EVALUATING DRAINAGE WATER RECYCLING IN TILE-DRAINED SYSTEMS

by

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To my children. I hope that you are inspired in everything you do.

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LIST OF ABBREVIATIONS

ARIS	annual relative irrigation supply
CPU	central processing unit
DPAC	Davis Purdue Agricultural Center (Purdue University)
DWR	drainage water recycling
EDWRD	Evaluating Drainage Water Recycling Decisions
FAO	Food and Agriculture Organization of the United Nations
FAS	Foreign Agricultural Service
GB	Gigabyte
NASS	National Agricultural Statistics Service
NIFA	National Institute of Food and Agriculture
NOAA	National Oceanic and Atmospheric Administration
NRCS	Natural Resources Conservation Service
REW	readily evaporable water
S	first-order sensitivity
SERF	Southeast Research Farm (Iowa State University)
SPAW	Soil-Plant-Air-Water Model
SRP	soluble reactive phosphorus
SSURGO	Soil Survey Geographic Database
S_T	total-order sensitivity

TAW	total available water
TEW	total evaporable water
USD	United States dollar
USDA	United States Department of Agriculture
USEPA	United States Environmental Protection Agency

ABSTRACT

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Drainage water recycling (DWR) is the practice of capturing, storing, and reusing subsurface drained agricultural water to support supplemental irrigation and has recently been proposed as a practice for improving the crop production and water quality performance in the tile-drained landscape of the U.S. Midwest. This study describes the development of a modeling framework to quantify the potential irrigation and water quality benefits of DWR systems in tile-drained landscapes and the application of the model using ten years of measured weather, tile drain flow and nutrient concentrations, water table, and soil data from two sites in the U.S. Midwest. From this modeling framework, the development and testing of an open-source online tool is also presented.

A spreadsheet model was developed to track water flows between a reservoir and drained and irrigated field area at each site. The amount of tile drain flow and associated nutrient loads that could be captured from the field and stored in the reservoir was estimated to calculate the potential water quality benefits of the system. Irrigation benefits were quantified based on the amount of applied irrigation annually. A reservoir size representing 6% to 8% of the field area with an average depth of 3.05 m was sufficient in meeting the annual irrigation requirements during the 10-year period at each site. At this reservoir size, average annual nitrate-N loads were reduced by 20% to 40% and soluble reactive phosphorus loads by 17% to 41%. Variability in precipitation within and across years, and differences in soil water characteristics, resulted in a wide range of potential benefits at the two sites.

An online tool was developed from the model, and a variance-based global sensitivity analysis was conducted to determine influential and low-sensitivity input parameters. The input parameter, depth of root zone, was the most influential input parameter suggesting that the estimation of total available water for the field water balance is a critical component of the model. Input settings describing the irrigation management and crop coefficients for the initial

establishment and mid-season crop growth periods were also influential in impacting the field water balance. Reservoir seepage rate was influential in regard to the reservoir water balance, particularly at larger reservoir sizes. Sensitivity analysis results were used to develop a user-interface for the tool, Evaluating Drainage Water Recycling Decisions (EDWRD).

This study shows that DWR is capable of providing both irrigation and water quality benefits in the tile-drained landscape of the U.S. Midwest. The developed modeling framework supports future research on the development of strategies to implement and manage DWR systems, and the online tool serves as a resource for users to increase their awareness and understanding of the potential benefits of this novel practice.

1. INTRODUCTION

1.1 Agricultural water management in the U.S. Midwest

Soil water is regarded as the key defining soil physical factor that influences agricultural productivity and plant growth (Kirkham, 2014). Consequently, human interventions to manipulate and manage water for agricultural use have long been established. Within the humid, U.S. Midwest, these agricultural water management practices are critical to advancing an agricultural economy which produces more than 30% of the world's corn and soybeans (USDA-FAS, 2019).

Poorly drained soils and excess seasonal water can lead to saturated field conditions which prohibit critical field management activities and impact crop development. Such conditions require artificial drainage to support productive cropping systems, and land draining activities expanded dramatically between the mid- to late-19th century with the passage of the Swampland Acts of 1849 and 1850 and the Reclamation Act of 1902 (Pavelis, 1987). The 2017 Agricultural Census estimated that more than 22 million ha in the U.S. is drained by means of artificial subsurface drainage (i.e., tile drainage) which is a 14% increase from the 2012 census and concentrated largely in the U.S. Midwest (Zulauf and Brown, 2019). Within the U.S. Midwest, tile drainage has become the predominant form of drainage and has seen increases in number of acres drained by tiles (Jaynes and James, 2007; Sugg, 2007). Anecdotally, agricultural producers and drainage contractors have noted a shift toward systems with greater drainage intensity, particularly through pattern drainage systems with narrower tile spacings (Bechman, 2014; Lien, 2012; Olson, 1999; Thomas and Mahanna, 2012).

Where growing season precipitation is insufficient to meet the water demand of growing crops, and in some soils characterized by a low water holding capacity, shallow rooting depth, or other restrictive feature, water deficits may occur. Crop production during deficit conditions is often supported through irrigation practices to meet at least a portion of the crop water requirement. The 2013 Farm and Ranch Irrigation Survey found that more than 25% of all cropland in the United States is irrigated, and while the area of irrigation across the western U.S. has decreased by more than half a million hectares over the past 15 years, increases in irrigated crop area in other areas of the country such as the U.S. Midwest have more than made up the difference resulting in a net increase in total irrigated area (NASS, 2014, 1999).

1.2 Impacts of artificial drainage practices on water quality

Widespread draining of agricultural lands in the U.S. Midwest has not been done without consequence. The water drained through subsurface tiles may also carry excess nutrients resulting from soil mineralization processes, nitrogen fixation, and agricultural fertilizers. Nitrogen and phosphorus loads from tile-drained lands contribute to downstream eutrophication, having resulted in water quality problems of local, regional, and national concern. The Gulf of Mexico has experienced dramatic increases in the presence, extent, and severity of eutrophic conditions and hypoxia during the past century, which have been linked to increased nutrient loading (Rabalais et al., 2001; USEPA, 2017). Drained agriculture in the U.S. Midwest has been identified as a major source of this increased nutrient loading to the Gulf of Mexico, contributing several times the amount estimated from elsewhere in the Mississippi River basin (David et al., 2010; Goolsby et al., 2001). In the Lake Erie basin, drained agricultural lands have been linked to record-setting algal blooms which threaten public health and drinking water supplies (Michalak et al., 2013; Smith et al., 2015).

As tile drainage increases in both intensity and extent, the magnitude of nutrient loss from drained lands is expected to increase. Skaggs et al. (2005) evaluated published field data from Indiana and North Carolina and found that nitrate loss through tile drains increased with increasing drainage intensity, which was defined as the drainage rate associated with a given tile drain spacing and depth. Kladivko et al. (2004) compared annual nitrate loads from three separate tile drain spacings during a 15-year period and showed that the load from the narrowest spacing (5 m) was significantly higher during most years compared to the widest spacing (20 m). Changes in drainage intensity can also impact phosphorus loss through tile drains. Shallower drains tend to be characterized by greater phosphorus concentrations; however, deeper drains, or those spaced closely together, remove greater volumes of water and are more often characterized by discharging greater phosphorus loads (King et al., 2015). When surface inlets are installed to promote the drainage of small, depressional areas in the field, phosphorus concentration and loading through the tile drain outlet will also often be greater since a higher portion of particulate phosphorus will be delivered to the tile drain.

A variety of conservation practices are often prescribed to tile-drained lands to mitigate water quality impacts, including better nutrient management, cover crops, and crop diversification (Dinnes et al., 2002). Pavelis et al. (2011) estimated that more than USD 4 billion yr^{-1} is spent on delivering conservation programs and funding practices, yet water quality issues have continued to worsen. McLellan et al. (2015) emphasized the need to combine both in-field agronomic management practices with practices that intercept and remove nitrate from drainage if the goal of a 45% reduction in nitrogen load delivered to the Gulf of Mexico is to be achieved. In a successful application of this approach, Drury et al. (2014) evaluated the effectiveness of combining a winter wheat cover crop with a controlled drainage system and showed that, when these practices were used together, nitrogen concentration and load reductions were greater than when used separately. It is becoming clearer that along with cropping system changes, new and innovative approaches to conservation in the tile-drained U.S. Midwest are needed to achieve targeted improvements in water quality.

1.3 Evaluating the need for drainage and irrigation

Boyer (1982) compiled USDA crop loss payments to agricultural producers for major U.S. crops between 1939 and 1978 and showed that crop loss due to excess water and drought accounted for nearly 60% of all payments made. For comparison, weather-related causes (e.g., cold, hail, wind, flood) accounted for 34.2%, insect damage accounted for 4.5%, 2.7% was linked to crop disease, and all other causes accounted for 1.5%.

While tile drainage may increase the loss of nutrients from the field, without it, agricultural production throughout much of the U.S. Midwest would experience extensive crop losses. To address issues with excess water, tile drainage has widely been used as a practice for improving crop yields (Beer et al., 1965; Bengtson et al., 1984; Fausey, 1983; Helmers et al., 2012; Kladivko et al., 2005; Nash et al., 2015). These improvements in crop production are often attributed to better soil aeration and more timely completion of agronomic activities (Evans and Fausey, 1999; Fausey et al., 1987; Reeve and Fausey, 1974).

However, relatively little research has been published on the impact of irrigation for addressing the issue of deficit water conditions in modern corn and soybean production systems on the poorly drained, high water capacity soils of the U.S. Midwest. Thornthwaite (1947) and Mather (1968) described the significance of low magnitude, but frequent, water deficits in humid and sub-humid areas such as the U.S. Midwest where yields are often impacted, sometimes without notable impacts on crop appearance during the growing season. These kinds of drought conditions are termed contingent droughts, where variable and unpredictable precipitation may occasionally be significant enough to result in some crop failure, and invisible droughts, where precipitation may occur in low volumes but yields are still impacted because crops are unable to grow at optimum rates (Thornthwaite, 1947). A brief description of irrigation studies from across the Midwest and southern Ontario are included below, and summarized in Table 1.1.

Table 1.1 Summary of studies from the U.S. Midwest and southern Ontario evaluating corn and soybean response to irrigation

Study	Irrigation type	Corn yield increase % (Avg.)	Soybean yield increase % (Avg.)
Cooper et al., 1991, 1992, 1999	Subirrigation	0–200 (68)	20–58 (35)
	Subirrigation	-4–45 (13)	-
Fisher et al., 1999	Subirrigation	7–45 (26)	36–107 (71)
Sipp et al., 1984; Walker et al., 1982	Sprinkler	-8–350 (131)	-6–23 (9)
	Sprinkler	-17–168 (67)	-10–14 (2)
	Sprinkler	4–175 (74)	-10–43 (16)
	Furrow	16–355 (125)	8–23 (16)
	Furrow	17–203 (82)	0–43 (21)
Belcher and Protasiewicz, 1995	Subirrigation	-50–33 (4)	-28–-2 (-13)
LeCureaux and Booms, 1991	Subirrigation[a]	18–49 (29)	-
Luetkemeier et al., 1950	Sprinkler	5–9 (7)	-
	Sprinkler	47	-
Ng et al., 2002	Subirrigation	64	-
Drury et al., 2009; Tan et al., 1993	Subirrigation	-2–9 (4)	-9–13 (2)

[b] Control treatment was a partial-irrigation treatment with irrigation starting after July 15 resulting in lower controlled water table elevation (35" to 48" depth)

Cooper et al. (1992, 1991) demonstrated the use of a groundwater-supported subirrigation system on a tile-drained silt loam soil in Ohio which resulted in a 20% to 58% increase in soybean yield over a non-irrigated control. Corn yields were increased by up to 200% in dry years and exhibited greater yield stability compared to drained, non-irrigated control treatments across years with varying amounts of precipitation (Cooper et al., 1999). Fausey and Cooper (1995) conducted a simplified water balance to estimate water deficits for soybeans at this site between 1960 to 1990 and estimated a 68% annual probability of having a deficit of at least 100 mm. Results by Fisher et al. (1999) showed similar results at a separate Ohio site with silt loam soils, where 2-year average corn yields increased by 26% and soybean yields by 71%.

In Illinois, Walker et al. (1982) and Sipp et al. (1984) reported results covering seven years of corn yield data and two years of soybean yield data from a drainage and irrigation study on a poorly drained silt loam claypan soil. This study compared multiple combinations of irrigation (sprinkler, furrow, non-irrigated) and drainage treatments (surface, subsurface, surface and subsurface). The combination of drainage and irrigation, regardless of type, resulted in average corn yield increases of 95% and average soybean yield increases of 12% compared to drained, non-irrigated treatments. Bowman and Collins (1987) estimated water deficits for corn in Illinois using a water budget approach based on 30-year mean climate conditions and concluded that, even in silt loam and clay loam soils with higher water holding capacities, water deficits of 75 to 150 mm were expected.

In Michigan, Belcher and Protasiewicz (1995) evaluated a subirrigation system on a poorly drained silty clay loam soil. Across the five-year period (1986–1990) corn yield increased by an average of about 4% compared to the conventional, free-draining treatment. However, this average was reduced by one abnormal year (1989) where corn yield in the subirrigated treatment was reduced by 50%, which was attributed to herbicide carryover and poor surface drainage. Excluding this year, the average corn yield increase was 18%. Subirrigated treatments showed an average soybean reduction of 13% compared to free-draining treatments. During a one-year study on a poorly drained loam soil, LeCureaux and Booms (1991) found a subirrigation treatment, maintaining the water table at approximately 15” to 20” below the soil surface throughout the growing season, increased the average corn yield across three replications by 29% compared to a partially subirrigated treatment which maintained the water table at 25” to 30” only after mid-July.

Luetkemeier et al. (1950) conducted a 2-year experiment in central Indiana, and despite above average rainfall, corn yield increases were 7% on a Brookston silt loam soil type and 47%

on a Fox loam soil type. The authors noted that yields would likely have been higher if not for experiencing untimely high winds and lodging during the two years of the study.

Nielsen (1979) simulated the irrigation potential of corn at nine sites with high water holding capacity soils in Iowa based on 20 years of weather data and estimated that yield was reduced due to deficit water stress to some degree almost every year, with yield reductions increasing from southeast to northwest Iowa. The estimated yield increases for corn due to irrigation trended similarly ranging from an average of 8% in southeast Iowa to 40% in northwest Iowa.

In Ontario, Ng et al. (2002) found during a two-year study between 1996 and 1997 that average corn yields increased by 64% with a subirrigation system compared to a free-drainage treatment. This increase was associated with 50% greater transpiration rates, 12% greater stomatal conductance, and an 11% increase in water use efficiency. Tan et al. (1993) and Drury et al. (2009) evaluated a subirrigation system on a clay loam soil with irrigation water serviced by a nearby pond. Average corn and soybean yields were increased by 2% to 4%, compared to conventional, free-draining treatments. The authors noted that average crop yield increases may have been hampered by inadequate tile drain spacing, given the low hydraulic conductivity of this soil, and by greater than average precipitation in some years indicating a need for more active management of the water control structures involved with this system.

The impact of contingent and invisible drought conditions on crop production is expected to become more pronounced given future predicted climate change. Hatfield et al. (2018) analyzed corn and soybean yield gaps and observed meteorological data and found that July to August temperatures and precipitation were significant factors in affecting the yield gap; and based on future climate scenarios these yield gaps are expected to increase, particularly for corn. Similar to the need for innovation to address growing water quality concerns around tile-drained landscapes, strategies for addressing seasonal excess and deficit water conditions in the U.S. Midwest that go beyond traditional agronomic management are required.

1.4 Drainage water recycling: integrating drainage and irrigation

Baker et al. (2012) outlined a vision for a more integrated approach to agricultural water management that linked both the practice of drainage and irrigation through water storage on the landscape. By capturing and storing drained water from fields in ponds or reservoirs, and reusing that water for supplemental irrigation, the crop production benefits of both drainage and irrigation may be realized, and the environmental consequences may be controlled. Frankenberger et al. (2017) and Reinhart et al. (2016) further refined this vision specifically for tile-drained landscapes and referred to the practice as drainage water recycling (DWR). DWR provides a water quality benefit since at least a portion of the tile drainage, and the nutrients associated with it, is captured and stored temporarily on the landscape instead of discharged to downstream waters. The stored drained water is then available as irrigation during periods of water deficit.

While the idea of creating reservoirs for irrigation has been studied previously (e.g., Arnold and Stockle, 1991; Edwards et al., 1992; Palmer et al., 1982a, 1982b; Prince Czarnecki et al., 2016; Wesström and Joel, 2010), most past research focused on capturing and storing surface runoff and irrigation tailwater. Relatively few studies have evaluated the idea of specifically integrating water capture and storage into the tile-drained landscapes of the U.S. Midwest to improve the environmental and agronomic performance of agricultural systems.

In Iowa, Melvin and Kanwar (1995) described a dual-level water management system utilizing reservoir storage to support subirrigation on a silty clay loam soil. Tile drainage was routed to the reservoir using a lift station. This study (1988–1989) did not include non-irrigated treatments, and due to issues with construction, equipment, and weather, data were not available in 1988. However, 1989 results showed corn yields 60% to 97% higher than statewide averages.

In Ohio, three demonstration sites were constructed where tile drainage was routed to constructed wetlands and then into a reservoir where it was stored and later applied through subirrigation to the field (Brown et al., 1998). Allred et al. (2014b) showed that the wetland component within this system removed 27% of nitrate-nitrogen loads, 79% of ammonium-nitrogen loads, and 28% of the total nitrogen load across a range of loading rates in 2009. Between 1996 to 2008, subirrigation resulted in an average corn yield increase of 19% and soybean yield increase of 12% compared to conventional, free-draining treatments (Allred et al., 2014a). These yield increases were greater (25% to 28%) during drier years of the study.

In Missouri, drainage-irrigation research plots were established on a poorly drained silt loam claypan soil (Nelson et al., 2011; Nelson and Smoot, 2012). Tile drainage was routed to a nearby reservoir which also served as the source of irrigation water. Between 2003 to 2006 soybean yields in drained, subirrigated treatments were on average 12% to 29% greater than non-drained treatments and 3% to 7% greater than drained, non-irrigated treatments. Differences in soybean yields were more pronounced during dry years and exhibited less yield variability compared to non-drained and drained, non-irrigated treatments. Between 2008 to 2010, corn yields in drained, subirrigated treatments were 10% to 50% greater than in non-drained treatments. There was little yield difference between drained, subirrigated treatments and drained, non-irrigated treatments due to greater than average precipitation during the study. Water quality impacts were not measured in this study.

