2013. Assessment of surface water resources and evapotranspiration in the Haihe River basin of China using SWAT model. Hydrol. Process. 27, 1200-1222.

Sun, C., Ren, L., 2014. Assessing crop yield and crop water productivity and optimizing irrigation scheduling of winter wheat and summer maize in the Haihe plain using SWAT model. Hydrol. Process. 28, 2478-2498.

Tang Y, Tang Q, Tian F, Zhang Z, Liu G. 2013. Responses of natural runoff to recent climatic variations in the Yellow River basin, China. Hydrol. Earth Syst. Sci. 17, 4471–4480. https://doi.org/10.5194/hess-17-4471-2013.

Tarawneh, E., Bridge, J., Macdonald, N., 2016. A pre-calibration approach to select optimum inputs for hydrological models in data-scarce regions. Hydrol. Earth Syst. Sci. 20, 4391–4407. https://doi.org/10.5194/hess-20-4391-2016

Thompson, T. L., Huan-cheng, P., Yu- yi, L. 2009. The Potential Contribution of Subsurface Drip Irrigation to Water-Saving Agriculture in the Western USA. Agricultural Sciences in China. 8, 850–854. https://doi.org/10.1016/S1671-2927(08)60287-4.

Tietjen, B., Schlaepfer, D.R., Bradford, J.B., Lauenroth, W.K., Hall, S.A., Duniway, M.C., Hochstrasser, T., Jia, G., Munson, S.M., Pyke, D.A., Wilson, S.D., 2017. Climate change-induced vegetation shifts lead to more ecological droughts despite projected rainfall increases in many global temperate drylands. Glob. Chang. Biol. 23, 2743–2754. https://doi.org/10.1111/gcb.13598

Tolson, B.A. and Shoemaker, C.A., 2007. Dynamically dimensioned search algorithm for computationally efficient watershed model calibration. Water Resour. Res. 43(1).

Townsend NT, Gutzler DS. 2020. Adaptation of climate model projections of streamflow to account for upstream anthropogenic impairments. JAWRA Journal of the American Water Resources Association, manuscript in revision.

TR-55, Urban hydrology for small watersheds, 2nd ed. USDA-NRCS, 1986, 3-3

Tuppad, P., Douglas-Mankin, K.R., Lee, T., Srinivasan, R., Arnold, J.G., 2011. Soil and water assessment tool (SWAT) hydrologic/water quality Model: extended capability and wider adoption. Trans. ASABE. 54(5), 1677–1684.

Udall B, Overpeck J. 2017. The twenty-first century Colorado River hot drought and implications for the future. Water Resources Research, 53(3), 2404-2418.

U.S. Bureau of Reclamation (USBR). 2016. West-wide climate risk assessments: Hydroclimate Projections, Tech. Memo. 86-68210-2016-01, US Department of the Interior, Bureau of Reclamation, Technical Service Center, Denver, Colorado, 58 pp.

U. S. Department of Agriculture. 1997. Irrigation Guide. National Engineering Handbook.

U.S. Department of Agriculture, USDA, 2019. 2018 Irrigation and Water Management Survey. AC-17-SS-1.

U.S. EPA 2013. National management measures for the control of non-point pollution from agriculture, EPA-841-B-03-004. US Environmental Protection Agency, Office of Water, Washington, DC.

Van Liew, M.W., Garbrecht, J., 2003. Hydrologic Simulation of the Little Washita River Experimental Watershed Using SWAT. J. Am. Water Resour. Assoc. 413-426.

Volschenk, T., 2020. Water use and irrigation management of pomegranate trees - A review. Agricultural Water Management. 241, 106375. https://doi.org/10.1016/j.agwat.2020.106375

Wada, Y., Wisser, D., Bierkens, M.F.P. 2014. Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. Earth Syst. Dyn. 5, 15–40. https://doi.org/10.5194/esd-5-15-2014.

Wagner, P.D., Fiener, P., Wilken, F., Kumar, S., Schneider, K., 2012. Comparison and evaluation of spatial interpolation schemes for daily rainfall in data scarce regions. J. Hydrol. 464–465, 388–400. https://doi.org/10.1016/j.jhydrol.2012.07.026.

Wallace, J.S., 2000. Increasing agricultural water use efficiency to meet future food production. Agriculture, ecosystems & environment, 82(1-3), 105-119.

Wang, D., Ayars, J.E., Tirado-Corbala, R., Makus, D., Phene, C.J., Phene, R., 2015. Water and nitrogen management of young and maturing pomegranate trees. Acta Horticulturae. 1089. 395-401.

Wang, J., Miller, D.R., Sammis, T.W., Gutschick, V.P., Simmons, L.J., Andales, A.A. 2007. Energy balance measurements and a simple model for estimating pecan water use efficiency. Agric. Water Manag. 91, 92-101.

Wang, R., Bowling, L.C. and Cherkauer, K.A., 2016. Estimation of the effects of climate variability on crop yield in the Midwest USA. Agric. For. Meteorol. 216, 141-156.

Wang, R., Yuan, Y., Yen, H., Grieneisen, M., Arnold, J., Wang, D., Wang, C. and Zhang, M., 2019. A review of pesticide fate and transport simulation at watershed level using SWAT: Current status and research concerns. Scien. Total Environ. 669, 512-526.