In Ontario, Canada, Tan et al. (2007) and Tan and Zhang (2011) evaluated a subirrigation system supported with irrigation water from a wetland-reservoir complex, and documented a 41% reduction in average annual nitrate loss, 18% reduction in dissolved inorganic phosphorus loss, 47% reduction in dissolved organic phosphorus loss, and 36% in total dissolved phosphorus loss. This site also found an average corn yield increase of 40% and soybean yield increase of 34%.

With the exception of the yield study in Allred et al. (2014a), these studies are of generally short duration (1 to 5 years). Also, given the wide variability in soil types, topography, and climate that are found across the U.S. Midwest, more studies and studies with longer periods of measured data are needed to adequately evaluate the potential of DWR systems within the tile-drained landscape of the region.

1.5 Objectives

This study set out to increase understanding of the potential water quality and crop production benefits provided by DWR within the tiled-drained U.S. Midwest and develop a resource to support the evaluation and planning of DWR systems throughout the region. To achieve this goal, the study objectives were to:

1. Quantify the amount of tile drainage that could be captured, stored, and utilized as supplemental irrigation at two monitored field sites to estimate the potential nutrient reductions and irrigation benefits.
2. Develop an online tool for evaluating drainage water recycling decisions that met the needs of target users.

1.6 Organization of thesis

This thesis is organized into four chapters. Chapter 1 includes the rationale and literature review on the need for advancing our knowledge of DWR systems and resources for evaluating these systems in tile-drained landscapes. Chapter 2 is a simulation study quantifying potential water quality and irrigation benefits resulting from DWR based on ten years of measured climate, tile drainage, and water quality data at research sites in Indiana and Iowa. It was published in *Agricultural Water Management* (Reinhart et al., 2019). Chapter 3 describes the development and testing of an online tool called Evaluating Drainage Water Recycling Decisions (EDWRD). Conclusions and future research suggestions are presented in Chapter 4.

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2. SIMULATED WATER QUALITY AND IRRIGATION BENEFITS FROM DRAINAGE WATER RECYCLING AT TWO TILE-DRAINED SITES IN THE U.S. MIDWEST

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2.1 Abstract

Drainage water recycling, the practice of capturing and storing water drained from fields and using the stored water to irrigate crops when there is a soil water deficit, has been proposed to increase the resiliency of drained agriculture, but the potential benefits have not been quantified. This study determined irrigation and nutrient reduction benefits of drainage water recycling for various reservoir sizes at two tile-drained sites in the U.S. Midwest with differing climates and soils. Field and reservoir water budgets were developed using ten years of measured tile drain flow and weather data. The calculated volume of drain flow that could be captured by the reservoir was combined with measured nitrate-nitrogen and soluble reactive phosphorus concentrations to determine nutrient load reductions. At the Indiana site, a reservoir size representing 6% of the field area (3.05 m depth) would provide water storage for meeting irrigation requirements in all ten years. This reservoir would capture 37% of annual tile drain flow on average, resulting in average annual load reductions of 11 kg ha^{-1} yr^{-1} (37%) for nitrate-N and 0.05 kg ha^{-1} yr^{-1} (39%) for soluble reactive phosphorus. At the Iowa site, a reservoir size of 8% was necessary to meet the irrigation requirements, which were zero in most years but were higher than at the Indiana site for the three years in which irrigation was needed. This larger reservoir would capture 23% of annual tile drain flow on average, with average annual load reductions of 9 kg ha^{-1} yr^{-1} (24%) for nitrate-nitrogen and 0.02 kg ha^{-1} yr^{-1} (21%) for soluble reactive phosphorus. Quantifying nutrient load reductions and irrigation potential at these two sites showed that drainage water recycling is a promising practice for the tile-drained landscape of the U.S. Midwest, providing a strategy to manage water-related risks while also contributing to water quality goals.

2.2 Introduction

Drained agricultural landscapes within the humid U.S. Midwest are faced with the challenge of addressing both excess and deficit water conditions, often within the same year, while also minimizing negative impacts on water quality and the environment (Baker et al., 2012). Subsurface (tile) drainage is widespread and necessary for managing seasonal excess water in this predominantly poorly drained landscape but has also been linked to increased losses of nitrogen (Porter et al., 2015) and phosphorus (King et al., 2015) from the field. Despite a wide range of conservation practices available to help address water quality concerns with an estimated USD 4 billion yr^{-1} of funding (Pavelis et al., 2011), nutrient levels are not decreasing in rivers across the region (Murphy et al., 2013). This suggests that new conservation innovations and approaches to managing agricultural water are needed to help address water quality concerns in this largely tile-drained landscape.

Historically less prevalent across the region than tile drainage, the adoption of irrigation practices to supplement growing season rainfall and address seasonal water deficit conditions has increased by more than 28% within the U.S. Midwest during a recent 15-year period (NASS, 2014, 1999). This growth in irrigation reflects the increasing recognition of the influence of water deficit during summer on the yield gap even in this relatively humid region, and that crop sensitivity to water stress may be increasing (Lobell et al., 2014). Wang et al. (2016) found that Midwestern U.S. corn yields were negatively correlated with drought stress in the early and middle reproductive growth stages. Supplemental irrigation can increase average yields and reduce inter-annual yield variation in this region (Grassini et al., 2015), and adoption is expected to increase as dry periods during the growing season increase in length (Hatfield et al., 2014).

The growing prevalence of both water excess and deficit presents critical water management challenges. Baker et al. (2012) reviewed ten years of records from federal crop insurance programs for the region and showed that indemnities paid out for corn and soybean yield losses for water-related yield losses totaled USD 5 to 6 billion yr^{-1}, and they were nearly equally divided between losses due to excess water and those due to drought. This amounts to 60% to 75% of the average annual claims paid to agricultural producers during this time (CRS, 2018) and highlights a significant opportunity for advancing integrated agricultural water management systems that combine the benefits associated with tile drainage and supplemental irrigation to reduce water-related yield losses.

Drainage water recycling (DWR) is the practice of capturing and storing water drained from fields in a pond, reservoir, or drainage ditch, and using the stored water to irrigate crops when there is a soil water deficit (Frankenberger et al., 2017). This practice has great potential to improve water quality by recovering nutrient loads that would normally be discharged from tile drains and provide supplemental irrigation to crops through increased water retention and storage in tile-drained landscapes. It could also reduce flood risk and lead to a more resilient landscape by dampening the impacts of fluctuating precipitation on yield and streamflow (Baker et al., 2012).

The few existing studies of drainage water recycling systems within tile-drained agriculture have shown encouraging results. In Missouri and Ohio, the implementation of drainage water recycling systems increased corn grain yields between 14 to 50% and soybean yields up to 7 to 29% compared to conventional free-draining and non-drained treatments (Allred et al., 2014; Nelson et al., 2011; Nelson and Smoot, 2012). Considerable water quality benefits have also been documented for these systems, with average nitrogen reductions ranging between 40% to 70% (Drury et al., 2009, 1996) and phosphorus reductions between 12% to 36% (Tan and Zhang, 2011; Tan et al., 2007).

Similar water management systems that integrate water capture, irrigation, and storage have been implemented in the southern U.S. in the form of tailwater recovery systems (Prince Czarnecki et al., 2016; Yaeger et al., 2018). These systems differ from drainage water recycling in their focus on capturing and reusing runoff associated with surface irrigation practices as opposed to seasonal excess water from tile drains. Nonetheless, research on tailwater recovery systems has highlighted the potential to capture, store, and reuse water from the field. Based on measurements of the water balance at tailwater recovery research sites, Omer et al. (2018a) estimated the water budgets for 180 constructed tailwater recovery systems in the Mississippi Delta and demonstrated the ability for these systems to provide reliable water supplies for irrigation by capturing and storing surface runoff resulting from precipitation and irrigation. Tailwater recovery has also been shown to be a valuable water quality practice, reducing annual loadings of total nitrogen and total phosphorus by 34% to 44% and 43% to 89%, respectively (Omer et al., 2018b; Omer and Baker, 2018).

No similar characterization of the water balance in drainage water recycling systems has been published. A model enabling this characterization is needed to provide more general estimates of potential benefits of the practice beyond the handful of site-specific published studies. Estimating water availability for irrigation and reductions in nutrient loads will allow a quantitative estimation of benefits and help to define the factors that are most likely to impact the potential benefits realized from drainage water recycling systems in tile-drained landscapes of the humid U.S. Midwest. Models for estimating the benefits of various sizes of irrigation reservoirs have been developed by Palmer et al. (1982), Arnold and Stockle (1991), Ouyang et al. (2017), and in the SPAW model (Saxton and Willey, 2005), but these models focus on surface runoff as the primary water source for capture and storage. Due to differences in the timing and volumes of surface runoff compared to tile drainage, storage relationships for drainage water recycling systems relying on tile drainage may differ from those supplied through surface runoff. Tile drainage patterns vary across the U.S. Midwest, and coupled with considerable variation in soils, are also expected to influence storage relationships, and these relationships have not been quantified.

Although no research has been published that includes all flows of a drainage water recycling system, tile drain flow has been measured at numerous sites across the Midwest. This study uses two of these sites, each of which has daily weather, tile drain flow, and water table records for more than ten years, along with extensive site and soil characterization data. These inputs to a drainage water recycling model allow for the first estimate of nutrient loss and supplemental irrigation benefits for drainage water recycling systems in a tile-drained landscape.

The objectives of this study were to: 1) determine the amount of tile drainage that can be captured, stored, and utilized as supplemental irrigation by drainage water recycling systems, 2) estimate the corresponding reductions in nitrate-N and soluble reactive phosphorus (SRP) loads, and 3) compare results between two tile-drained sites in the U.S. Midwest with differing climates and soils. Results from this study will advance the understanding of the potential for DWR systems to improve water quality and crop production performance within the tile-drained U.S. Midwest and identify key research needs.

2.3 Materials and methods

2.3.1 Experimental sites

This study used measured weather, tile drain flow, and soil characteristics data from sites in Indiana (Eastern Corn Belt Plains) and Iowa (Western Corn Belt Plains) for the 10-year period between 2007 and 2016 (Figure 2.1). The Davis Purdue Agricultural Center (DPAC) in east-central Indiana included four tile drainage plots to evaluate hydrologic and water quality impacts between conventional, free-draining tile systems and controlled drainage systems. Detailed descriptions of the site and measurements are in Saadat et al. (2018a, 2018b). The Iowa State University Southeast Research Farm (SERF) is in southeast Iowa and includes eight tile drainage plots to compare free-draining, shallow drainage, controlled drainage, and non-drained treatments (Helmers et al., 2012; Schott et al., 2017). Both of these sites had more than one tile drainage treatment, but only the conventional free drainage treatments were used in this study.

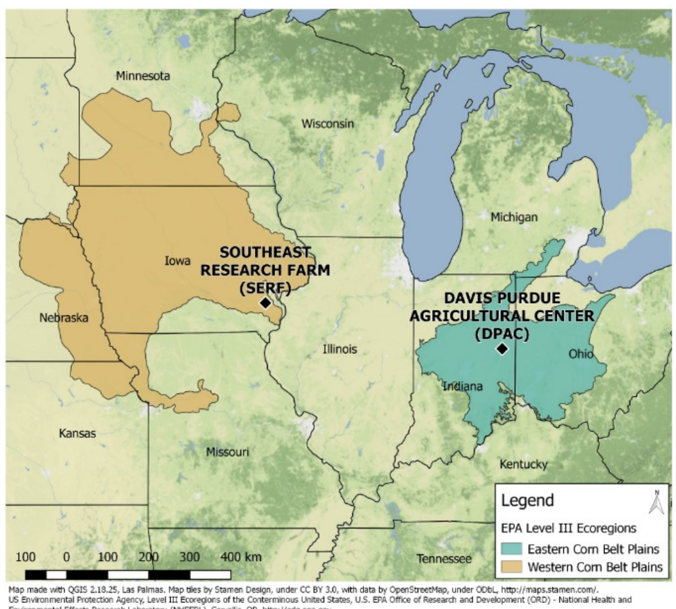

Fig. 2.1 Southeast Research Farm (SERF, Iowa State University, 41.19°N 91.48°W) and Davis Purdue Agricultural Center (DPAC, Purdue University, 40.26°N 85.16°W) with U.S. EPA Level III Ecoregions (https://www.epa.gov/eco-research/ecoregions)

2.3.1.1 Soil properties

Soil water characteristics were collected in order to model the water balance at each site. Water retention at 0-, 0.05-, 0.1-, 0.33-, and 15-bar water potential at each site was measured using hand core samples representing depth layers of 0 to 10 cm, 10 to 20 cm, 20 to 40 cm and 40 to 60 cm (Abendroth et al., 2017; Kladivko et al., 2014). At SERF, water retention for soil depths greater than 20 cm was not measured for the 0.05-, 0.1-, and 15-bar water potential and therefore was estimated using the program ROSETTA (Schaap et al., 2001). Because these soils do not drain freely due to a restricting layer, field capacity was defined as the volumetric water content at 0.1-bar water potential, reflecting the tile drain depth of approximately 1 m and following the practice in the Netherlands where shallow water tables are common (Bouma and Droogers, 1999; Reynolds et al., 2000).

Soil water conditions in the field were estimated following the FAO-56 dual crop coefficient approach (Allen et al., 1998), which distinguishes total available water (TAW) in the entire soil profile and in an evaporation layer on the soil surface. Water conditions within the evaporation layer are defined by the total evaporable water (TEW), which is the total amount of water that can be evaporated from the evaporation layer, and readily evaporable water (REW) which is the portion of TEW that freely evaporates from the evaporation layer under saturated conditions. The soil profile depth was defined by the depth of the tile drains and the depth of the evaporation layer was assumed to be the top 10 cm of the soil profile, based on Allen et al. (1998). TAW was calculated as the difference between the average measured field capacity and wilting point (15-bar potential) across sampled layers and applied to the depth of the soil profile. TEW was estimated as the difference between measured field capacity and one-half the water content at wilting point within the 0 to 10 cm sampling depth and applied to the depth of the evaporation layer (Table 2.1). Typical values of REW were obtained from Allen et al. (1998) based on soil texture classification.

Table 2.1 Soil water parameters used in soil water budget calculations at DPAC and SERF experimental sites. Water content at field capacity (θ_{fc}), water content at wilting point (θ_{wp}), total available water (TAW), total evaporable water (TEW), readily evaporable water (REW)

	Soil profile				Evaporation layer				
	Tile depth (mm)	θ_{fc}	θ_{wp}	TAW (mm)	Layer depth (mm)	θ_{fc}	θ_{wp}	TEW (mm)	REW (mm)
DPAC	1,000	0.36	0.22	141	100	0.34	0.19	25	11
SERF	1,200	0.41	0.15	313	100	0.42	0.11	37	11

2.3.1.2 Water table and tile drain flow

Water table depth and tile drain flow were measured on an hourly basis and aggregated to daily values. Missing data were filled using a combination of methods. At DPAC, Saadat et al. (2018a) used the Hooghoudt equation and measured water table depth, when available, to estimate missing tile drain flow measurements and a linear regression relationship between replicate treatment plots otherwise. At SERF, data gaps of less than four hours were filled using linear interpolation and larger data gaps were filled following a linear regression relationship between replicate treatment plots, when replicate plot data was available. At both sites, remaining missing daily values (DPAC: 1.9% of total period days, SERF: 9.8% of total period days), which occurred primarily during low-flow conditions, were filled using a linear regression relationship with measured precipitation. Average annual tile drain flow at DPAC was 342 mm yr^{-1} (range: 232 to 454 mm) and 301 mm yr^{-1} (range: 46 to 536 mm) at SERF (Figure 2.2).

2.3.1.3 Tile drain flow nutrient concentration and load

Nitrate-N concentration of the tile drain flow was measured at each site during the 10-year study period, and soluble reactive phosphorus (SRP) concentration was measured starting in 2012 at DPAC and 2011 at SERF. Automated water samplers were utilized at DPAC to collect hourly samples from tile drain flow when flow was present and combined into weekly composite samples except during the winter when weekly grab samples were collected in place of the automated samplers. At SERF, weekly grab samples were collected directly from the tile drain when flow was present. Continuous daily datasets for nitrate-N and SRP concentrations were developed by Saadat et al. (2018b) for DPAC and by Craft et al. (2018) for SERF. For the composited samples, the concentration was used for all days since the previous measurement, while linear interpolation was used to estimate daily concentration between measured grab samples. If no samples were taken for more than a month, the average concentration for that month in other years of measurement was used.

Daily concentration values were applied to daily tile drain flow amounts to calculate nutrient loads at each site. Average monthly nitrate-N concentration varied between 5.4 to 13.1 mg L^{-1} at DPAC and 9.0 to 11.6 mg L^{-1} at SERF, and nitrate-N loads ranged from 0.04 to 5.2 kg ha^{-1} mo^{-1} at DPAC and 0.08 to10.1 kg ha^{-1} mo^{-1} at SERF. Average monthly SRP concentration ranged from 0.015 to0.056 mg L^{-1} at DPAC and 0.021 to 0.038 mg L^{-1} at SERF, and SRP loads ranged from <0.001 to 0.023 kg ha^{-1} mo^{-1} at DPAC and <0.001 to 0.021 kg ha^{-1} mo^{-1} at SERF (Figure 2.3).

2.3.1.4 Weather data

Daily weather data were collected from National Weather Service and on-site automated weather stations (Abendroth et al., 2017; Craft et al., 2018). Average annual rainfall was 1,043 mm yr^{-1} (range: 800 to 1,542 mm) at DPAC and 1,077 mm yr^{-1} (range: 771 to 1,468 mm) at SERF (Figure 2.2). The 30-year normal annual precipitation at the closest National Weather Service weather stations for DPAC and SERF was 1,000 mm yr^{-1} and 927 mm yr^{-1}, respectively (Arguez et al., 2010). Results were evaluated across dry, average, and wet years, defined as the years most closely matching the minimum, median, and maximum annual and growing season precipitation amounts during the 10-year study period. Results from each year are provided as supplementary material (Appendix A).