Ward, F.A, Crawford, T.L., Schurr, B., 2014. Economic Study of Agriculture in Southwest New Mexico from the 2004 Arizona Water Settlements Act (AWSA) Water and Funding. Department of Agricultural Economics and Agricultural Business. New Mexico State University. Las Cruces, NM. Prepared for New Mexico Interstate Stream Commission (NMISC).

Ward, F.A., Mayer, A.S, Garnica, L.A, Townsend, N.T, Gutzler, D.S. 2019. The economics of aquifer protection plans under climate water stress: New insights from hydroeconomic modeling. J. Hydrol. 576, 667–684. https://doi.org/10.1016/j.jhydrol.2019.06.081.

Ward, F.A., Pulido-Velazquez, M. 2008. Efficiency, equity, and sustainability in a water quantity–quality optimization model in the Rio Grande basin. Ecological economics, 66(1), 23-37.

Wei, X., Bailey, R.T., Tasdighi, A., 2018. Using the SWAT Model in Intensively Managed Irrigated Watersheds: Model Modification and Application. J. Hydrol. Eng. 23.

Wellen, C., Kamran-Disfani, A.R., Arhonditsis, G.B., 2015. Evaluation of the current state of distributed watershed nutrient water quality modeling. Environ. Sci. Technol. 49, 3278-90.

Wilson, C.A., White, R.R., Orr, B.R., Roybal, R.G. 1981. Water resources of the Rincon and Mesilla Valleys and adjacent areas, New Mexico (No. 43). New Mexico State Engineer.

Williams, W.D., 1999. Salinisation: A major threat to water resources in the arid and semi-arid regions of the world. Lakes Reserv. Res. Manag. 4, 85–91. https://doi.org/10.1046/j.1440-1770.1999.00089.x

Witt, T.W., Ulloa, M., Schwartz, R.C. and Ritchie, G.L., 2020. Response to deficit irrigation of morphological, yield and fiber quality traits of upland (Gossypium hirsutum L.) and Pima (G. barbadense L.) cotton in the Texas High Plains. Field Crops Research, 249, 107759.

World Bank. 2020. Water in Agriculture. Retrieved on October 2020 from: https://www.worldbank.org/en/topic/water-in-agriculture.

Worqlul, A.W., Ayana, E.K., Yen, H., Jeong, J., Macalister, C., Taylor, R., Gerik, T.J., Steenhuis, T.S., 2018. Evaluating hydrologic responses to soil characteristics using SWAT model in a paired-watersheds in the Upper Blue Nile Basin. Catena 163, 332-341.

Wu, Y., Li, C., Zhang, C., Shi, X., Bourque, C.P., Zhao, S., 2016. Evaluation of the applicability of the SWAT model in an arid piedmont plain oasis. Water Sci. Technol. 73, 1341-8.

Wurbs, R.A., 2002. Natural salt pollution control in the southwest. Journal of American Water Works Association. 94, 58–67. https://doi.org/10.1002/j.1551-8833.2002.tb10249.x

Xie, H., You, L., Wielgosz, B., Ringler, C., 2014. Estimating the potential for expanding smallholder irrigation in Sub-Saharan Africa. Agric. Water Manag. 131, 183–193. https://doi.org/10.1016/j.agwat.2013.08.011.

Xiong, L., Xu, X., Ren, D., Huang, Q., Huang, G., 2019. Enhancing the capability of hydrological models to simulate the regional agro-hydrological processes in watersheds with shallow groundwater: Based on the SWAT framework. J. Hydrol. 572, 1–16. https://doi.org/10.1016/j.jhydrol.2019.02.043

Xu, F., Dong, G., Wang, Q., Liu, L., Yu, W., Men, C., Liu, R., 2016. Impacts of DEM uncertainties on critical source areas identification for non-point source pollution control based on SWAT model. J. Hydrol. 540, 355-367.

Yu, M., Chen, X., Li, L., Bao, A., Paix, M.J., 2011. Streamflow Simulation by SWAT Using Different Precipitation Sources in Large Arid Basins with Scarce Raingauges. Water Resour. Manag. 25, 2669-2681.

Yuan, Y., Khare, Y., Wang, X., Parajuli, P.B., Kisekka, I., Finsterle, S., 2015. Hydrologic and Water Quality Models: Sensitivity. Trans. ASABE. 58(6), 1721-1744.

Zarrineh, N., Abbaspour, K., Van Griensven, A., Jeangros, B., Holzkämper, A., 2018. Model-Based Evaluation of Land Management Strategies with Regard to Multiple Ecosystem Services. Sustain. 10 (11). https://doi.org/10.3390/su10113844

Zeng, R., Cai, X., 2014. Analyzing streamflow changes: Irrigation-enhanced interaction between aquifer and streamflow in the Republican River basin. Hydrol. Earth Syst. Sci. 18, 493–502. https://doi.org/10.5194/hess-18-493-2014

Zettam, A., Taleb, A., Sauvage, S., Boithias, L., Belaidi, N., Sánchez-Pérez, J., 2017. Modelling Hydrology and Sediment Transport in a Semi-Arid and Anthropized Catchment Using the SWAT Model: The Case of the Tafna River (Northwest Algeria). Water 9.