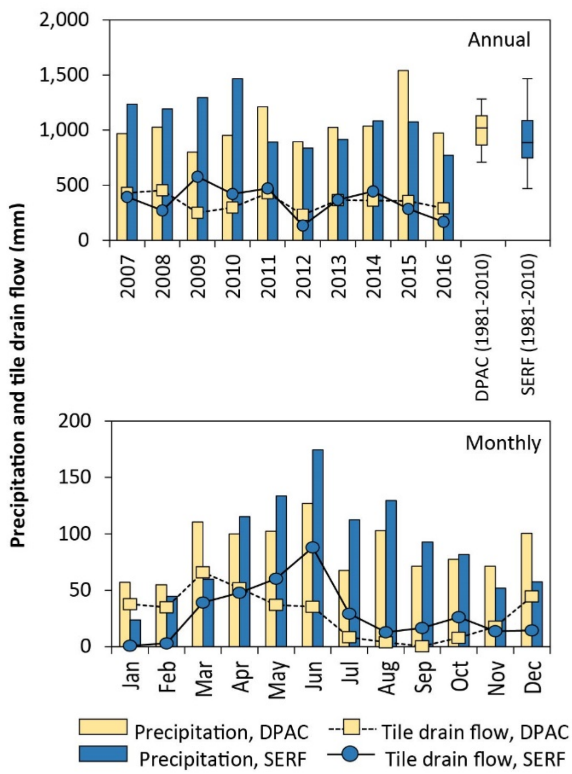

Fig. 2.2 Annual (top) and average monthly (bottom) precipitation and tile drain flow for the experimental sites in Indiana (DPAC) and Iowa (SERF). Dry years were 2009 (DPAC) and 2012 (SERF). Average years were 2008 (DPAC) and 2014 (SERF). Wet years were 2015 (DPAC) and 2010 (SERF). Boxplots show the range of annual precipitation over 30 years for comparison (boxes show 25th to 75th percentile and whiskers represent minimum and maximum)

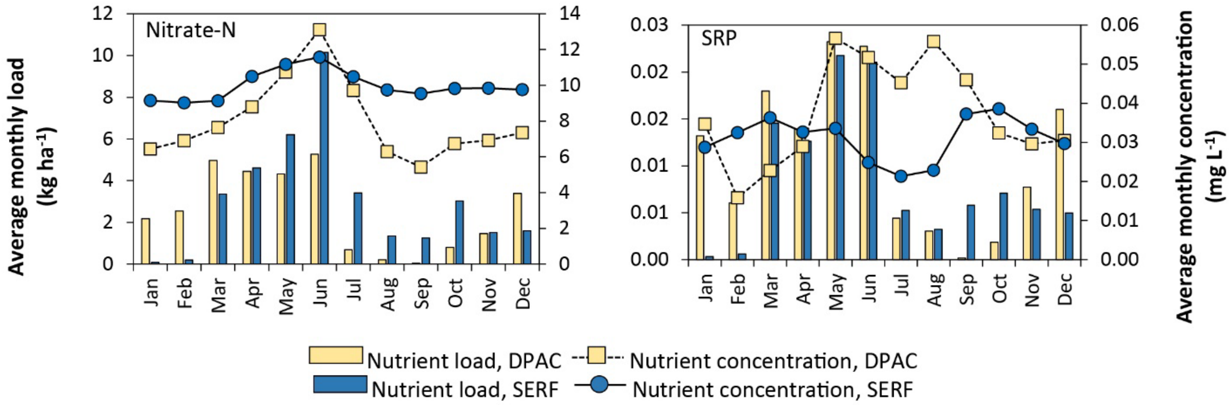

Fig. 2.3 Average monthly loads and concentrations for nitrate-N (left) and soluble reactive phosphorus (SRP, right) for DPAC and SERF experimental sites

2.3.2 Water balance model

A spreadsheet model was developed using Visual Basic for Applications in Microsoft® Excel (Office 2016) to conduct daily water budgeting for the two primary components of drainage water recycling systems, the reservoir and irrigated field (Figure 2.4).

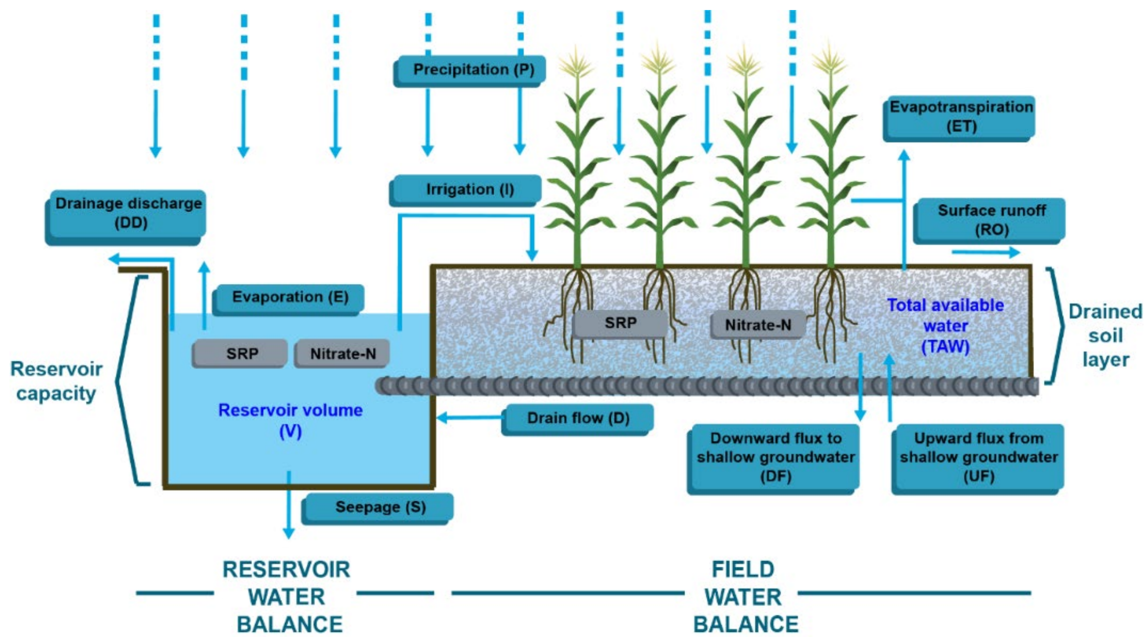

Fig. 2.4 Schematic diagram of a drainage water recycling system water balance and components

2.3.2.1 Reservoir water balance

The daily reservoir water volume in the reservoir was estimated based on Eq. (1).

$$V_t = V_{t-1} + P_t + D_t - I_t - S_t - E_t - DD_t \tag{1}$$

Where V_{t-1} is the volume of water in the reservoir on the previous day, P_t is the precipitation volume over the surface area of the reservoir, D_t is the tile drain flow volume entering the reservoir from the tile-drained field area, I_t is the amount of water withdrawn for irrigation purposes, and S_t, E_t, and DD_t are daily losses due to seepage, evaporation from the reservoir surface, and drainage discharge resulting when reservoir water volumes exceeded reservoir capacity, respectively. Daily values for V_t ranged between zero, representing an empty reservoir, and a maximum capacity set by a given reservoir size. To summarize across a variety of reservoir sizes and shape configurations, calculations of reservoir water volume were based on a reservoir with constant surface area and an average depth of 3.05 m (10 feet). A range of reservoir sizes, with surface areas representing 2%, 4%, 6%, 8%, and 10% of field area, were simulated to evaluate the role of storage capacity in providing water quality and irrigation benefits. A seepage rate of 0.9 mm day^{-1} was used based on USDA Natural Resources Conservation Service design standards for waste storage lagoons (NRCS, 2009). Open water evaporation was estimated by Lee (2017) using the Penman-Monteith equation for a free water surface and daily weather data.

2.3.2.2 Field water balance

A daily water balance was used to track soil water depletion in the soil layer above the tile drains based on Eq. (2).

$$Z_t = Z_{t-1} - (P_t - RO_t) - UF_t - I_t + ET_{c,t} + DF_t \tag{2}$$

Where Z_{t-1} is the soil water depletion on the previous day, $P_t$and RO_t are precipitation and runoff, UF_t is upward flux from a shallow groundwater table below the tile drains, I_t is applied irrigation, $ET_{c,t}$ is crop evapotranspiration, and DF_t is the downward flux of excess soil water resulting in drainage or deep percolation occurring whenever the soil profile is at or above field capacity. Surface runoff was estimated using the NRCS curve number approach (Allen et al., 2007). A curve number of 65 was assumed for average antecedent soil moisture conditions, which is lower than standard values for poorly drained agricultural fields (NRCS, 2004), to account for increased soil water storage capacity in tile-drained soils.

The software program REF-ET (Allen, 2016) was used to calculate the FAO-56 Penman-Monteith grass-based reference evapotranspiration from daily weather data at each site. Daily crop evapotranspiration ($ET_{c,i}$) under stressed and non-stressed soil water conditions was estimated following the FAO-56 dual crop coefficient approach (Allen et al., 1998). Growing period dates, crop height, and water depletion fractions were assigned based on common conditions for a corn (*Zea mays* L.) crop in the U.S. Midwest, and mid-season basal crop coefficients were corrected for local climate conditions (Table 2.2). During the non-growing season both the basal crop coefficient and fraction of living cover were set to zero to reflect the lack of growing vegetation during this period. During a 30-day post-harvest period, TEW was limited by 15% at the soil surface assuming a mulch tillage regime with 30% residue cover. A 30-day pre-planting period assumed bare soil conditions leading up to crop planting and total evaporative losses during this time were calculated based on a water balance for the evaporation layer. Following the post-harvest period and prior to the pre-planting period, when freezing temperatures and snow cover result in violations of coefficient-based approaches for estimating ET_c, a coefficient value of 0.44 was used as an overall average coefficient value for estimating evaporative losses during the non-growing season (Hay and Irmak, 2009). A graphical example of the crop coefficient method showing the 10-year average of daily basal crop coefficient and soil evaporation coefficient at DPAC is provided in the supplementary materials (Appendix A).

Table 2.2 Crop parameters for corn used in calculating crop evapotranspiration

Growing period	Length[1] (days)	Crop height[2] (m)	Basal crop coefficient	
			DPAC	SERF
Initial/End	30	0.1	0.15	0.15
Development	40	1.5	-	-
Mid-season	50	2.0	1.09	1.13
Late	30	2.0	-	-

[1] Start of growing season on May 01 of each year
[2] Indicates the crop height at the end of each respective growing period

Daily soil water deficit was calculated as the difference between soil water depletion (Z_t) and readily available water, which estimates the portion of TAW that can be depleted before water stress occurs. Irrigation scheduling followed an ET-based approach, applying irrigation equal to the soil water deficit amount each time it exceeded a threshold of 8 mm, representing the average maximum water use per day for corn. Irrigation application efficiency was not considered since the purpose of this study was not to evaluate irrigation approaches within

DWR. If the deficit amount was less than 8mm, or if the available reservoir water volume was incapable of meeting the threshold amount, no irrigation was applied.

Upward flux from a shallow or perched water table can also contribute towards meeting the crop water requirement (Ayars et al., 2006). A relationship between water table depth and the maximum potential rate of upward flux from a shallow groundwater table was established at each site using the soil utility module in DRAINMOD (Skaggs et al., 2012) to estimate the amount of water that was capable of being added to the soil water balance during situations of soil water deficit (Figure 2.5). Within the DRAINMOD soil utility, unsaturated hydraulic conductivity is estimated from saturated hydraulic conductivity following methods by Millington and Quirk (1961) and Marshall (1958). The water table-upward flux relationship is then calculated based on the Darcy-Buckingham equation (Skaggs, 1980). Daily estimates of potential upward flux (mm day^{-1}) were calculated by summing the estimated hourly volumes of potential upward flux for each day based on the hourly water table measurements. Actual daily upward flux was assumed to be zero unless soil water deficit conditions existed and did not occur during periods when measured water table was above the depth of the tile drain. If a soil water deficit persisted following any applied irrigation, upward flux was added to the water balance at a volume less than or equal to the estimated daily potential upward flux based on water table observations in order to contribute towards the remaining irrigation requirement.

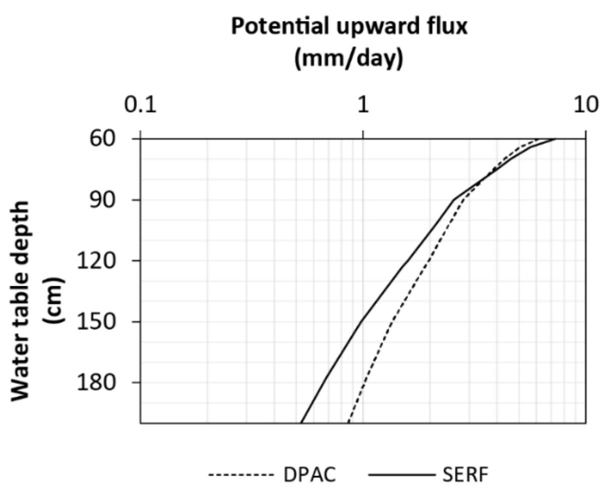

Fig. 2.5 Potential upward flux of water from a shallow groundwater table as a function of water table depth. Actual upflux did not occur when water table conditions were above the tile drain depth (DPAC: 100 cm, SERF: 120 cm)

2.3.3 Quantifying potential water quality and irrigation benefits

Two types of drainage water recycling benefits were quantified using metrics selected for both absolute volumes and relative percentages (Table 2.3).

Table 2.3 Performance measures quantifying the benefits of a drainage water recycling system

DWR system benefits	Absolute volumes and loads	Relative percent and index value
Irrigation supplied	Applied irrigation (mm yr^{-1}) Annual days of crop water stress ($K_s < 1$)	Annual Relative Irrigation Supply (ARIS, index)
Reduction in discharge volume and nutrient load	Captured tile drain flow (mm yr^{-1})	Annual tile drain flow (% reduction)
	Captured nitrate-N load (kg ha^{-1} yr^{-1})	Annual nitrate-N load (% reduction)
	Captured soluble reactive phosphorus, SRP load (kg ha^{-1} yr^{-1})	Annual SRP load (% reduction)

Irrigation benefits were quantified in absolute terms as the amount of irrigation supplied by a given reservoir size. The ability of the reservoir to meet the total irrigation requirement was quantified using the annual relative irrigation supply (ARIS) index defined by Malano and Burton (2001) (Eq. 3). ARIS index values between zero and one represent the fraction of the total irrigation requirement met by the reservoir.

$$ARIS_{jy} = \left(I_{jy}/IR_y\right) \tag{3}$$

Where I_{jy} is the annual applied irrigation from a reservoir with size j during year y and IR_y is the annual irrigation requirement, calculated as the total irrigation that would be applied given an unlimited water supply and irrigation scheduling approach during the corresponding year.

Water quality benefits were described in absolute terms as the reduction in tile drainage discharge and corresponding nutrient loads from the field. Daily tile drain flow was captured and stored if reservoir capacity was available when drainage occurred. The quantity of captured tile drain flow represents the total reduction of discharged flow from the field and corresponding loads were estimated based on measured nutrient concentrations. The annual percent nutrient reduction, R_{jy} of a given reservoir size and year was then calculated based on Eq. (4).

$$R_{jy} = C_{jy}/N_y \tag{4}$$

Where C_{jy} is the cumulative annual captured nutrient load and N_y is the cumulative annual nutrient load associated with the annual tile drain flow volume for the corresponding year.

2.4 Results

2.4.1 Supplemental irrigation

Irrigation requirements occurred during each of the ten years at DPAC with the total annual requirement varying between 17 and 153 mm yr^{-1} with a median of 110 mm yr^{-1} (Figure 2.6). Irrigation requirements were less frequent at SERF, occurring in only three dry years (2011, 2012, and 2013). However, during these dry years the total annual irrigation requirement was greater than at DPAC: 111 mm yr^{-1} in 2011, 191 mm yr^{-1} in 2012, and 207 mm yr^{-1} in 2013.

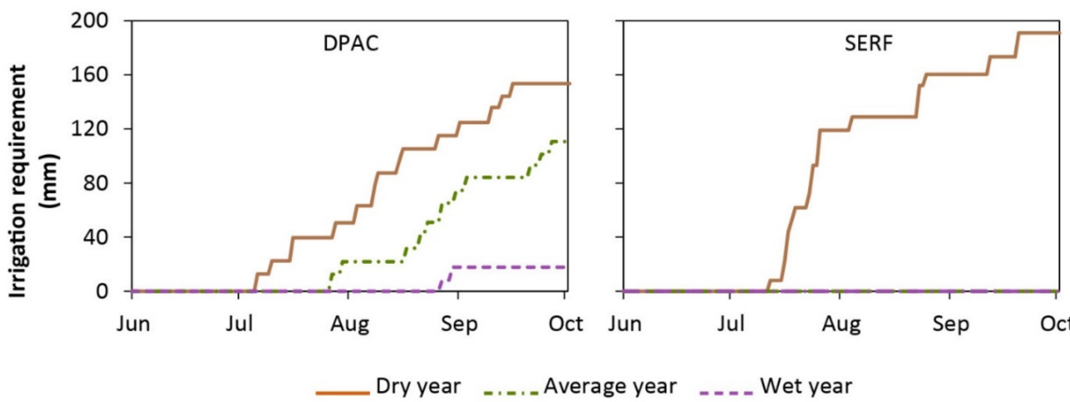

Fig. 2.6 Cumulative annual irrigation requirement for a corn crop in east-central Indiana (DPAC, left) and southeast Iowa (SERF, right). Dry years were 2009 (DPAC) and 2012 (SERF). Average years were 2008 (DPAC) and 2014 (SERF). Wet years were 2015 (DPAC) and 2010 (SERF). Lines representing the average and wet year at SERF overlap and show no irrigation requirement.