Zhang, H., Wang, D., Ayars, J.E., Phene, C.J., 2017. Biophysical response of young pomegranate trees to surface and sub-surface drip irrigation and deficit irrigation. Irrig. Sci. 35, 425–435. https://doi.org/10.1007/s00271-017-0551-y

Zhang, L., Jin, X., He, C., Zhang, B., Zhang, X., Li, J., Zhao, C., Tian, J., DeMarchi, C., 2016. Comparison of SWAT and DLBRM for hydrological modeling of a mountainous watershed in arid northwest China. J. Hydrol. Eng. 21, 1–11. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001313

Zhang, X., Ren, L., Wan, L., 2018. Assessing the trade-off between shallow groundwater conservation and crop production under limited exploitation in a well-irrigated plain of the Haihe River basin using the SWAT model. J. Hydrol. 567, 253–266. https://doi.org/10.1016/j.jhydrol.2018.09.041

Zou, M., Kang, S., Niu, J., Lu, H., 2019. Untangling the effects of future climate change and human activity on evapotranspiration in the Heihe agricultural region, Northwest China. J. Hydrol. 124323. https://doi.org/10.1016/j.jhydrol.2019.124323

Zou, M., Kang, S., Niu, J., Lu, H., 2018. A new technique to estimate regional irrigation water demand and driving factor effects using an improved SWAT model with LMDI factor decomposition in an arid basin. J. Clean. Prod. 185, 814-828.

APPENDICES

APENDIX A

This table presents an extensive list of the SWAT parameters reported in the reviewed literature for model parametrization and calibration when SWAT was applied to irrigated agricultural watersheds in arid/semi-arid climates. The parameters were broadly grouped under surface runoff, ET, soil water, and groundwater based on parameter definitions and their effect. The information summarized in Table S1 and accompanying references may be used to start the calibration process. However, it is necessary to note that the list of parameters and the general range of calibrated parameters are merely based on what has been reported in published journal articles and they may not be directly applicable to other watershed modeling efforts using SWAT. The sensitive parameters and their range for a particular SWAT application to an arid/semi-arid irrigated agricultural watershed should be selected based on the characteristics of the watershed and modeling approaches and objectives.

Extended list of SWAT model parameters, initial parameter values, and calibrated values extracted from the reviewed publications (see note below).

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
Surface runoff	**CN2:** SCS curve number for moisture condition II	35–98	35-98 (-40% –40%)	Ahn et al. (2018); Chen et al. (2011); Reshmidevi and Kumar (2014); Fallatah et al. (2019); Dechmi et al. (2012); Ficklin et al. (2013); Reshmidevi et al. (2018); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Becker et al. (2019); Delavar et al. (2020); Epelde et al. (2016); Gebremicael et al. (2013); Hammouri et al. (2017); Kannan et al. (2011); Li et al. (2013); Luan et al. (2018); Luo et al. (2008a); McInerney et al. (2018); Molina-Navarro et al. (2016); Notter et al. (2012); Perrin et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santhi et al. (2001&2006); Santos et al. (2018); Setegn et al. (2010); Shrestha et al. (2016); Srivastava et al. (2010); Wu et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018); Zettam et al. (2017); Masud et al. (2018)
	CNCOEF: Plant ET curve number coefficient)	0.5–2	1-1.89	Ahn et al. (2018); Aliyari et al. (2019); Bressiani et al. (2015)
	ICN: Daily curve number method	0, 1, 2	1 (ET method)	Bressiani et al. (2015)
	SURLAG: Surface runoff lag coefficient (days)	4	0.001–15	Ahn et al. (2018); Chen et al. (2011); Reshmidevi and Kumar (2014); Fallatah et al. (2019); Dechmi et al. (2012); Ficklin et al. (2013); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Epelde et al. (2016); Gebremicael et al. (2013); Kannan et al. (2011); Li et al. (2013); McInerney et al. (2018); Molina-Navarro et al. (2016); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Shrestha et al. (2016); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018)
	OV_N: Manning's "n" value for overland flow	0.008–0.5 (based on land surface)	0.05–2.13 (-19%–2%)	Ahn et al. (2018); Ficklin et al. (2013); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Kannan et al. (2011); Marek et al. (2016); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Wei et al. (2018); Worqlul et al. (2018); Masud et al. (2018)
	CH_N1: Manning's "n" value for the tributary channel	0.008–0.5	0.01–5.54	Ahn et al. (2018); Jones et al. (2008); Fallatah et al. (2019); Aliyari et al. (2019); Kannan et al. (2011); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sun and Ren (2013); Worqlul et al. (2018)
	CH_N2: Manning's n value for the main channels	0.008–0.5	0–0.2 (-32% –30%)	Reshmidevi and Kumar (2014); Jones et al. (2008); Fallatah et al. (2019); Ficklin et al. (2013); Reshmidevi et al. (2018); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Ang and Oeurng (2018); Kannan et al. (2011); Notter et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Shrestha et al. (2016); Sun and