Reservoir water depth and availability for irrigation varied considerably throughout the growing season across the evaluated reservoir sizes as well as the annual precipitation and resulting tile drain flow amounts. Reservoir sizes including 2%, 4%, and 6% of field area were drained completely during dry years at both sites and all reservoir sizes remained mostly full during wet years (Figure 2.7). During 2008, the average year at DPAC, larger reservoir sizes (6%, 8%, and 10%) maintained a surplus of water throughout the growing season while smaller reservoir sizes (2% and 4%) were depleted to levels below what was adequate to meet the irrigation requirement. While annual and growing season precipitation totals during 2014 at

SERF were near median values for the study period, reservoir water levels were impacted by a preceding 3-year dry period where growing season precipitation was between 57% to 78% of the 10-year average. Combined with increased levels of irrigation requirement during this dry period, all reservoir sizes at SERF entered 2014 with reduced water levels.

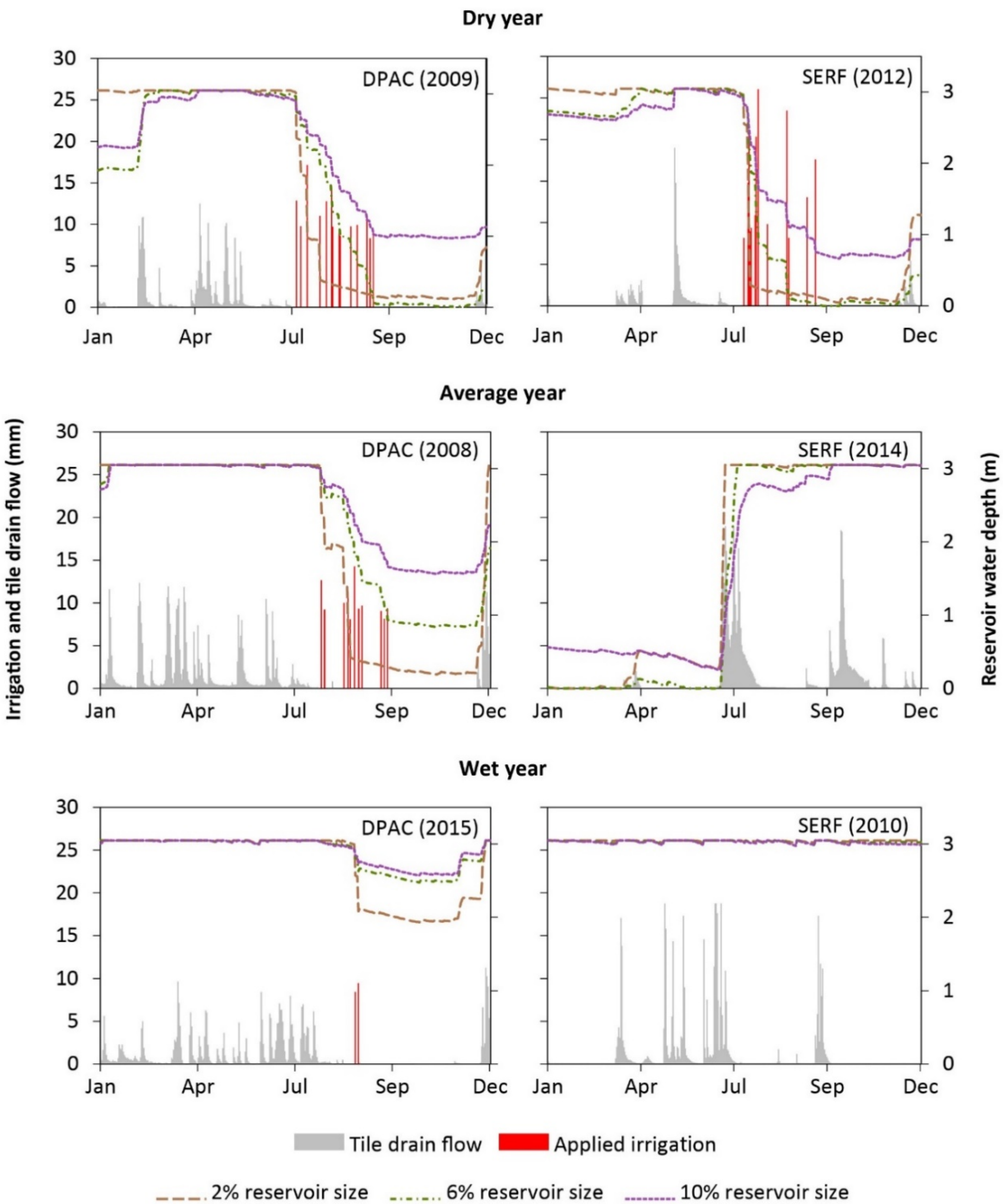

Fig. 2.7 Simulated reservoir water depth, irrigation, and measured tile drain flow for reservoir sizes representing 2%, 6%, and 10% of field area during a dry (top), average (middle), and wet (bottom) years at DPAC (left) and SERF (right)

Deficit water stress was reduced at both sites with increasing reservoir storage size before reaching a maximum reduction at reservoir sizes 6% and larger. At this point any remaining water stress was minor and can be attributed to the irrigation management approach chosen for this study. The minimum application threshold of 8 mm creates an allowable deficit even when there is water availability within the reservoir. At DPAC, a reservoir size representing 6% of the field area would reduce the probability of experiencing 20 days of deficit water stress for corn from 90% to 20% (Figure 2.8). Reductions in the frequency of days experiencing deficit water stress were less at SERF across all reservoir sizes due to a lower frequency of irrigation requirement during the study period.

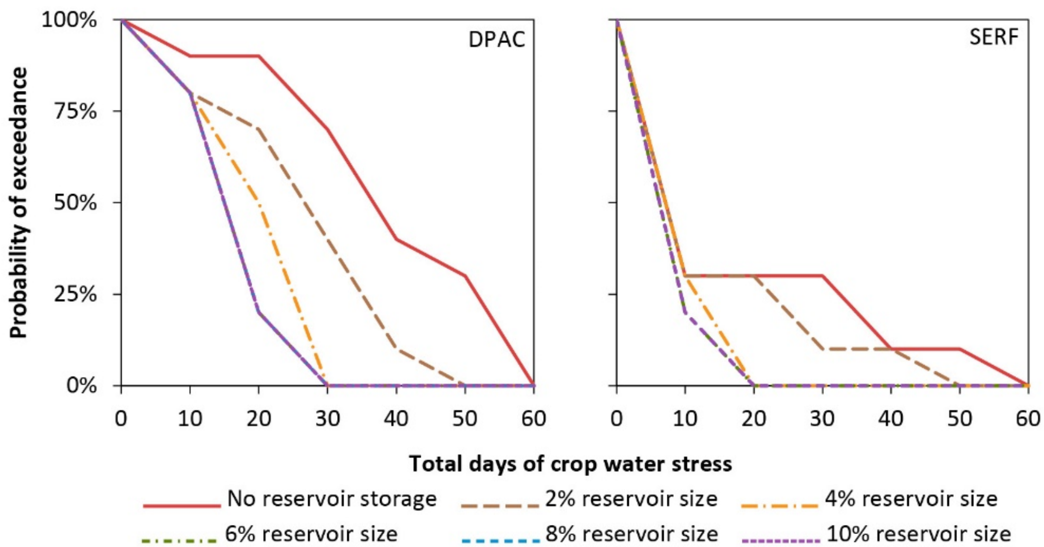

Fig. 2.8 Probability of exceedance for the total annual days of deficit water stress for a corn crop during 2007 to 2016 for experimental sites in Indiana (DPAC, left) and Iowa (SERF, right) and across varying degrees of reservoir water storage supplying water for supplemental irrigation. Lines representing reservoir sizes 6%, 8%, and 10% overlap indicating no differences between reservoir sizes.

During dry years when irrigation was most needed, the total amount of irrigation applied increased with reservoir size at both sites (Figure 2.9). The annual amount of applied irrigation at DPAC increased by more than 100 mm during 2009 at DPAC and 140 mm during 2012 at SERF as reservoir size increased in size from 2% to 10%. At DPAC, a reservoir of size 6% was able to supply enough water to meet the total irrigation requirement during all years with no additional irrigation benefit added from larger reservoir sizes (Figure 2.10). Comparatively, given the larger magnitude of irrigation requirements that occurred during dry years at SERF, a reservoir size of 8% was required to satisfy the irrigation requirement across all years.

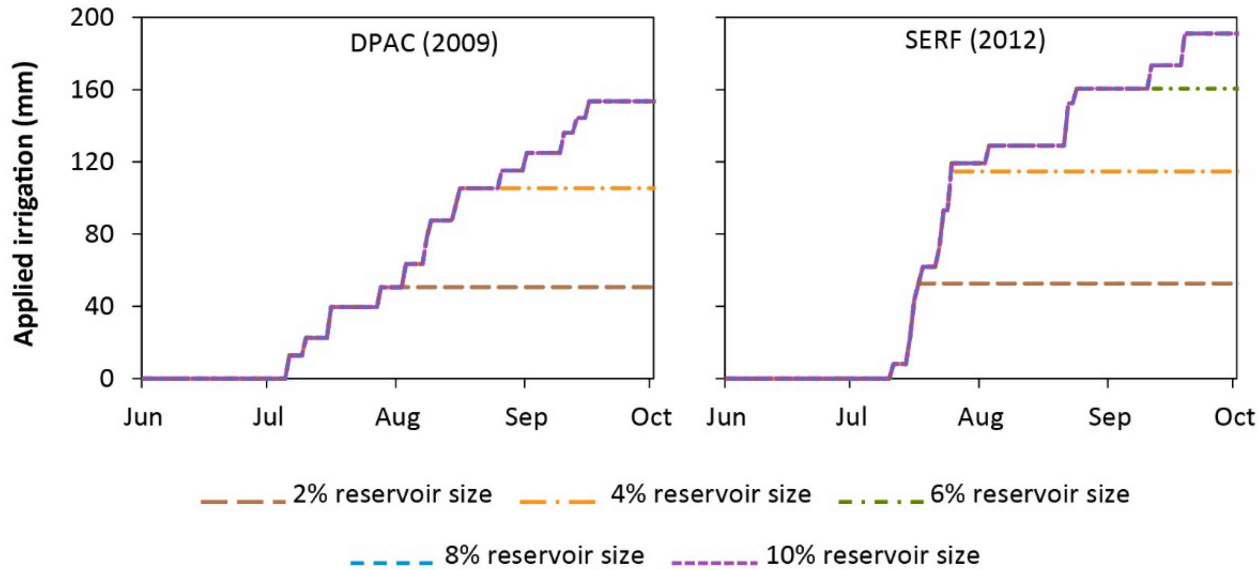

Fig. 2.9 Cumulative applied irrigation to corn from various levels of reservoir water storage during dry years for DPAC (2009, left) and SERF (2012, right). Lines representing reservoir sizes of 6% and larger at DPAC and 8% and larger at SERF overlap indicating no differences between these reservoir sizes.

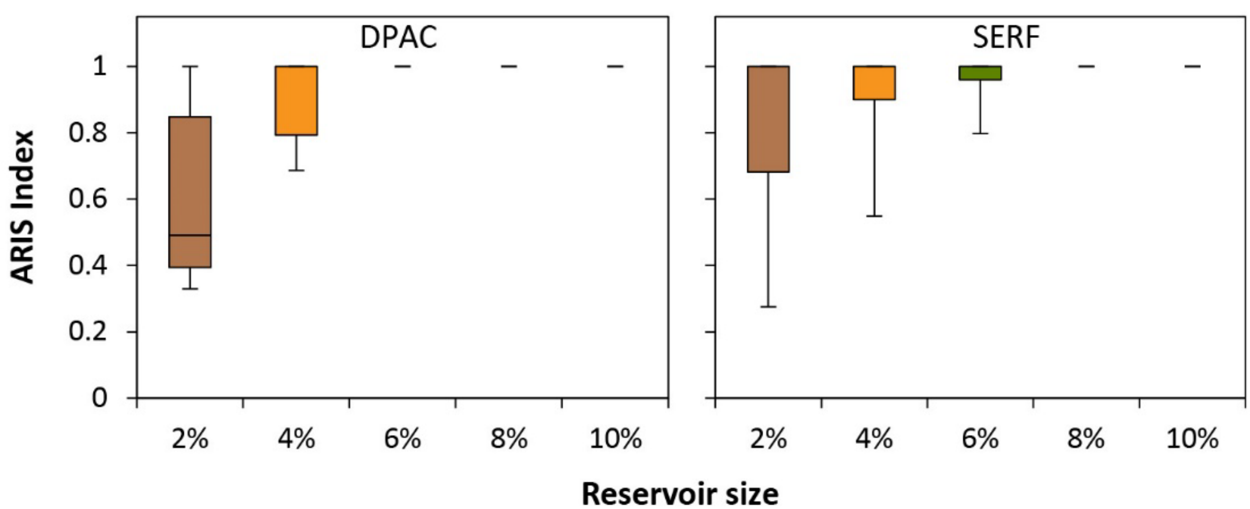

Fig. 2.10 Distribution of annual relative irrigation supply (ARIS) index values between 2007 to 2016 at DPAC (left) and SERF (right) for reservoir sizes representing 2%, 4%, 6%, 8%, and 10% of field surface area and supplying supplemental irrigation for a corn crop.

2.4.2 Drainage water storage

Water quality benefits were quantified by the amount and percentage of tile drain flow and nutrient loads that were captured and stored by the various reservoir sizes. As expected, these quantities varied considerably based on the amount and timing of precipitation, tile drain flow and irrigation requirements. However, in all scenarios evaluated, the amount of captured tile drain flow increased with reservoir size.

The capture and accumulation of tile drain flow within the reservoir generally began earlier in the year at DPAC compared to SERF (Figure 2.11). During dry years at both sites the largest incremental gains in captured tile drain flow occurred as reservoir size increased from 2% to 6%. The total cumulative amount of captured tile drain flow was greater at DPAC during these years across reservoir sizes ranging between 4% and 10%. Average precipitation years at DPAC showed minimal increases in captured tile drain flow between smaller reservoir sizes (2% and 4%) and the largest increases occurred as reservoir size increased from 6% to 10%. Comparatively, at SERF relatively large increases in the amount of capture tile drain flow were simulated across all reservoir sizes. However, as mentioned in section 3.1, conditions in 2014 at SERF were largely influenced by a preceding 3-year dry period which drained the reservoir for irrigation and resulted in the maximum capacity for water capture and storage when subsequent precipitation and tile drain flow occurred. Increases in the amount of tile drain flow captured during wet years were minimal compared to other years and largely a function of volumetric increases in reservoir size, as indicated by the regularly spaced lines in Figure 2.11.

During the 10-year study period the average annual amount of captured tile drain flow varied from 54 mm yr^{-1} (2% reservoir size) to 145 mm yr^{-1} (10% reservoir size) at DPAC, which corresponded to between 16% and 43% of the average annual tile drain flow (Table 2.4). At SERF, total amounts of captured tile drain flow and percent of tile drain flow captured were lower in the majority of years evaluated, with the exception being the large captured tile drain flow volumes in 2014.

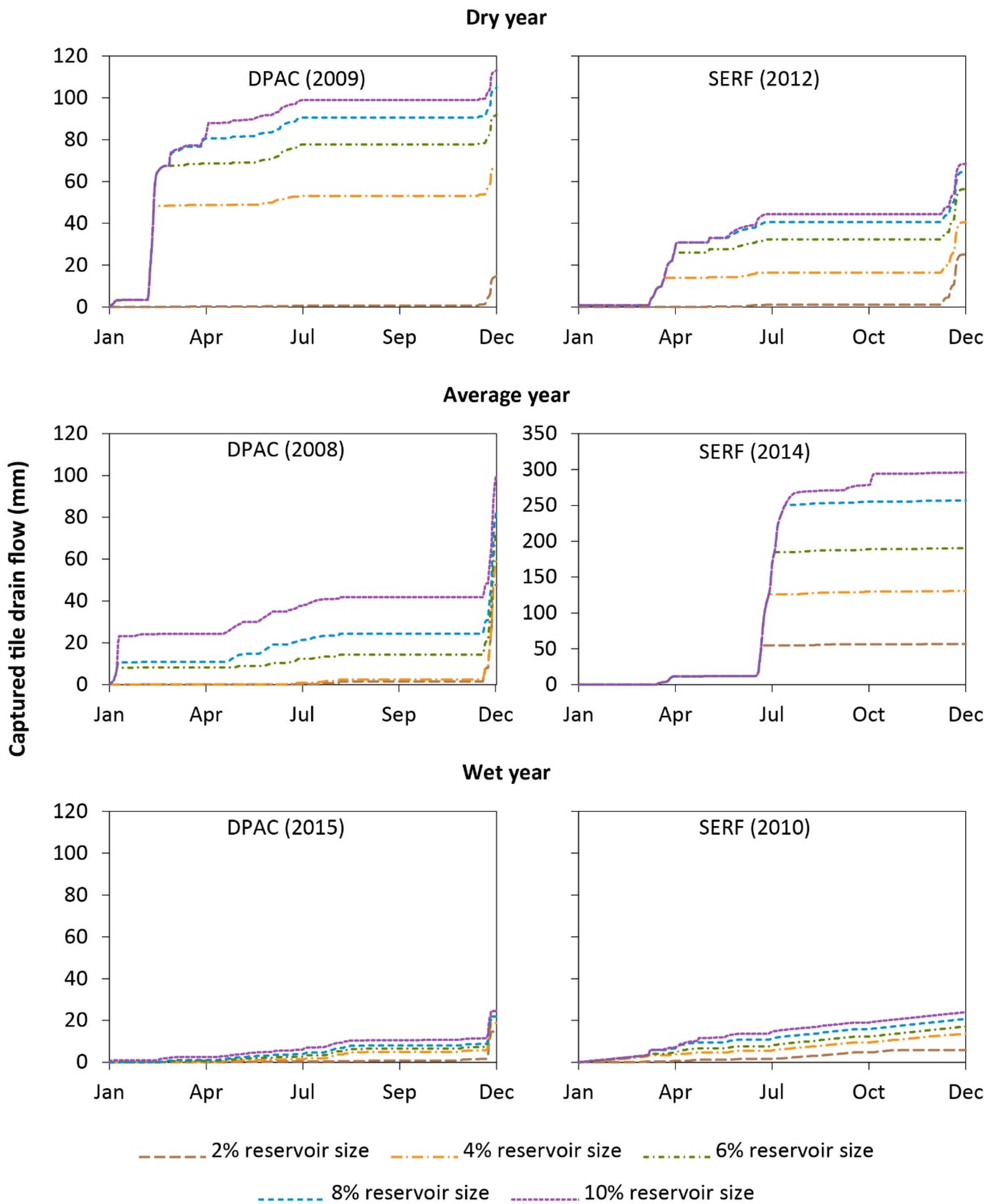

Fig. 2.11 Cumulative captured tile drain flow given reservoir sizes of 2%, 4%, 6%, 8%, and 10% during a dry (top), average (middle), and wet (bottom) year at DPAC (IN, left) and SERF (IA, right).