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
				Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018)
	CH_K1: Effective hydraulic conductivity in tributary channel alluvium (mm/h)	0–300*	0.025–276	Jones et al. (2008); Fallatah et al. (2019); Aliyari et al. (2019); Kannan et al. (2011); Rivas-Tabares et al. (2019)
Surface runoff	**CH_K2:** Effective hydraulic conductivity in main channel (mm/h)	-0.01–500*	0–406	Reshmidevi and Kumar (2014); Jones et al. (2008); Ficklin et al. (2013); Reshmidevi et al. (2018); Abeysingha et al. (2015); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Gebremicael et al. (2013); Kannan et al. (2011); Molina-Navarro et al. (2016); Notter et al. (2012); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santos et al. (2018); Setegn et al. (2010); Shrestha et al. (2016); Sun and Ren (2013); Wei et al. (2018); Worqlul et al. (2018)
	CH_S1: Average slope of tributary channels	NR**	NR**	Worqlul et al. (2018)
	CH_S2: Average slope of main channel (m/m**)**	NR**	(2.3%)	Aliyari et al. (2019); Ang and Oeurng (2018); Worqlul et al. (2018)
	SFTMP: Snowfall temperature (ºC)	-5 – 5	-1.1–5	Jones et al. (2008); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Delavar et al. (2020); Qiu et al. (2019); Wei et al. (2018)
	SNOCOVMX: Minimum snow water content that corresponds to 100% snow cover (mmH2O)	1	150-530.8	Jones et al. (2008); Aliyari et al. (2019)
	SNO50COV: Fraction of snow volume represented by SNOCOVMX that corresponds to 50% snow cover	0.01–0.99	0.4–0.58	Jones et al. (2008); Aliyari et al. (2019)
	TIMP: Snow pack temperature lag factor	0.01–1	0.01–0.81	Jones et al. (2008); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Qiu et al. (2019); Wei et al. (2018)
	SMTMP: Snow melt base temperature (ºC)	-5–5	1.9–5	Jones et al. (2008); Akhavan et al. (2010); Aliyari et al. (2019); Delavar et al. (2020); Qiu et al. (2019); Wei et al. (2018); Yu et al. (2011)
	SMFMX: Melt factor for snow on June 21 (mmH_2O/ºC day)	1.4–8	0.2–4.5	Jones et al. (2008); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Li et al. (2013); Qiu et al. (2019); Wei et al. (2018); Yu et al. (2011)
	SMFMN: Melt factor for snow on December 21 (mmH_2O/ºC day)	1.4–8	0–0.5	Jones et al. (2008); Aliyari et al. (2019); Andaryani, et al. (2019b); Qiu et al. (2019); Wei et al. (2018); Yu et al. (2011)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	SLSUBBSN: Average slope length (m)	50	0–137.96 (-35%)	Akhavan et al. (2010); Gebremicael et al. (2013); Qiu et al. (2019); Rivas-Tabares et al. (2019); Worqlul et al. (2018)
	HRU_SLP: Average slope steepness (m/m)	0–0.6*	0.029–0.28 (-9%–22%)	Gebremicael et al. (2013); Li et al. (2013); Qiu et al. (2019); Rivas-Tabares et al. (2019); Aliyari et al. (2019); Masud et al. (2018)
	SLSOIL: Slope length for lateral subsurface flow (m)	0-150*	65.97	Rivas-Tabares et al. (2019); Santos et al. (2018)
	ALPHA__BNK: Baseflow alpha factor for bank storage (days)	<1	0.01–0.69	Akhavan et al. (2010); Shrestha et al. (2016)
Surface runoff	**EV_POT:** Pothole evaporation coefficient	0.5	0.5	Chen et al. (2017); Marek et al. (2016)
	POT_VOLX: Maximum volume of water stored in the pothole (mm) over the entire HRU	0–∞*	50	Chen et al. (2017); Marek et al. (2016)
	MUSK_CO1: Weighting factor for influence of normal flow on storage time constant value	NR**	0.01–10	Kannan et al. (2011)
	MUSK_CO2: Weighting factor for influence of low flow on storage time constant value	NR**	0.01–10	Kannan et al. (2011)
	IRR_SQ: Irrigation surface runoff ratio	0–1	0.001–0.5	McInerney et al. (2018)
	IRR_EFF: Irrigation efficiency	0-100	NR**	Masud et al. (2018)
	EVRCH: Reach evaporation adjustment factor	0–1	0.669–0.85	Rivas-Tabares et al. (2019); Worqlul et al. (2018)
	TRNSRCH: Fraction of transmission losses from main channel that enter deep aquifer	0–1	0.21	Worqlul et al. (2018)
	LAT_TTIME: Lateral flow travel time (days)	NR**	5–165	Ficklin et al. (2013); Ba et al. (2020); Rivas-Tabares et al. (2019); Masud et al. (2018)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	PLAPS: Precipitation laps rate (mmH_2O/km)	NR**	77.58 (-7.5–(-5.8))	Delavar et al. (2020); Qiu et al. (2019); Rivas-Tabares et al. (2019)
	TLAPS: Temperature laps rate ($^oC/km$)	-6	(-3%– 18%)	Delavar et al. (2020); Qiu et al. (2019)
Evapotranspiration	**CANMX:** Maximum canopy storage (mmH_2O)	0–100*	0–57.6	Ahn et al. (2018); Fallatah et al. (2019); Abeysingha et al. (2015); Aliyari et al. (2019); Becker et al. (2019); Gebremicael et al. (2013); Hammouri et al. (2017); Li et al. (2013); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Shrestha et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Masud et al. (2018)
	EVLAI: Leaf area index at which no evaporation occurs from water surface	0–10	4	Chen et al. (2017); Marek et al. (2016)
	CANMX: Maximum canopy storage (mmH_2O)	0.01–1	0–1 (39%-99%)	Chen et al. (2011); Reshmidevi and Kumar (2014); Ficklin et al. (2013); Reshmidevi et al. (2018); Abeysingha et al. (2015); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Ang and Oeurng (2018); Becker et al. (2019); Chen et al. (2017); Epelde et al. (2016); Hammouri et al. (2017); Kannan et al. (2011); Marek et al. (2016); Melaku and Wang (2019); Notter et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santhi et al. (2001&2006); Shrestha et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Worqlul et al. (2018); Masud et al. (2018)
	ESCO: Soil evaporation compensation coefficient	0.01–1	0–1 (23%-55%)	Ahn et al. (2018); Chen et al. (2011); Reshmidevi and Kumar (2014); Jones et al. (2008); Dechmi et al. (2012); Ficklin et al. (2013); Reshmidevi et al. (2018); Abeysingha et al. (2015); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Ba et al. (2020); Becker et al. (2019); Bressiani et al. (2015); Chen et al. (2017); Epelde et al. (2016); Gebremicael et al. (2013); Hammouri et al. (2017); Kannan et al. (2011); Li et al. (2013); Luan et al. (2018); Marek et al. (2016); McInerney et al. (2018); Melaku and Wang (2019); Molina-Navarro et al. (2016); Notter et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santhi et al. (2001&2006); Setegn et al. (2010); Shrestha et al. (2016); Wu et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018); Masud et al. (2018)
Soil water	**SOL_AWC:** Soil available water capacity (mmH_2O/mm soil)	0–1*	0– 0.91 (-50%–62%) (default + 0.01) (0-3 times)	Ahn et al. (2018); Chen et al. (2011); Reshmidevi and Kumar (2014); Jones et al. (2008); Fallatah et al. (2019); Dechmi et al. (2012); Ficklin et al. (2013); Reshmidevi et al. (2018); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Becker et al. (2019); Delavar et al. (2020); Gebremicael et al. (2013); Kannan et al. (2011); Li et al. (2013); Luan et al. (2018); Luo et al. (2008a); McInerney et al. (2018); Molina-Navarro et al. (2016); Notter et al. (2012); Perrin et al. (2012);

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
				Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santos et al. (2018); Setegn et al. (2010); Shrestha et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018); Zettam et al. (2017); Masud et al. (2018)
	FFCB: Initial soil water storage	0–1	0.5–0.75	Chen et al. (2017); Marek et al. (2016)
	SOL_K: Saturated hydraulic conductivity (mm/hr)	0–2000*	0.13–180 (-50%–62%)	Ahn et al. (2018); Chen et al. (2011); Reshmidevi and Kumar (2014); Fallatah et al. (2019); Xiong et al. (2019); Ficklin et al. (2013); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Becker et al. (2019); Delavar et al. (2020); Hammouri et al. (2017); Kannan et al. (2011); Li et al. (2013); Molina-Navarro et al. (2016); Notter et al. (2012); Perrin et al. (2012); Qiu et al. (2019); Sahana and Timbadiya (2020); Santos et al. (2018); Shrestha et al. (2016); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018); Masud et al. (2018)
	SOL_BD: Moist bulk density (Mg/m^3 or g/cm^3)	1.1–1.9	(-18% –30%)	Ficklin et al. (2013); Andaryani, et al. (2019b); Andersson et al. (2009); Becker et al. (2019); Notter et al. (2012); Shrestha et al. (2016); Masud et al. (2018)
	SOL_ALB: Moist soil albedo	NR**	0.4-0.81 (-7%)	Aliyari et al. (2019); Andaryani, et al. (2019b); Hammouri et al. (2017); Masud et al. (2018)
Soil water	**SOL_CBN:** Organic carbon content (% soil weight)	NR**	0-10	Becker et al. (2019); Masud et al. (2018)
	SOL_ZMX: Maximum rooting depth (mm)	NR**	600-2030	Becker et al. (2019); Marek et al. (2016)
	SOL_Z (layer): Soil depth (mm)	NR**	0–3500 (-32%–22%)	Fallatah et al. (2019); Aliyari et al. (2019); Ang and Oeurng (2018); Delavar et al. (2020); Gebremicael et al. (2013); Li et al. (2013); Molina-Navarro et al. (2016); Qiu et al. (2019); Rivas-Tabares et al. (2019); Santos et al. (2018); Wu et al. (2016); Worqlul et al. (2018); Zettam et al. (2017)
Groundwater	**GW_DELAY:** Groundwater delay time (days)	0–500*	0 – 365	Ahn et al. (2018); Reshmidevi and Kumar (2014); Jones et al. (2008); Fallatah et al. (2019); Dechmi et al. (2012); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Ba et al. (2020); Becker et al. (2019); Delavar et al. (2020); Epelde et al. (2016); Gebremicael et al. (2013); Kannan et al. (2011); McInerney et al. (2018); Melaku and Wang (2019); Notter et al. (2012); Perrin et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santos et al. (2018); Shrestha et al. (2016); Srivastava et al. (2010); Wu et al. (2016); Wagner et al. (2012); Worqlul et al. (2018)
	GWQMN: Threshold depth of water in shallow aquifer for	0–5000*	0 – 4772 (default +1002.25)	Ahn et al. (2018); Reshmidevi and Kumar (2014); Jones et al. (2008); Fallatah et al. (2019); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Ang and Oeurng