Table 2.4 Minimum, average, and maximum volumes of annual captured tile drain flow and percent relative to annual tile drain flow for various reservoirs sizes at DPAC (IN) and SERF (IA).

	Reservoir size (% of field area)	Annual captured tile drain flow		
		Minimum, mm yr^{-1} (%)	Average, mm yr^{-1} (%)	Maximum, mm yr^{-1} (%)
DPAC	2	15 (4)	54 (16)	104 (35)
	4	19 (5)	97 (29)	176 (59)
	6	20 (6)	124 (37)	245 (82)
	8	22 (6)	135 (41)	262 (88)
	10	25 (7)	145 (43)	281 (94)
SERF	2	1 (1)	24 (7)	95 (20)
	4	5 (1)	44 (13)	131 (31)
	6	9 (2)	61 (19)	190 (43)
	8	13 (2)	77 (23)	257 (58)
	10	20 (3)	88 (27)	296 (66)

2.4.3 Nutrient load reduction

At both sites, reductions in nutrient loads and percent reductions increased with reservoir size (Figure 2.12). At DPAC, the median annual load reduction varied from 5 to 10 kg ha^{-1} yr^{-1} nitrate-N and 0.02 to 0.05 kg ha^{-1} yr^{-1} SRP, as reservoir size increased from 2% to 10%. The maximum annual reductions during this time increased from 9 kg ha^{-1} yr^{-1} nitrate-N and 0.05 kg ha^{-1} yr^{-1} SRP at a reservoir size of 2%, to 29 kg ha^{-1} yr^{-1} nitrate-N and 0.1 kg ha^{-1} yr^{-1} SRP given a reservoir size of 10%. The average annual percent reductions ranged between 18% to 42% for nitrate-N and 20% to 43% for SRP at DPAC.

Lower average annual percent reductions for nitrate-N (8% to 26%) and SRP (9% to 24%) were estimated at SERF. The median annual load reduction varied from 1 to 5 kg ha^{-1} yr^{-1} nitrate-N and 0.003 to 0.01 kg ha^{-1} yr^{-1} SRP. However, the maximum annual load reduction in nitrate-N (42 kg ha^{-1} yr^{-1}) exceeded those at DPAC and occurred during 2014 following an extended 3-year dry period. This pattern of higher amounts of nutrient reduction following exceptionally dry conditions presents an intriguing scenario suggesting that drainage water recycling may help mitigate some of the impact from excess residual nutrients within the soil profile that go unused by crops during drought conditions. An example of these abnormally high rates of nutrient loading were documented by Van Metre et al. (2016) following the 2012 drought that impacted much of the U.S. Midwest.

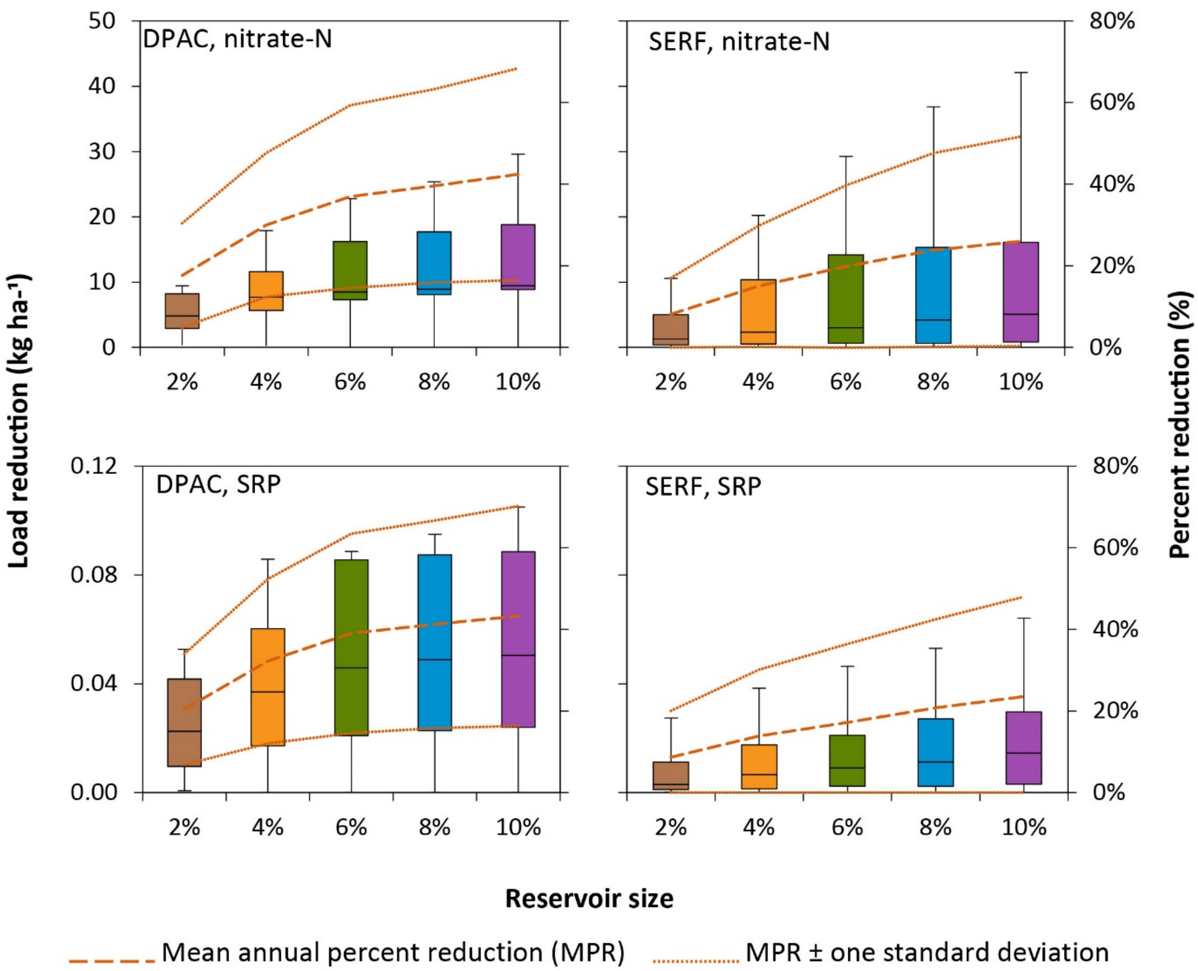

Fig. 2.12 Variation in the annual nitrate-N (top) and SRP (bottom) load reduction (boxplots) and percent load reduction (lines) at DPAC (left) and SRF (right) between 2007 to 2016 given reservoir sizes of 2%, 4%, 6%, 8%, and 10%.

2.5 Discussion

2.5.1 Effect of climate

Average annual precipitation across the study period was similar at both sites but differences in the distribution of precipitation between the growing and non-growing seasons played a critical role in the timing and magnitude of irrigation and water quality benefits achieved through drainage water recycling. On average 45% of the annual precipitation at DPAC occurred during growing season months, whereas 59% of the annual precipitation on average occurred during the growing season at SERF. The higher proportion of precipitation within the growing season at SERF contributed to a lower frequency of irrigation requirement and higher monthly average tile drain flow during the growing season. Under these conditions, reservoirs would fill with early spring tile drain flow and remain full throughout the growing season due to limited irrigation requirement, reducing the ability to capture and store subsequent tile drain flow events. At DPAC, where less of the annual precipitation occurred within the growing season and more frequent irrigation requirement was estimated, reservoirs would fill with tile drain flow during the non-growing season, but water was routinely withdrawn from the reservoir during the growing season creating capacity to store subsequent tile drain flow. These results suggest a positive relationship between irrigation requirement and water quality benefits. Where water is routinely withdrawn from the reservoir, opportunities for water quality benefit are also created through increased capacity for storing future tile drain flow.

Climate effects on irrigation and water quality benefits were compounded across years where precipitation patterns were consistently wetter or drier than average. Despite little to no irrigation requirement estimated for much of the study period, SERF experienced an extended dryer than average period between 2011 to 2013. During this time, the growing season precipitation was between 57% to 78% of the 10-year average, and irrigation requirements increased each year, peaking at 207 mm in 2013. However, higher levels of irrigation requirement during this dry period at SERF served to drawdown reservoir water levels and created capacity for capturing tile drain flow and reducing nutrient loss at a much higher level than was estimated during other years. The highest annual nutrient load reduction of either site, by mass, was estimated at SERF during 2014. DPAC experienced more balance between dry and wet years during the study period and as a result more consistent and higher overall average nutrient load reductions were estimated across all reservoir sizes.

The potential for drainage water recycling to provide irrigation and water quality benefits is expected to increase within the U.S. Midwest as future climate is projected to be characterized by wetter non-growing seasons, hotter growing seasons, and greater variability and magnitude of precipitation within and across years. Baule et al. (2017) and Gunn et al. (2018) found that the benefits of supplemental irrigation and on-farm water recycling are expected to increase under three future climate scenarios, with estimated average corn and soybean yield increases between 15% to 30% and 19% to 22%, respectively, over non-irrigated conditions.

2.5.2 Effect of soil water characteristics

In conjunction with a greater proportion of precipitation falling during the growing season, the deeper soils and higher water holding capacity at SERF contributed to supporting crop water requirements, reducing irrigation requirements and consequently water quality benefits. The estimated total available water within the soil profile at SERF was more than double that estimated at DPAC. Where the soil profile can store adequate water to overcome the variability in annual and seasonal precipitation, the benefits received from drainage water recycling and reservoir water storage may be reduced.

While soils at DPAC had a lower water holding capacity, the combination of a shallower tile drain depth and lower levels of hydraulic conductivity deeper in the soil profile created conditions for a shallow, perched groundwater table, contributing towards meeting the crop water requirement through an upward flux of water. Under non-irrigated, free draining conditions at DPAC, an average of 67 mm yr^{-1} of water through upward flux was estimated across the study period representing between 4% to 22% of the annual crop evapotranspiration. Given deeper tile drains at SERF, the depth of a shallow groundwater table is increased and the potential for upward flux is reduced. During 2011 to 2013 when irrigation requirement occurred at SERF, an average of 14 mm yr^{-1} of water was supplied through upward flux representing only 2% to 3% of the annual crop evapotranspiration. Regardless, results from both sites suggest that the contribution of water through upward flux from a shallow, perched groundwater table can contribute towards meeting crop water requirements and may help reduce the peak magnitudes of irrigation requirement at sites.

2.5.3 Effect of reservoir size

Larger reservoir sizes were necessary to meet irrigation requirements during extended drought periods. At DPAC, a reservoir size representing 6% of the field area was able to fully satisfy the irrigation requirement whereas at SERF a reservoir size of 8% was required to fully meet irrigation requirements across all years. A better balance between dry and wet years at DPAC, and greater contribution of water through upward flux from a shallow groundwater table, moderated peak irrigation requirement across the study period thereby reducing the need for larger reservoir sizes. At SERF, a 3-year period of dryer than average conditions resulted in peak levels of irrigation requirement in 2013 and required a larger reservoir. However, even small reservoir sizes proved to be beneficial, particularly at DPAC where irrigation was of lesser magnitude than peak levels estimated at SERF but was more frequent. Small reservoirs, such as those less than 6%, were able to greatly reduce the number of days where crop water stress occurred. At SERF, given the low frequency but high magnitude of irrigation requirement, the benefit of these smaller reservoir sizes was less but still contributed to reducing the total number of days where deficit water stress occurred. The influence of these small reservoirs at both sites is represented by the amount of area between corresponding lines in Figure 2.8.

Reservoir size had a positive relationship with the magnitude of nutrient load reductions, particularly maximum load reductions, and extended the period of captured tile drain flow at both sites. Large increases in the maximum nutrient reductions for each respective reservoir size can be seen in the boxplots shown in Figure 2.12. There was relatively little increase in average nutrient reductions across reservoir sizes above 6% compared to the increases in the upper tails of the distribution. Also, these additional reductions occurred later in the peak tile drain flow season at each site thereby extending the period of captured tile drain flow at each site.

2.5.4 Opportunities and potential enhancements

While not the primary focus of this study, our results help to shed light on future opportunities and point towards potential management strategies for enhancing the benefits of drainage water recycling in tile-drained landscapes. Extended or diversified cropping rotations such as those that incorporate cover crops into traditional corn-soybean rotations, double cropping, and relay cropping, can provide multiple benefits such as improving soil quality, biological function, and increase resource use efficiencies (Davis et al., 2012; King and Hofmockel, 2017). However, this intensification of the cropping system may also increase water requirements, either through increases in individual crop water requirements such as with alfalfa (Garcia y Garcia and Strock, 2018) or due to extending the active crop growing season such as with double cropping systems (Gesch and Johnson, 2015). The ability of drainage water recycling to provide both a drainage benefit and supplemental irrigation may be able to better support more intensive cropping systems, and additional water use through irrigating these crops can create added capacity for capturing tile drain flow and improve the water quality benefits provided by drainage water recycling.

Modifying irrigation scheduling and technology is likely to influence the benefits received from drainage water recycling by impacting the amount of water use for supplemental irrigation. The irrigation scheduling approach used in this study may overestimate irrigated amounts compared to deficit irrigation approaches or underestimate water use for irrigation when considering less efficient systems or implementing high-volume applications under a full irrigation strategy. Roy et al. (2009) found that the optimum reservoir size for irrigation decreased when allowable depletion thresholds increased for a rainfed rice-mustard cropping system due to changes in irrigation requirements. Temperature-based thresholds may be used in place of soil water deficit thresholds as an alternative approach to irrigation scheduling and as a result can lead to different levels of irrigation water use (Evett et al., 1996). Given the importance of water use for generating the capacity for water quality benefits to occur, irrigation scheduling may be used as a management tool to increase the water quality performance of drainage water recycling systems.

At both DPAC and SERF, observed nutrient concentrations and loads exhibited seasonality suggesting that seasonal water level management within drainage water recycling reservoirs may be used to prioritize the capture, storage, and reuse of tile drain flow during times of peak concentration and tile drain flow. Reservoirs can also capture nutrients from surface runoff, which were not quantified in this analysis. Omer et al. (2018b) found that the fullness and overall capacity of tailwater recovery systems were important predictors in the water quality performance and suggested that manipulating water levels within the system could increase performance. Active management of reservoir water levels within drainage water recycling reservoirs may also create opportunities for not only improving water quality but also flood control downstream, particularly if implemented across a landscape scale (Camnasio and Becciu, 2011; Nakanishi, 2004). Physical enhancement of the reservoir, through practices such as the creation of shallow wetland-like areas and including floating islands (Yeh et al., 2015), may further increase the water quality performance of drainage water recycling reservoirs.

2.5.5 Research to advance drainage water recycling

Drainage water recycling represents a new approach to managing excess and deficit water conditions in the tile-drained U.S. Midwest and few sites have been implemented within the region. This study provided needed estimates of irrigation and water quality benefits resulting from drainage water recycling and has also revealed key areas for future research to advance our understanding of this practice.

Large capital expenses will be needed for the installation of the tile drainage, irrigation, and water storage infrastructure, and projects will carry a life expectancy of approximately 25 to 50 years (Crabbé et al., 2012; Solomon et al., 2007). Given this large investment of both time and money, new tools will be necessary to inform decision-making by potential adopters and funders. Irrigation research has been relatively sparse for the U.S. Midwest, compared to more traditionally irrigated areas, but will be particularly important to support economic analyses and inform irrigation management approaches suitable for providing supplemental irrigation in the region. Decisions tools should also be capable of evaluating both current and future climate scenarios due to the long-term nature of drainage water recycling.

The two sites analyzed here provided some variation in soils, but additional research needs to consider the variability that exists across the U.S. Midwest. Soil water characteristics, such as water holding capacity, saturated hydraulic conductivity, and the influence of upward flux from a shallow or perched water table, will be critical in defining the total irrigation requirement at a site and, therefore, are likely to influence the potential water quality benefits of drainage water recycling. Direct physical measurement of these soil properties, particularly the contribution of shallow groundwater to crop water requirements, are not widely described for this region (Dyer and Boisvert, 1985). Additional research, particularly from sites which include direct physical measurement of drainage water recycling systems (Reinhart et al., 2016), is needed in the U.S. Midwest in order to fully evaluate the variability in benefits provided by drainage water recycling and better characterize site characteristics that influence performance.

Research also should address water and conservation policies and programs that will need to be developed if the full suite of crop production and water quality benefits resulting from the practice are to be achieved. To meet water quality objectives and provide both private and public benefits, policy and financing efforts to support the costs of designing, implementing and managing drainage water recycling systems will be necessary to encourage the construction of reservoirs that are larger than would be needed for irrigation benefits alone.

2.6 Conclusion

This study quantified the potential irrigation and water quality benefits that can be realized from drainage water recycling systems in the tile-drained U.S. Midwest. A reservoir size representing 6% of the field area can meet the irrigation requirement during all but the worst drought periods and could reduce average annual nitrate-N loads by 20% to 37% and soluble reactive phosphorus loads by 17% to 39% from sites in Iowa and Indiana with varying climate and soils. The load reductions of both nutrients show that drainage water recycling is one of the few conservation practices that can play a critical role in achieving both nitrogen and phosphorus reduction goals in this tile-drained landscape. There was a tight linkage between irrigation requirement and water quality benefits which highlighted the role of agricultural water use in creating capacity within drainage water recycling systems to capture and store tile drain flow and nutrients. This relationship between agricultural water use and water quality point towards opportunities to further enhance the benefits received from drainage water recycling through practices that increase or diversify the use of tile drain water. Drainage water recycling is a promising new practice for the tile-drained landscape of the U.S. Midwest, providing a strategy for agricultural producers to manage water-related risks to crop production while also contributing to water quality goals associated with both nitrate-N and SRP loss.