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	return flow to occur (mmH_2O)			(2018); Bressiani et al. (2015); Delavar et al. (2020); Epelde et al. (2016); Gebremicael et al. (2013); Kannan et al. (2011); Luo et al. (2008a); McInerney et al. (2018); Melaku and Wang (2019); Molina-Navarro et al. (2016); Notter et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santhi et al. (2006); Setegn et al. (2010); Shrestha et al. (2016); Srivastava et al. (2010); Wu et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018)
	ALPHA_BF: Base flow recession constant factor (1/days)	0.1–1	0.001–1	Ahn et al. (2018); Reshmidevi and Kumar (2014); Jones et al. (2008); Fallatah et al. (2019); Dechmi et al. (2012); Ficklin et al. (2013); Reshmidevi et al. (2018); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Ba et al. (2020); Becker et al. (2019); Bressiani et al. (2015); Delavar et al. (2020); Epelde et al. (2016); Gebremicael et al. (2013); Kannan et al. (2011); Li et al. (2013); McInerney et al. (2018); Melaku and Wang (2019); Molina-Navarro et al. (2016); Notter et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Setegn et al. (2010); Shrestha et al. (2016); Wu et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018); Yu et al. (2011); Masud et al. (2018)
	REVAPMN: Threshold water level in shallow aquifer for "revap" or deep percolation (mmH_2O)	0–8000*	0.65–2000	Ahn et al. (2018); Reshmidevi and Kumar (2014); Jones et al. (2008); Abeysingha et al. (2015); Akhavan et al. (2010); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Bressiani et al. (2015); Delavar et al. (2020); Epelde et al. (2016); Hammouri et al. (2017); McInerney et al. (2018); Melaku and Wang (2019); Molina-Navarro et al. (2016); Perrin et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Setegn et al. (2010); Shrestha et al. (2016); Wu et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018)
Groundwater	**GW_REVAP:** Groundwater "revap" coefficient	0.02–0.2	0.02–0.4	Ahn et al. (2018); Jones et al. (2008); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Ang and Oeurng (2018); Ba et al. (2020); Bressiani et al. (2015); Delavar et al. (2020); Epelde et al. (2016); Gebremicael et al. (2013); Kannan et al. (2011); Luan et al. (2018); McInerney et al. (2018); Melaku and Wang (2019); Molina-Navarro et al. (2016); Perrin et al. (2012); Qiu et al. (2019); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santhi et al. (2006); Santos et al. (2018); Setegn et al. (2010); Shrestha et al. (2016); Srivastava et al. (2010); Wu et al. (2016); Sun and Ren (2013); Wagner et al. (2012); Wei et al. (2018); Worqlul et al. (2018)
	REVAPC: "revap" coefficient	NR**	0.03	Santhi et al. (2001)
	DEP_IMP: Depth to impervious layer in soil profile (mm)	0–6000*	3202	Aliyari et al. (2019); Worqlul et al. (2018)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	GW_SPYLD: Specific yield of the shallow aquifer (m^3/m^3)	-0.5–1*	-0.48–0.06	Aliyari et al. (2019); Melaku and Wang (2019); Masud et al. (2018)
	GWHT: Initial groundwater height (m)	0–25*	4.86	Aliyari et al. (2019)
	GWSOLP: Concentration of soluble phosphorus in groundwater (mg N/L or ppm)	0-1000*	NR**	Masud et al. (2018)
	SHALLST: Initial depth of water in the shallow aquifer (mmH_2O)	NR**	1000	Bressiani et al. (2015); Rivas-Tabares et al. (2019); Wei et al. (2018); Masud et al. (2018)
	RCHRG_DP: Deep aquifer percolation fraction	0–1	0–0.972	Reshmidevi and Kumar (2014); Jones et al. (2008); Dechmi et al. (2012); Reshmidevi et al. (2018); Abeysingha et al. (2015); Aliyari et al. (2019); Andaryani, et al. (2019b); Andersson et al. (2009); Becker et al. (2019); Bressiani et al. (2015); Gebremicael et al. (2013); McInerney et al. (2018); Melaku and Wang (2019); Molina-Navarro et al. (2016); Notter et al. (2012); Rivas-Tabares et al. (2019); Sahana and Timbadiya (2020); Santhi et al. (2006); Santos et al. (2018); Shrestha et al. (2016); Wu et al. (2016); Sun and Ren (2013); Wei et al. (2018); Worqlul et al. (2018)
	ANION_EXCL: Fraction of porosity from which anions are excluded	NR**	NR**	Masud et al. (2018)