2.7 Acknowledgments

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3. DEVELOPMENT AND SENSITIVITY ANALYSIS OF AN ONLINE TOOL FOR EVALUATING DRAINAGE WATER RECYCLING DECISIONS

3.1 Abstract

The U.S. Midwest is experiencing growth in both irrigation and tile drainage. Capturing, storing, and reusing tile drain water, a practice called drainage water recycling, represents a strategy for supporting supplemental irrigation while also reducing nutrient loads in tile-drained landscapes. This paper describes the development and testing of the open-source online tool, Evaluating Drainage Water Recycling Decisions (EDWRD), which integrates soil and reservoir water balances for a tile-drained field and estimates potential benefits of drainage water recycling systems across multiple sizes of reservoir water storage. Irrigation benefits are quantified by the amount of applied irrigation. Water quality benefits are quantified by the amount of tile drain flow that is captured by the reservoir. Global sensitivity analysis identified input parameters affecting total available water as the most influential factors in estimating outputs. Crop coefficients for initial- and mid-season crop growth, irrigation management, and reservoir seepage rates were also influential. Curve number, fraction of wetted surface during irrigation, crop coefficients for the end of crop growth and frozen conditions, and the non-growing season residue amount were identified as low-sensitivity parameters. Results from the sensitivity analysis were used to prioritize and simplify user interaction with the tool. EDWRD represents the first open-source tool capable of evaluating drainage water recycling systems and can be used by multiple user groups to estimate the potential irrigation and water quality benefits of this innovative practice.

3.2 Introduction

Drainage water recycling (DWR) is an innovative practice for tile-drained landscapes, which combines the crop production benefits resulting from drainage and supplemental irrigation with the water quality benefit of capturing and storing drained water and nutrients (Frankenberger et al., 2017; Reinhart et al., 2019). Initial research of DWR systems has shown potential increases in yield for corn and soybeans up to 40% or more during years with relatively dry growing seasons, provided adequate water supplies were available within the DWR reservoir (Allred et al., 2014a; Melvin and Kanwar, 1995; Tan et al., 2007). DWR systems have also reduced nitrate loads between 27% to 41% and total dissolved phosphorus by 36% (Allred et al., 2014b; Tan and Zhang, 2011). While the potential for DWR to improve both crop production and water quality performance of tile-drained fields has been demonstrated, more widespread and longer-duration evaluations are needed to better understand the potential impact of the practice.

Models may be used as tools to help evaluate practice performance under variable conditions and durations, particularly with practices such as DWR that have yet to be widely adopted. Given the multiple benefits provided by DWR, tools allowing for the rapid evaluation of various reservoir, field, and cropping configurations within a DWR system would be of interest to multiple potential users. Evaluations of crop production benefits resulting from DWR would be of interest to the agricultural producer interested in implementing practices which may increase yields and/or decrease yield variability from year to year. Estimates of water quality benefits resulting from DWR would be of interest to the conservation planner tasked with developing and delivering programs, standards, or policies meant to reduce non-point source loading from agriculture.

Multiple models have been developed to evaluate other systems that include a field and irrigation reservoir, but their suitability as a tool for evaluating DWR systems is limited. Palmer et al. (1982) developed a field-scale model, and Arnold and Stockle (1991) developed a basin-scale model to simulate supplemental irrigation from water storage reservoirs by combining existing crop and hydrology models. The Soil-Plant-Air-Water (SPAW) model (Saxton and Willey, 2005) is a well-known model that combines connected daily water balance routines for a field and reservoir and has been used as a tool in designing and evaluating agricultural wetland and pond systems (Andersen et al., 2010; Millhollon et al., 2009). Roy et al. (2009) developed a software tool using Visual Basic programming to evaluate rainwater harvesting systems typical of surface irrigated crop production. The Pond Irrigation Model is an example of a more recent model which provides the ability to estimate water availability within an irrigation pond and crop irrigation demands simultaneously (Ouyang et al., 2018). None of these models include specific representations of tile drain flow or nutrient loads which are necessary in order to describe the water quality benefits of the DWR system. Also, these models do not account for the contribution of an upward flux of water from a shallow water table to the soil water balance which can be an important contributor of water in the poorly drained soils of the U.S. Midwest.

Model accessibility is another important consideration in maximizing the potential value of a model as a decision tool. Of the models listed above, only the SPAW model is publicly available, and the authors were unable to find a download site for its source code. Widespread use of this tool may be limited by the extensive user inputs required to describe field and reservoir conditions, and the requirement of software download and installation presents potential technological limitations for users with non-compatible operating systems or administrative restrictions on downloading and installing software. The Pond Irrigation Model was developed using the commercial software STELLA (https://www.iseesystems.com), and the reliance on pay-for-use software may restrict use of the model as a decision tool by stakeholders. Open source software has become increasingly common in the development of decision tools for agriculture (De Wit et al., 2019; Foster et al., 2017; Jones et al., 2003) and can provide multiple benefits such as improved scalability, accessibility, transparency, and reproducibility of these analytical tools and their applications (Holzworth et al., 2014; Ince et al., 2012). The delivery of tools through online, web-based applications can also further increase accessibility and user interaction (Biehl et al., 2017; Han et al., 2012).

One of the challenges of using models in decision making is the uncertainty of many of the parameters. Some cannot be measured accurately or precisely, and others can only be estimated with difficulty and high expense. Sensitivity analysis is an approach to better understand and quantify which input parameters are most influential in determining model outputs (Pianosi et al., 2016). Local sensitivity analysis methods evaluate the influence of changes in individual input parameters on model outputs and can be effective in prioritizing influential factors within the model. However, local sensitivity analysis methods do not account for interaction effects among multiple input parameters and rely on the assumption that the model is linear (Cariboni et al., 2007). Global sensitivity methods move beyond local-based methods to evaluate parameter influence across a multi-parameter input space. In this way, global sensitivity analysis methods can quantify interaction effects among input parameters and serve multiple purposes including ranking input parameters by their relative influence, identifying non-influential or low-sensitivity input parameters, and characterizing regions of the multi-parameter input space that result in target model output values. In the case of identifying non-influential or low-sensitivity input parameters, global sensitivity analysis may be used in developing more parsimonious models (Saltelli et al., 2008).

In order to advance understanding of DWR systems and aid users in evaluating potential locations for practice suitability, there is a need for an open modeling framework and tool capable of simulating the entire DWR system under various settings. The objectives of this study were to: 1) describe a modeling framework to simulate the field and reservoir water balance of DWR systems, 2) conduct a global sensitivity analysis to determine influential and low-sensitivity input parameters to better understand the potential variability in model outputs, and 3) develop an openly distributed online tool for evaluating DWR systems in applied settings. The resulting open-source framework provides a foundation for modeling DWR systems and advances understanding of the potential benefits of this novel practice.

3.3 Materials and methods

3.3.1 Modeling the drainage water recycling system

The model is based on the framework developed by Reinhart et al. (2019) who applied it at two tile-drained sites with measured tile drain flow, soil, and weather data. This modeling framework consists of interconnected water balances for a cropped field and a drainage water storage reservoir (Figure 3.1).

The field component of the DWR system is described by the drained area that provides tile drainage to the reservoir, the irrigated area that receives irrigation from the reservoir, and the crop being simulated. Surface runoff is estimated based on the NRCS curve number approach (Allen et al., 2007; Natural Resources Conservation Service, 2004). Crop ET is calculated following the FAO-56 dual crop coefficient approach (Allen et al., 1998). Basal crop coefficient values are climate-corrected for local conditions based on monthly values for wind speed and minimum relative humidity.

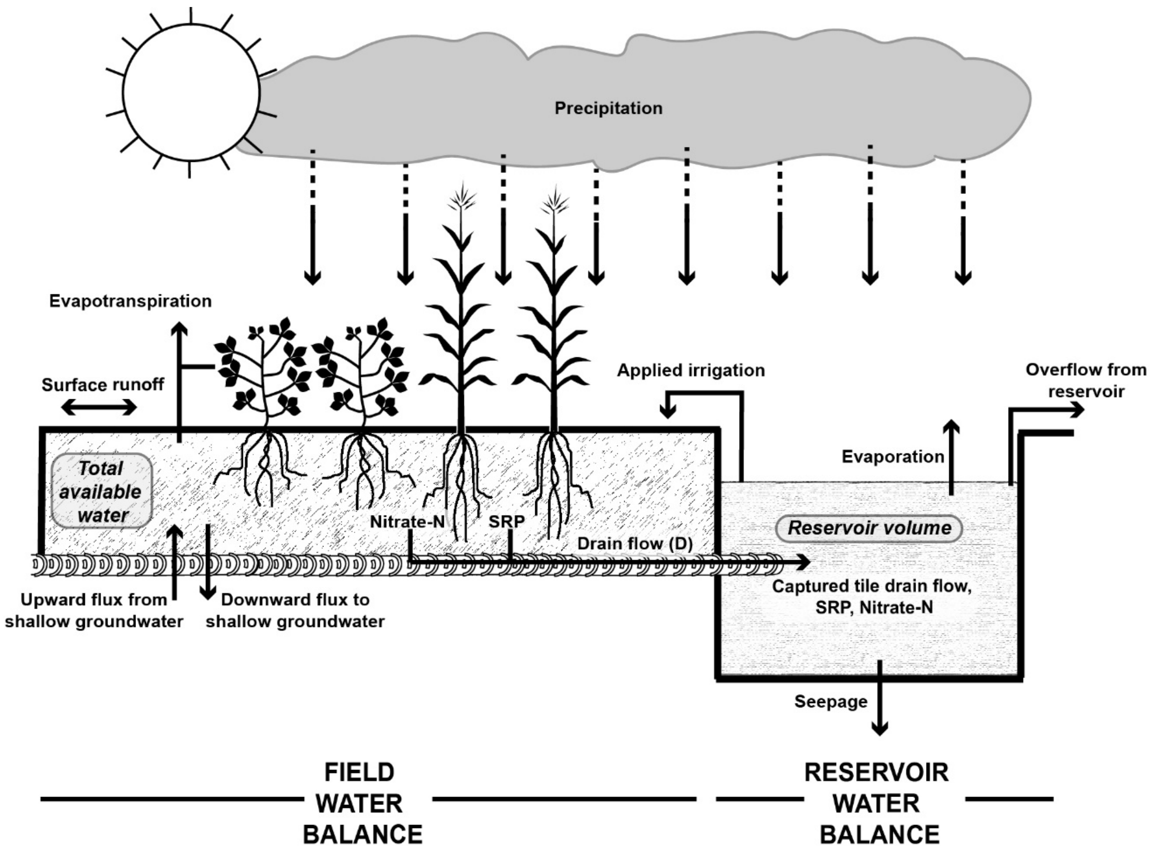

Fig. 3.1 Schematic representation of the drainage water recycling system.

The dual crop coefficient approach partitions evaporation and transpiration processes through the application of corresponding soil water balances for an evaporation layer and a soil layer describing the root zone of the crop. An evaporation layer on the surface of the soil establishes the total amount of evaporable water from a bare soil surface, based on estimated water contents at field capacity and wilting point within the layer. Following soil wetting by precipitation or irrigation, a portion of total evaporable water, termed readily evaporable water, evaporates at the maximum rate subject to available energy at the soil surface before being limited by the hydraulic capacity of the soil. If the depth of evaporation from the evaporation layer exceeds the amount of readily evaporable water an evaporation reduction coefficient is calculated to reduce daily soil evaporation. Within the daily soil water balance for the evaporation layer, daily amounts of irrigation are weighted by the fraction of surface wetted, and evaporation values are weighted by the fraction of the soil surface exposed (i.e., not shaded by vegetation) in order to reflect actual amounts of irrigation and evaporation applied to the wetted and exposed surface area of the soil evaporation layer rather than averaged values across the entire field. The fraction of surface wetted is assumed to be 1.0 whenever precipitation greater than 3 mm occurs or is set to a value indicative of the irrigation system type whenever irrigation is applied. The fraction of the soil surface exposed for evaporation is estimated based on a relationship with the daily basal crop coefficient.

The soil layer extending from the soil surface to the tile drain depth is defined as the zone where crops may access and use water through transpiration processes. The total amount of crop available water that can be held within this layer is described by the average water contents at field capacity and wilting point within the layer. Depending on the tolerance of the crop being simulated to deficit water stress, the threshold amount of total available water that can be used by the crop before deficit water stress occurs is calculated based on a water depletion fraction. This amount of water is referred to as readily available water. The water depletion fraction used to calculate readily available water is adjusted daily based on reference crop ET to incorporate daily variability in coinciding evaporative demand. The result of this adjustment is that at low rates of reference crop ET the water depletion fraction may increase, meaning that more water may be used by the crop before deficit water stress occurs since the evaporative demand is less, and vice versa. Deficit conditions are encountered whenever the amount of water depleted from the soil layer exceeds readily available water, and a water stress coefficient is applied to the basal crop coefficient to reduce transpiration. Under deficit conditions, a daily irrigation requirement is calculated based on the difference between the amount of water depleted from the soil layer and readily available water, or a fixed depth representing a targeted irrigation application amount. Irrigation applications are applied on the following day of the simulation to satisfy the irrigation requirement.

An impermeable layer is common in the poorly drained soils of the U.S. Midwest and can result in a perched, shallow water table that provides a source of water flow into the root zone (Stuff and Dale, 1978). In order to account for this contribution, an upward flux of water from a shallow water table is added to the soil water balance during periods of soil water deficit. The total amount of upward flux is set less than or equal to the maximum potential upward flux, based on the water table position and soil type, or the daily soil water deficit amount, whichever is less. The maximum potential upward flux is determined from water table-upward flux relationships that were developed using the soil utility module in DRAINMOD (Reinhart et al., 2019; Skaggs et al., 2012).

Evaporation and transpiration during the non-growing season are divided into four stages: post-harvest, frozen, thaw, and pre-plant. The post-harvest period is defined as the period extending from harvest to the point at which soils become frozen, and the pre-plant period defines the period between the start of preparatory tillage activities and crop planting date. During post-harvest and thaw stages K_{cb} is set to zero to reflect a lack of a growing crop and f_e is set to 1.0 to account for a fully exposed surface for evaporation. TEW is reduced by 0.5% for each percent of residue cover to reflect increased moisture retention from crop residue. These limitations on TEW are removed during the pre-plant stage. During the frozen stage a single average coefficient value is used to estimate any evaporative losses (Hay and Irmak, 2009).

The reservoir component of the DWR system is described by a maximum reservoir storage capacity that is calculated based off of the average reservoir depth and surface area when the reservoir is completely full. The reservoir is supplied with water through daily precipitation and tile drainage from the field where each are stored and later used as an irrigation water supply for the field. Measures of open water evaporation are required to estimate the amount of water evaporating from the water surface of the reservoir. Seepage losses from the reservoir are estimated based on an average daily rate of reservoir seepage. Nutrient concentration data for dissolved constituents that travel with tile drain flow, such as nitrate and soluble reactive phosphorus, are combined with tile drain flow to calculate the associated nutrient loads that are in drainage water. Daily tile drain flow and nutrient loads are recorded as being captured by the reservoir whenever reservoir water storage capacity is available or discharged through overflow whenever the reservoir would exceed maximum capacity.

All model input data and parameters for field and reservoir water balance and water quality calculations in the model are listed in Table 3.1. Default values can be used for many of these, and sensitivity analysis was conducted to determine which input parameters were less influential in affecting model outputs making the use of default values appropriate.

The model provides daily soil and reservoir water balance outputs across multiple reservoir sizes (Table 3.2). Two annual metrics are provided to evaluate the irrigation performance of the DWR system: annual applied irrigation and Annual Relative Irrigation Supply (Malano and Burton, 2001). ARIS is calculated for a DWR system as the annual applied irrigation from a given reservoir size divided by the amount of irrigation that would be applied given an unlimited water supply. Water quality performance of the DWR system is evaluated based on the absolute and percent tile drain flow and nutrient load reductions. Percent reductions are calculated as the amount of tile drain flow or nutrient load that is captured by a given reservoir size divided by the total amount of flow or nutrients that are delivered through the tile drains.

Table 3.1 Complete list of input data and parameters for water balance and water quality calculations.

Daily time-series data	Precipitation
	Reference crop evapotranspiration, Open water evaporation
	Tile drain flow, Nutrient concentrations
	Water table depth
Input parameters	**Weather:** Monthly average wind speed, Monthly average minimum relative humidity, Average crop coefficient for frozen conditions
	Reservoir: Average reservoir surface area and depth, Daily rate of reservoir seepage
	Soil: Runoff curve number, Depth of soil[a] and evaporation layers, Field capacity and wilting point of soil and evaporation layers, Readily evaporable water
	Crop: Crop type, Planting date, Length of Crop Stages and non-growing season periods, Basal coefficients for each crop stage, Water depletion fraction, Crop heights for each crop stage
	Field: Drained and irrigated field area, Irrigation application depth, Fraction of surface wetted by irrigation, Non-growing season residue amount

[a] The soil profile depth is defined by the average tile drain depth in the field.

Table 3.2 Daily and annual calculated outputs for the model.

Soil water balance (depth units)	Precipitation, Applied irrigation, Upward flux from the water table into the root zone, Runoff, Potential evapotranspiration, Actual evapotranspiration, Tile drain flow, Soil water
Reservoir water balance (volumetric units)	Precipitation, Tile drain flow, Tile drain nutrient load, Runoff, Irrigation withdrawal, Seepage, Surface Evaporation, Overflow, Captured tile drain flow, Captured tile drain nutrient load, Water level depth
Annual metrics	Annual applied irrigation, Annual Relative Irrigation Supply, Percent tile drain flow reduction, Percent tile drain nutrient load reduction

3.3.2 Sensitivity analysis

A sensitivity analysis was conducted to achieve two goals. The first was to compare the influence of uncertainty in model input parameters on the overall uncertainty in the model estimated outputs, applied irrigation and captured tile drain flow volume. By prioritizing which input parameters create the most variability in model outputs, user interaction within an online tool may be focused on which parameters are most important in order to obtain reliable results. The second goal was to identify any input parameters that have minimal effect on model outputs across their range of potential values and may therefore be “fixed” with default values in the model. User interaction with these input parameters may be simplified by assigning default values within the tool or inferring values based on common soil types, crops, or locations, with minimal impact on outputs. User interactions with the tool can then become more focused by emphasizing influential input parameters and deemphasizing low-sensitivity parameters within the user interface. These goals can be referred to as factor prioritization and factor fixing (Saltelli et al., 2008; Sobol, 2001).