	SOL_CRK: Potential or maximum crack volume of the soil profile	NR**	NR**	Masud et al. (2018)
	SOL_CRK: Crack volume potential of soil (mm)	NR**	0.01-0.9	McInerney et al. (2018)
Auto-irrigation/Auto-	**FLOWMIN:** Minimum in-stream flow for irrigation diversions (m^3/s)	0–100*	0	Ahn et al. (2018)
	DIVMAX: Maximum daily irrigation diversion (mm or 10^4 m^3)	-150 – 150*	45	Ahn et al. (2018)
	FLOWFR: Fraction of available flow	0–1	0.01–0.92	Ahn et al. (2018); Ficklin et al. (2013)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	allowed to be used for irrigation			
	AUTO_WSTRS: Water stress threshold that triggers irrigation	0–1(for plant water demand)	0.25– 0.9	Ahn et al. (2018); Ficklin et al. (2013); Andersson et al. (2009); Masud et al. (2018); Wei et al. (2018)
	IRR_EFF: Irrigation efficiency	0–1***	0.65	Ahn et al. (2018); Masud et al. (2018)
	IRR_MX: Amount of irrigation water applied each time auto irrigation (mm)	0–100	20-50	Ahn et al. (2018); Masud et al. (2018)
	IRR_ASQ: Irrigation surface runoff	0–1	0.05	Ahn et al. (2018)
	AUTO_NSTRS: Plant nitrogen stress threshold triggering automatic fertilization	0.85–0.95	NR**	Andersson et al. (2009); Masud et al. (2018)
Crop Growth	**LAI_INIT:** Initial leaf area index	0–8*	0–8	Ahn et al. (2018)
	HEAT UNITS: Total heat units for cover/plant to reach maturity	0–6000*	1750–2400 (-9% –10%)	Ahn et al. (2018); Ficklin et al. (2013); Akhavan et al. (2010); Andersson et al. (2009); Xiong et al. (2019); Masud et al. (2018)
	BIO_E: Radiation use efficiency or Biomass-energy ratio (kg/ha)/(MJ/m^2)	NR**	20–45	Niu et al. (2018) ; Dechmi et al. (2012); Andersson et al. (2009); Marek et al. (2017&2020)
	HVSTI: Harvest index	NR**	0.1–1.23	Niu et al. (2018) ; Dechmi et al. (2012); Akhavan et al. (2010); Andersson et al. (2009); Marek et al. (2017&2020)
	BLAI: Maximum potential leaf area index	NR**	1–10.25 (based on crop type)	Niu et al. (2018); Xiong et al. (2019); Dechmi et al. (2012) Marek et al. (2017&2020); Sahana and Timbadiya (2020); Sun and Ren (2013)
	DLAI: Fraction of plant heat unit when LAI begins to decline	NR**	0.5–0.99	Niu et al. (2018); Xiong et al. (2019); Marek et al. (2017&2020)
	BIOMIX: Biological mixing efficiency	0.2	0.2-0.4	Ba et al. (2020); Santhi et al. (2001&2006)
	FRGRW1: Fraction of plant heat unit at the 1^{st} point	NR**	0.15-0.17	Niu et al. (2018); Marek et al. (2017&2020)
Crop	**FRGRW2:** Fraction of plant heat unit at the 2^{nd} point	NR**	0.45–0.5	Niu et al. (2018); Marek et al. (2017&2020)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	LAIMX1: Fraction of leaf area index at the 1st point	NR**	0.01–0.05	Niu et al. (2018); Marek et al. (2017&2020)
	LAIMX2: Fraction of leaf area index at the 2nd point	NR**	0.95	Niu et al. (2018); Marek et al. (2017&2020)
	T_BASE: Minimum temperature for plant growth (°C)	NR**	0–18	Niu et al. (2018); Xiong et al. (2019); Dechmi et al. (2012)
	GSI: Maximum stomatal conductance (m/s)	NR**	0.004–0.01	Niu et al. (2018)
	EXT_COEF: Light extinction coefficient	0.65	0.5–0.9	Niu et al. (2018); Dechmi et al. (2012)
	CHTMX: Maximum Canopy Height (m)	NR**	0.7–2.7	Niu et al. (2018)
	RDMX: Maximum root depth (m)	NR**	1.5–2.5	Dechmi et al. (2012)
	T_OPT: Optimum temperature for growth (°C)	NR**	15–25	Dechmi et al. (2012)
Sediment	**PRF:** Peak rate adjustment factor for sediment routing in the main channels	1.0	0.18–0.9	Shrestha et al. (2016); Worqlul et al. (2018)
	LAT_SED: Sediment concentration in lateral and groundwater flow (mg/L)	0-5000*	NR**	Masud et al. (2018)
	SPEXP: Channel reentrained exponent parameter	1.0	1.35–1.47	Gebremicael et al. (2013); Santhi et al. (2001&2006); Shrestha et al. (2016)
	SPCON: Channel reentrained linear parameter	0.0001-0.01	0.0008–0.002 (1%)	Gebremicael et al. (2013); Luo et al. (2008a); Santhi et al. (2001&2006); Shrestha et al. (2016)
	USLE_P: Support practice factor	See SWAT input data:.mgt	0.003–0.8 (-60% – (–10) %)	Ba et al. (2020); Gebremicael et al. (2013); Shrestha et al. (2016); Worqlul et al. (2018)
	USLE_K: soil erodibility factor (ton m^2 hr/m^3 ton cm)	NR**	0.005 (-19%–50%)	Shrestha et al. (2016); Worqlul et al. (2018); Masud et al. (2018)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	CH_COV1: Channel erodibility factor (Also named CH_EROD)	0, 1	0.12–0.14	Luo et al. (2008a)
	CH_COV2: Channel cover factor	0, 1	0.2–0.5	Shrestha et al. (2016)
Phosphorus and Nitrate	**PSP:** Phosphorus availability index	0.4	0.08–0.7	Shrestha et al. (2016)
	ERORGP: P enrichment ratio with sediment loading	NR**	2–4	Shrestha et al. (2016)
	RCN: Concentration of N in rain (mg N/L)	1.0	-0.1–1.3	Akhavan et al. (2010)
	ERORGN: Organic N enrichment for loading with sediment	NR**	2.75	Shrestha et al. (2016)
	NPERCO: Nitrate percolation coefficient	0.01-1	0.1–0.8	Akhavan et al. (2010); Ba et al. (2020); Epelde et al. (2016); Santhi et al. (2001&2006); Shrestha et al. (2016)
	PPERCO: Phosphorous percolation coefficient (10 m^3/Mg)	10-17.5	10	Santhi et al. (2001&2006); Shrestha et al. (2016)
	PHOSKD: Phosphorous soil-partitioning coefficient (m^3/Mg)	175	100-193	Santhi et al. (2001&2006); Shrestha et al. (2016)
	CDN: Denitrification exponential rate coefficient	0–3	0.1–1.4	Akhavan et al. (2010); Epelde et al. (2016); Shrestha et al. (2016)
	SDNCO: Denitrification threshold water content	1.1	1	Akhavan et al. (2010); Epelde et al. (2016); Shrestha et al. (2016)
	RSDCO: residue decomposition coefficient	0.05	0.01-0.05	Epelde et al. (2016); Santhi et al. (2001&2006)
	CMN: Rate factor for humus mineralization of active organic nutrients	0.0003	0.002	Epelde et al. (2016)
	HLIFE_NGW: Half-life of nitrate in shallow aquifer (days)	0–5000*	2500	Epelde et al. (2016); Masud et al. (2018)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	FRT_SURFACE: Fraction of fertilizer applied to top 10mm of soil	NR**	0–0.2	Akhavan et al. (2010)
	SHALLST_N: Initial concentration of nitrate in shallow aquifer (mgN/L or ppm)	NR**	0–1	Akhavan et al. (2010); Masud et al. (2018)
	N_UPDIS: Nitrogen uptake distribution parameter	20	63–65	Akhavan et al. (2010)
	SOL_ORGN: Initial organic N concentration in the soil (mg N/kg soil)	NR**	800-5000	Santhi et al. (2001&2006)
	SOL_ORGP: Initial organic P concentration in soil layer (mg P/kg soil)	NR**	100-700	Santhi et al. (2001&2006)
Phosphorus and Nitrate	**SOL_MINP**: Initial mineral P concentration in soil layer for a particular land use (ppm)	NR**	3-351	Santhi et al. (2001&2006)
	AUTO_NAPP: Maximum amount of mineral N allowed in any one application (kg N/ha)	200	NR**	Masud et al. (2018)
	BC1: Rate constant for biological oxidation of NH_4 to NO_2 (1/day)	0.55	0.55	Ba et al. (2020)
	BC2: Rate constant for biological oxidation NO_2 to NO_3(1/day)	1.1	0.3-1.1	Ba et al. (2020); Santhi et al. (2006)
Reservoir	**RES_K:** Hydraulic conductivity of the reservoir bottom (mm/h)	NR**	0.3	Perrin et al. (2012); Qiu et al. (2019)
	EVRSV: Lake evaporation coefficient	0.6	0–1	Qiu et al. (2019)
	NDTARGR: Number of days to reach target	NR**	1–200	Qiu et al. (2019)

	SWAT Model Parameter	Initial Value[a]	Calibrated Values (Relative Change)[b]	Citation
	storage from current reservoir storage			
Pesticides	**HLIFE_S:** Degradation half-life of the chemical in the soil (days)	NR**	0.37-0.78	Luo et al. (2008a)
	SKOC: Soil adsorption coefficient normalized for soil organic carbon content (mg/kg)/(mg/L)	NR**	-0.25−(-0.62)	Luo et al. (2008a)

[a] Initial value is based on the range of default parameter values in SWAT documentation. In cases where a default value was unavailable (marked with an asterisk), the range is based on the lowest and highest values of initial attempts among all applications.

[b] Relative change indicates the range over which the parameter values were varied.

NOTE: The list of parameters, initial ranges, and the range of calibrated parameter values are provided an idea about initiating model parametrization and calibration. Model parametrization and calibration should be finalized based on region-specific data (if available) and characteristics of the watershed.

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