A variance-based global sensitivity analysis method was chosen to avoid any assumptions related to model linearity or additivity. Sobol’s method (Sobol, 2001) was implemented in the open-source Python package SALib (Herman and Usher, 2017) to explore first-order and total-order sensitivities across 13 field, soil, crop, and reservoir input parameters (Table 3.3). Input parameters such as reservoir and field sizes, crop planting and growth dates, and daily time-series data were not included in the sensitivity analysis as they are expected to be known values for a specific site and crop being simulated by a user.

The depth and volumetric water contents at field capacity and wilting point represent key input parameters that define the total plant available water in the root zone layer of the soil profile and total evaporable water in the evaporation layer of the soil surface. In order to reduce the total number of input parameters included in the sensitivity analysis, only the depth of root zone and depth of soil evaporation zone were varied. While this analysis evaluated the influence of varying the depth of each zone while keeping field capacity and wilting point constant, the results are equivalent to an approach where field capacity and wilting point are allowed to vary while depth is held constant. Sensitivity of model outputs to any of these input parameters represent sensitivity to changes in the total plant available water or total evaporable water for the corresponding water balances.

Table 3.3 Input parameters used in the model sensitivity analysis.

Input parameter	Abbrv.	Minimum	Maximum	Source
Curve Number	cn	50	98	Natural Resources Conservation Service (2004)
Rate of Reservoir Seepage (mm/day)	rseep	0.0	6.35	Natural Resources Conservation Service (2009)
Crop Coefficient, initial crop period	kc_ini	0.15	1	Allen et al. (1998)
Crop Coefficient, mid-season crop period	kc_mid	0.45	1.2	
Crop Coefficient, end of crop period	kc_end	0.15	1.1	
Water Depletion Fraction	pfract	0.2	0.7	
Depth of Root Zone[a] (m)	zr	0.2	3	
Depth of Soil Evaporation Zone (m)	ze	0	0.15	
Readily Evaporable Water (mm)	rew	2	12	
Fraction of Wetted Surface	fw	0.3	1	
Crop Coefficient for Frozen Conditions	kc_frz	0	1	Entire range up to a fully evapotranspiring reference surface
Irrigation Application Depth (mm)	irr	8	56	Minimum = average peak daily water use for corn and soybean; Maximum = average peak weekly water use for corn and soybean
Non-Growing Season Residue Amount	residue	0	1	Entire range of possible values

[a] Within the model, the depth of root zone input parameter is set based on the average tile drain depth of the field and influences the estimation of total soil available water for the soil water balance. Results for this input parameter also pertain to the uncertainty in identifying appropriate water contents at field capacity and wilting point, which were not included in the sensitivity analysis.

Time-series data for the sensitivity analysis was obtained from a tile-drained site in east-central Indiana (Reinhart et al., 2019; Saadat et al., 2018). The 2007 calendar year was used, for which annual precipitation was 970 mm, nearly equal to the 30-year normal annual precipitation, but only 36% of the annual precipitation occurred between May to September which indicated drier than average growing season conditions. Multiple reservoir sizes representing 2%, 4%, 6%, 8%, and 10% of the irrigated field area with an average depth of 3.05 m (10 ft) were simulated in order to evaluate any changes in sensitivity due to varying levels of water storage.

Input parameters were sampled based on a uniform distribution using the Saltelli extension of the Sobol Sequence (Saltelli, 2002). First-order sensitivity values describe the individual effect of an input parameter on the overall variance of the output and provides an appropriate measure for factor prioritization within the user interface (Eq. 1).

$$S_{X_i} = \frac{V\big(E(Y|X_i)\big)}{V(Y)} \tag{1}$$

Where S_{X_i} is the first-order sensitivity of input parameter X_i, $E(Y|X_i)$ is the conditional expectation of the output Y when X_i is fixed, $V\big(E(Y|X_i)\big)$ is the variance in the conditional expectation taken across all values of X_i, and the denominator is the unconditional variance in the output Y across all input parameters. When the variance in the conditional expectation is large, this indicates that the input parameter X_i shows a large contribution to the overall variance in the output and suggests that X_i is an influential input parameter.

The total-order sensitivity includes the first-order sensitivity as well as all interactions among higher-order combinations of input parameters (Eq. 2).

$$S_{T_{X_i}} = \frac{E\big(V(Y|X_{\sim i})\big)}{V(Y)} \tag{2}$$

Where $S_{T_{X_i}}$ is the total-order sensitivity of input parameter X_i, $V(Y|X_{\sim i})$ is the conditional variance of the output Y when all parameters excluding X_i (i.e., $X_{\sim i}$) are fixed, $E\big(V(Y|X_{\sim i})\big)$ is the average value of the conditional variance taken across all parameters but X_i. If this average value is small, this indicates that the input parameter X_i, either individually or through any higher-order combination of parameters, contributes minimally to the overall variance in the output and suggests that X_i is insensitive with respect to Y. Since total-order sensitivity values capture both the influence of an individual input parameter and its interaction effects, total-order sensitivity measures are more appropriate for the goal of factor fixing.

All first-order and total-order sensitivity values can range from zero to one with values closer to one indicating more influential input parameters or higher levels of interaction involving the input parameter. Because the goal of factor fixing in this study was to simplify user interaction with the online tool, a relatively high screening threshold of 0.05 for total-order sensitivity is used to identify input parameters as candidates for simplification. The result of using this high screening threshold leads to a set of input parameters with low sensitivity as opposed to identifying completely insensitive input parameters (Sarrazin et al., 2016).

Estimated first-order and total-order sensitivity values were tested across multiple sample sizes (N = [1,000; 2,000; 4,000; 8,000; 17,500]) to evaluate for convergence and stability in input parameter ranking. A maximum sample size of 17,500 was chosen based on results from Sarrazin et al. (2016) which showed convergence at this sample size for a model with a similar number of inputs when evaluating input parameter sensitivity for the purpose of parameter ranking and screening. Convergence of estimated values for first-order and total-order sensitivity was assessed based on the width of 95% confidence intervals. Sensitivity values were considered to have converged given confidence intervals less than or equal to 0.05 (Sarrazin et al., 2016). Convergence of input parameter ranking was evaluated qualitatively based on rank plots across each sample size to visually evaluate the extent of rank reversals across the set of input parameters (Rank 1 = most sensitive input parameter, Rank 13 = least sensitive input parameters). Input parameter rank was considered to have converged given no rank reversals among input parameters with sensitivity values greater than the screening threshold of 0.05.

3.3.2.1 Convergence and rank stability of input parameter sensitivity

The tests for convergence and rank stability showed that a sample size of 17,500 was sufficient to meet the sensitivity analysis goals of prioritizing inputs and determining which can be fixed because they have minimal impact on results. The first-order and total-order convergence results are shown in Figure 3.2 for a reservoir size representing 6% of the irrigated field area with an average depth of 3.05 m, while results for all reservoir sizes are provided in the supplementary materials (Appendix B).

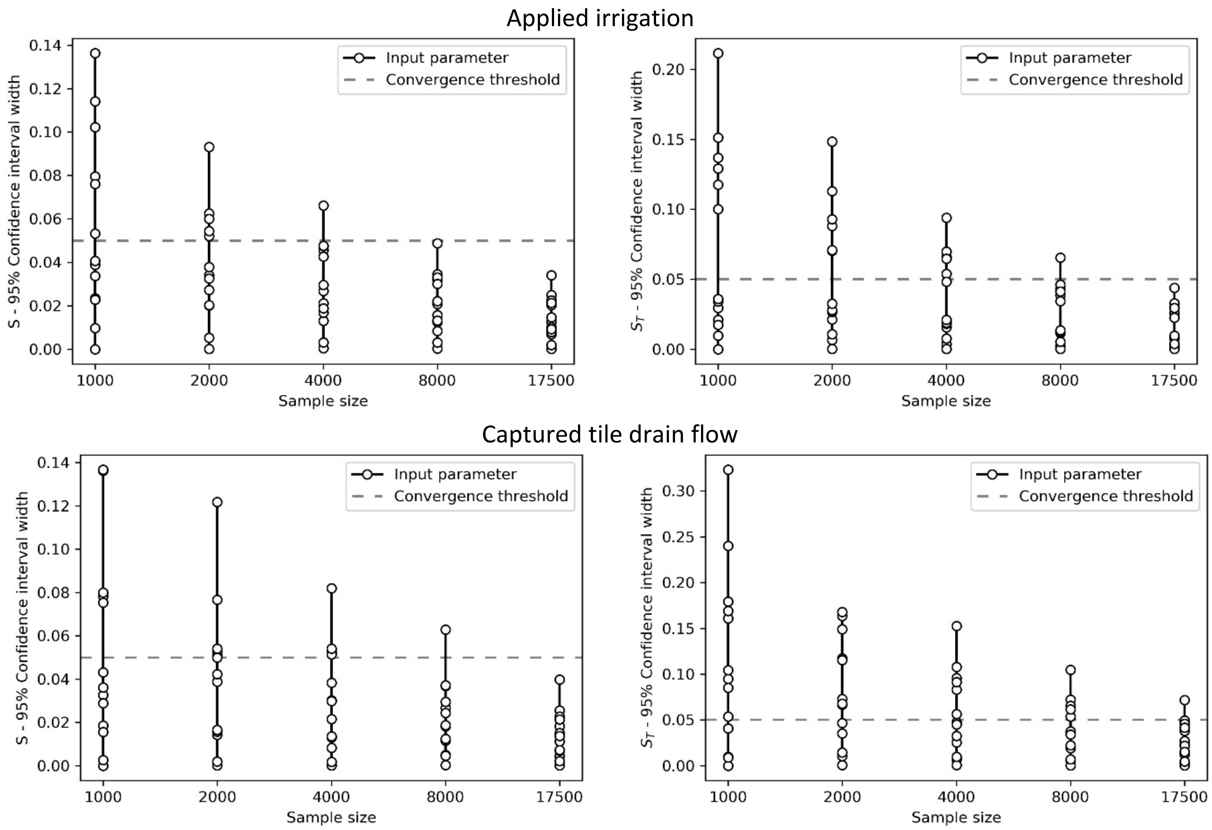

Fig. 3.2 First-order (S) and total-order (S_T) convergence analysis for all input parameters. Reservoir size is equal to 6% of irrigated field area with an average depth of 3.05 m.

At a sample size of 1,000, many input parameters showed first-order and total-order confidence intervals for both applied irrigation and captured tile drain flow exceeding the 0.05 convergence threshold when averaged across all reservoir sizes. As sample size increased to 17,500, first-order and total-order confidence intervals for applied irrigation and captured tile drain flow for all but two input parameters fell below the convergence threshold, providing confirmation that sensitivity values had converged across the range of reservoir sizes.

Rank analysis of first-order sensitivity values across all input parameters showed minimal reversing of rank order among the top five to six input parameters, and overall rank order in regards to applied irrigation and captured tile drain flow stabilized at larger sample sizes (Figure 3.3). The stability in the rank of the highest ranked input parameters for both first-order and total-order sensitivity at a sample size of 17,500 provides confidence for the factor prioritization goal of this sensitivity analysis.

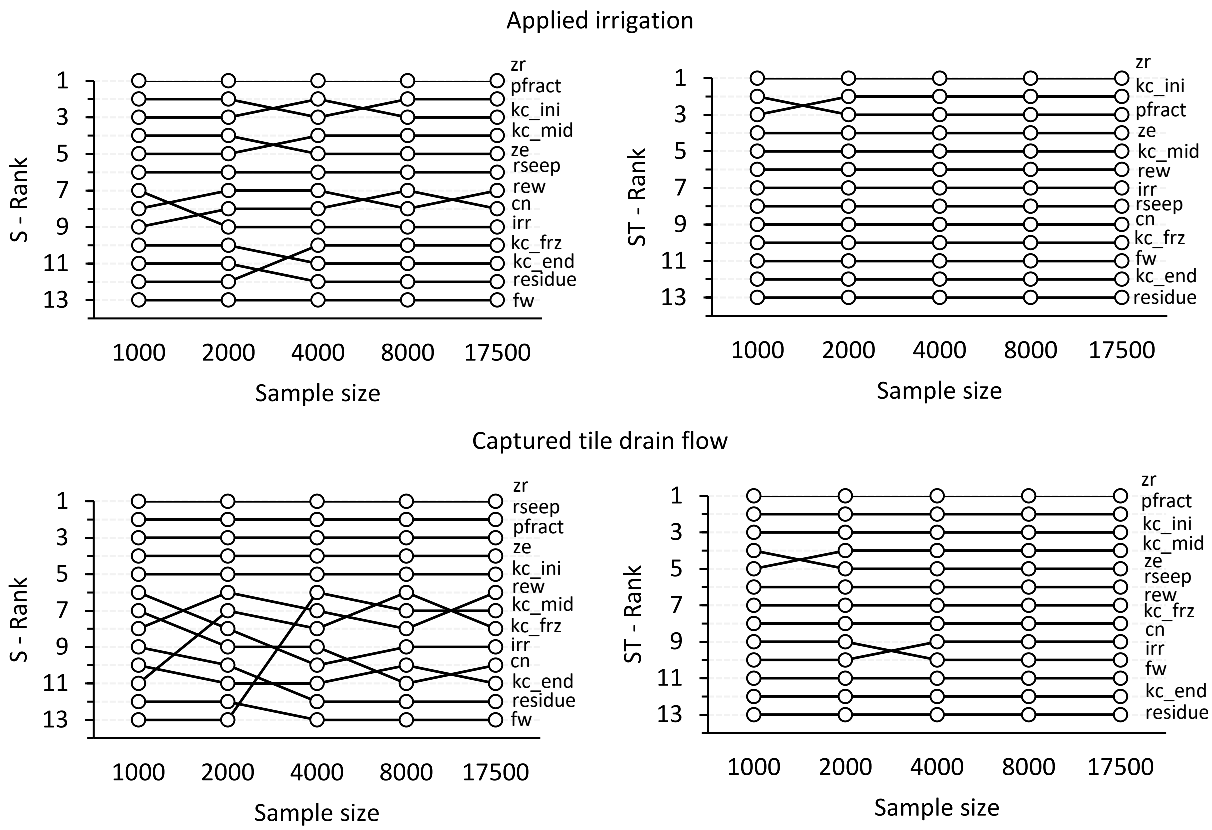

Fig. 3.3 First-order (S) and total-order (S_T) rank analysis for all input parameters. (Rank 1 = most sensitive input parameter, Rank 13 = least sensitive input parameters. cn: curve number; rseep: rate of reservoir seepage; kc_ini: crop coefficient, initial crop period; kc_mid: crop coefficient, mid-season crop period; kc_end: crop coefficient, end of crop period; pfract: water depletion fraction; zr: depth of root zone; ze: depth of soil evaporation zone; rew: readily evaporable water; fw: fraction of wetted surface; kc_frz: crop coefficient for frozen conditions; irr: irrigation application depth; residue: non-growing season residue amount). Reservoir size is equal to 6% of irrigated field area with an average depth of 3.05 m.

3.3.3 Online tool

The algorithms were developed into an online tool, which is called Evaluating Drainage Water Recycling Decisions (EDWRD). It is an open-source model that allows users to simulate the potential benefits of DWR systems across a range of field and reservoir settings.

EDWRD is hosted on a virtual Linux server with 2 CPUs and 2 GB memory and served by a NGINX web server (Figure 3.4). The tool user interface was developed using the JavaScript libraries React, Formik, and Yup. React is useful for creating reusable components within a user interface which makes for more efficient programming and code maintenance. The Formik library provides a simple structure to store form data, apply validation rules, issue error messages, and submit the form, while the library Yup provides a specific integration with Formik to efficiently handle input data validation. Help icons for each user input provide additional background on the input and typical values. As a user interacts with the form inputs, they dynamically receive notifications of values that fall outside the typical ranges, or can access additional information on inputs by clicking on help icons. Leaflet was used to create an interactive map component to collect the site location from the user.

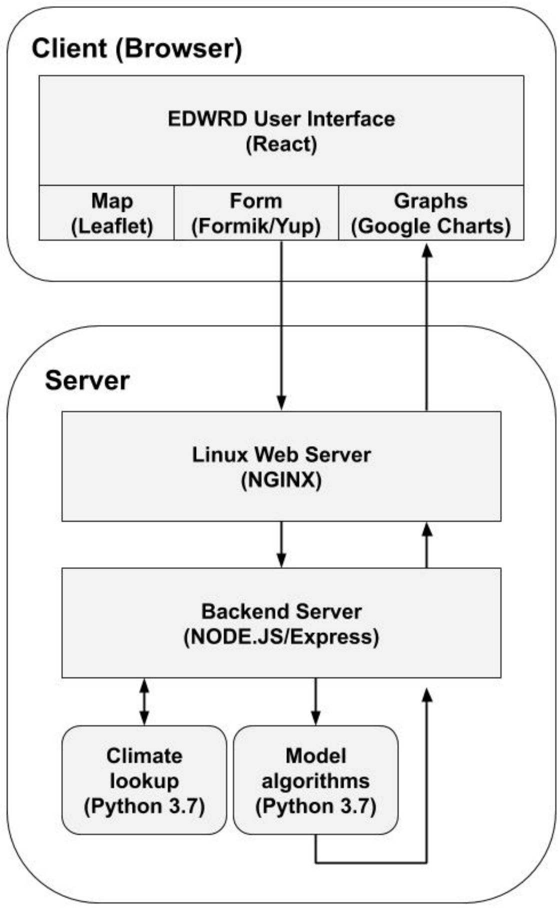

Fig. 3.4 Development architecture of the online tool, Evaluating Drainage Water Recycling Decisions (EDWRD).

A backend Node.js server was developed using the Express web framework to process submitted input form data from the React application and location information from the Leaflet application. Python 3.7 scripts handle location information to identify average climate conditions (e.g., wind speed, relative humidity, soil freeze/thaw dates) from nearby National Oceanic and Atmospheric Administration (NOAA) weather stations. These climate and input form data are parsed and passed to a separate Python 3.7 script that executes the model algorithms. Output from the script is routed back through the Node.js server to the client application where output data and graphs are provided. Graphs were developed using the Google charts web service.

3.4 Results and discussion

3.4.1 Model outputs and variability

Across the sampled input parameter values, the impact of drainage water recycling on applied irrigation and captured drain flow vary widely, even for one site and a single year (Figure 3.5). Violin plots were generated using the Matplotlib library (Hunter, 2007) in Python 3.7, with the probability density function estimated using a Gaussian kernel with a bandwidth determined by Scott's Rule (Scott, 2015). The overall mean and standard deviations of the applied irrigation and captured tile drain flow outputs for each reservoir size are provided in Table 3.4.

The median annual applied irrigation varied from 51 mm at a reservoir size representing 2% of the irrigated field area (average depth = 3.05 m) to 236 mm at a reservoir size of 10%. While the majority of applied irrigation estimates were centered around the median, an additional clustering of points occurred around zero (0) for all reservoir sizes. Since water inflows to the reservoir (i.e., precipitation, tile drain flow) were not varied in the sensitivity analysis, this indicates that there are certain input parameter conditions that either lead to large water losses from the reservoir (e.g., high rate of reservoir seepage) thereby limiting water availability for irrigation, or reductions in the crop irrigation requirement (e.g., low crop coefficients, high water depletion fraction, deep root zone) resulting in little to no demand for irrigation. The median annual captured tile drain flow varied from 63 mm at a reservoir size of 2% to 163 mm at a reservoir size of 10%. The distribution of captured tile drain flow estimates experienced the largest shift as reservoir size increased from 2% to 4%. There were only minor differences in the distribution of captured tile drain flow estimates between reservoir sizes of 6%, 8%, and 10%. Larger reservoir sizes (8% and 10%) showed longer tails in their distribution at greater volumes of captured tile drain flow indicating that certain input parameter conditions impact the capacity to capture tile drain flow at these larger reservoir sizes. These conditions would include increases in reservoir water loss (e.g., high rate of reservoir seepage) or applied irrigation amounts (e.g., high irrigation application depth, high crop coefficients, low water depletion fraction, shallow root zone) which create water storage capacity within the reservoir.

(a)

(b)

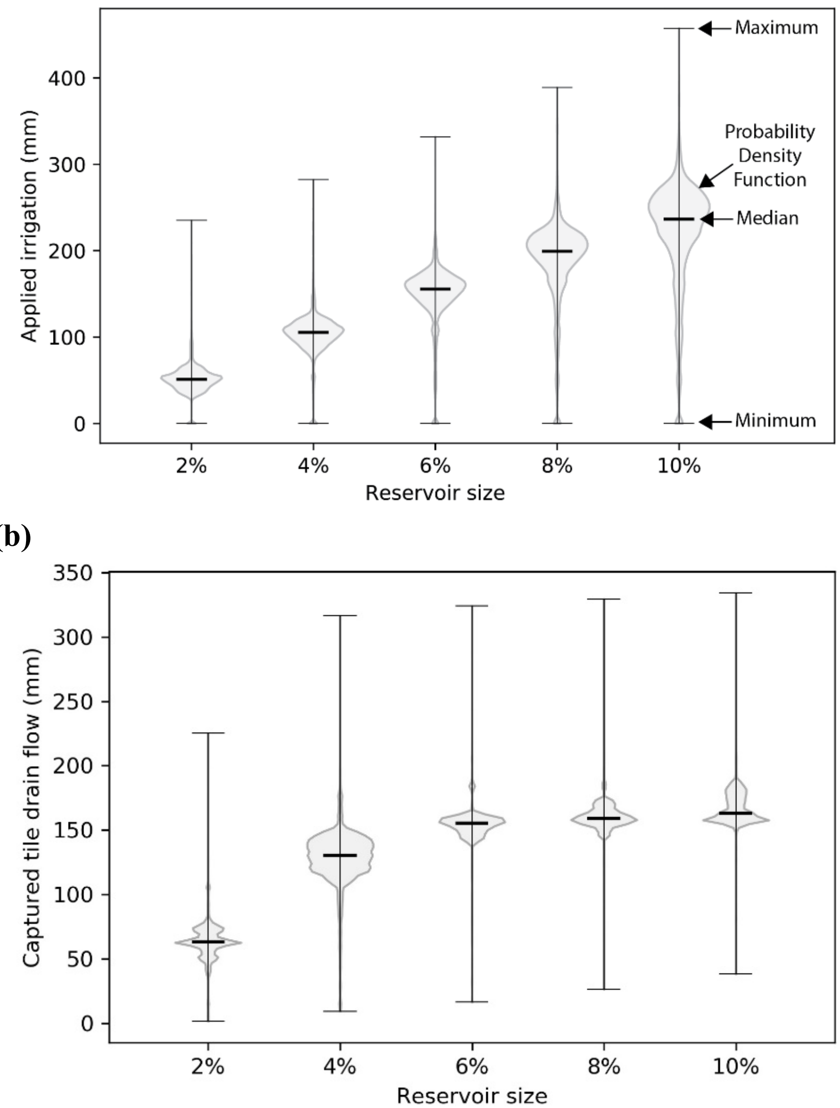

Fig. 3.5 Violin plots of (a) simulated annual applied irrigation, and (b) captured tile drain flow across the input parameter space. Reservoir size expressed as a percent of the irrigated field area with an average depth of 3.05 m.

Table 3.4 Overall mean and standard deviations (in parentheses) for the model outputs, applied irrigation and captured tile drain flow.

	Reservoir size				
	2%	4%	6%	8%	10%
Applied irrigation	51.6 (16.7)	103.3 (24.0)	149.3 (35.0)	187.6 (48.6)	219.3 (63.5)
Captured tile drain flow	64.4 (16.4)	128.7 (23.7)	152.7 (20.8)	159.6 (18.5)	166.6 (18.3)

3.4.2 Sensitivity of applied irrigation and captured tile drain flow

The sensitivity analysis showed that the most influential parameter for both model outputs was the depth of the root zone (*zr*), which is defined in the model based on the average tile drain depth. In this analysis, the sensitivity to the depth of the root zone also represents the sensitivity to total plant available water in the root zone of the soil profile, which also depends on the volumetric water contents at field capacity and wilting point. First-order sensitivity for depth of the root zone varied between 0.21 and 0.28 for applied irrigation, and between 0.14 and 0.30 for captured tile drain flow across all reservoir sizes (Figures 3.6 and 3.7). Incorporating interaction effects with other input parameters, the total-order sensitivity showed that the depth of the root zone described 48% to 66% of the variance in applied irrigation and 50% to 64% of the variance in captured tile drain flow across all reservoir sizes. As reservoir size increased, total-order sensitivity of the depth of the root zone decreased steadily for applied irrigation but showed no consistent pattern in regard to captured tile drain flow. Results for each reservoir size that was evaluated are provided in the supplementary materials (Appendix B).

Changes to total available water, through uncertainty in any of the physical components defining it (e.g. average tile drain depth defining the depth of the root zone, field capacity water content, wilting point water content), play a central role in the soil water balance within the model and have a cascading effect through the DWR system thereby influencing both applied irrigation and captured tile drain flow outputs. Within the context of the model, if total available water is underestimated, soil water deficit conditions would be expected to occur earlier in the growing season and be of greater magnitude than actual field conditions since potential evapotranspiration would exceed available water within the soil profile. This would lead to a greater demand for irrigation from the reservoir. Subsequently, the increased use of water from the reservoir for irrigation would create additional water storage capacity for capturing tile drain flow during or after the growing season. These results are consistent with others who have found that soil hydraulic parameters that describe total available water are highly influential in estimating evapotranspiration based on soil water balance approaches (DeJonge et al., 2012; Zhao et al., 2015).

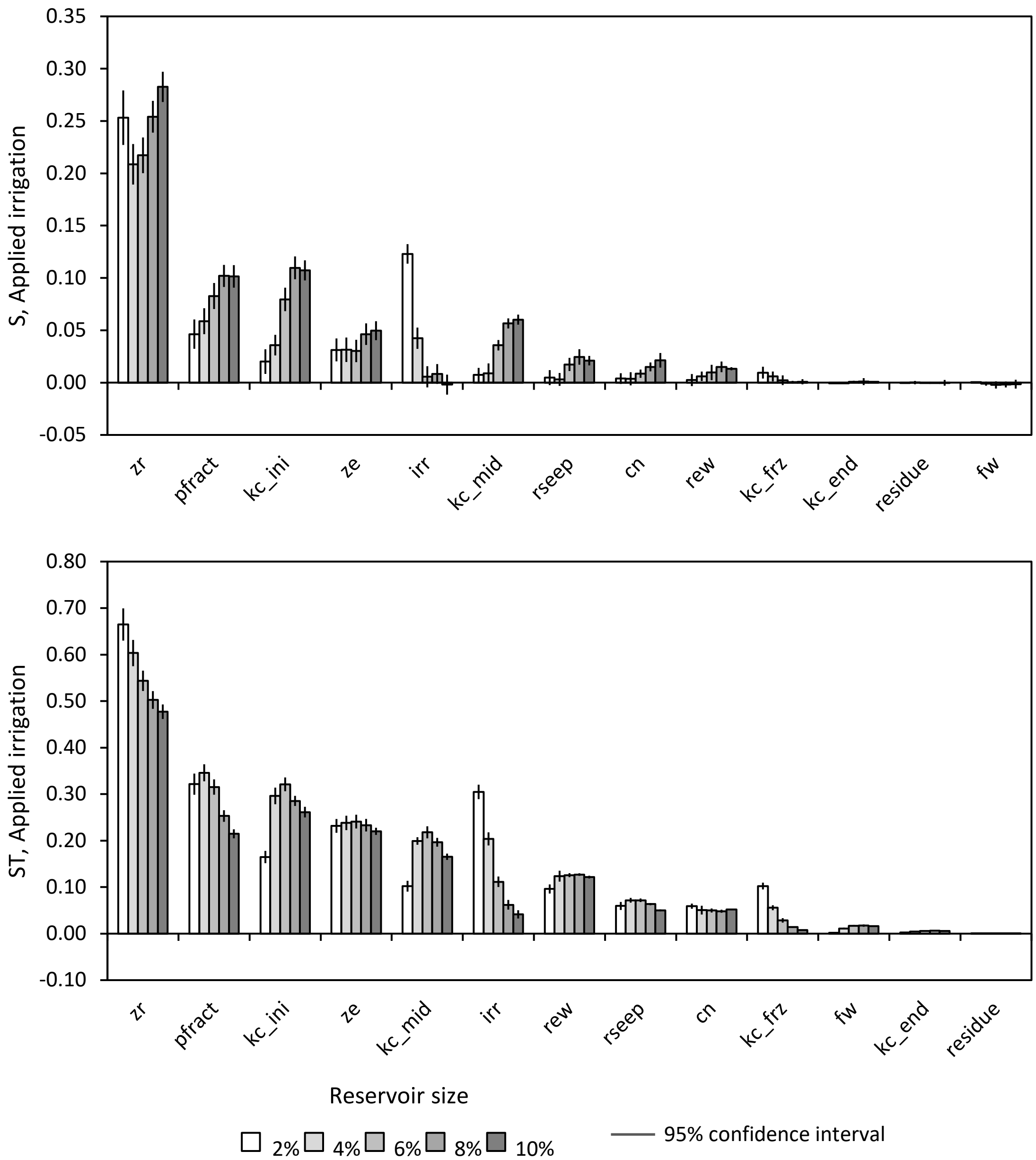

Fig. 3.6. First-order (S) and total-order (S_T) sensitivity of applied irrigation to input parameters (cn: curve number; rseep: rate of reservoir seepage; kc_ini: crop coefficient, initial crop period; kc_mid: crop coefficient, mid-season crop period; kc_end: crop coefficient, end of crop period; pfract: water depletion fraction; zr: depth of root zone; ze: depth of soil evaporation zone; rew: readily evaporable water; fw: fraction of wetted surface; kc_frz: crop coefficient for frozen conditions; irr: irrigation application depth; residue: non-growing season residue amount).

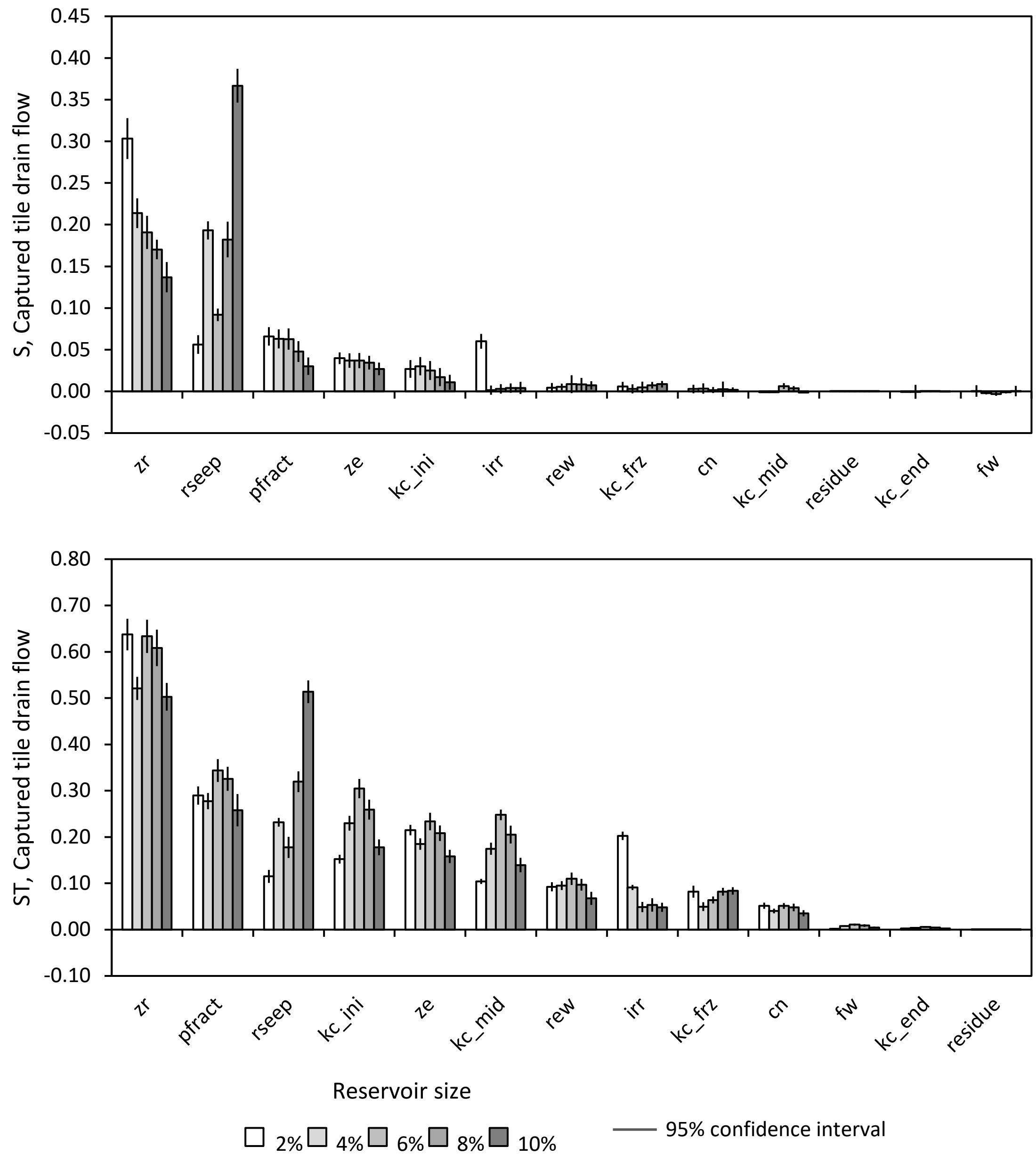

Fig. 3.7. First-order (S) and total-order (ST) sensitivity of captured tile drain flow to input parameters (cn: curve number; rseep: rate of reservoir seepage; kc_ini: crop coefficient, initial crop period; kc_mid: crop coefficient, mid-season crop period; kc_end: crop coefficient, end of crop period; pfract: water depletion fraction; zr: depth of root zone; ze: depth of soil evaporation zone; rew: readily evaporable water; fw: fraction of wetted surface; kc_frz: crop coefficient for frozen conditions; irr: irrigation application depth; residue: non-growing season residue amount).

The input value for the water depletion fraction (*pfract*) becomes important within the model because it serves as the threshold for initiating irrigation by setting the amount of water that can be depleted before deficit water stress occurs. The water depletion fraction was the second most sensitive input parameter for applied irrigation ($S = 0.05$ to 0.10, $S_T = 0.21$ to 0.34)

and third most sensitive input parameter for captured tile drain flow ($S = 0.03$ to 0.07, $S_T = 0.26$ to 0.34) when averaged across all reservoir sizes. Total-order sensitivity of water depletion fraction decreased with increasing reservoir size for the applied irrigation output but showed no pattern with increasing reservoir size for captured tile drain flow.

Given low input values for the water depletion fraction, the timing of irrigation is expected to occur earlier in the growing season and the frequency of irrigation throughout the growing season is expected to increase, since less water is required to be depleted from the soil profile before the onset of deficit water stress. With a greater demand for irrigation, applied irrigation amounts would increase resulting in reduced reservoir water level and a greater capacity for capturing tile drain flow. The resulting effect in model output is similar to underestimating the amount of total available water as both would result in a greater and more frequent occurrence of deficit water stress.

In respect to captured tile drain flow, the rate of reservoir seepage (*rseep*) was more sensitive than water depletion fraction ($S = 0.06$ to 0.37, $S_T = 0.11$ to 0.51), particularly at larger reservoir sizes. While the rate of reservoir seepage was influential in impacting captured tile drain flow, it had a lesser impact on applied irrigation. This difference in sensitivity to the two model outputs likely reflects the modeling approach of applying a daily average rate of reservoir seepage throughout each day of simulating the reservoir water balance. Seepage losses from the reservoir reduce reservoir water levels and create capacity for capturing and storing additional tile drainage, but the reduction in reservoir water levels due to seepage are small in comparison to irrigation withdrawals from the reservoir. The timing of the seepage in relation to reservoir filling and irrigation is also a factor, as applied irrigation is impacted by seepage between reservoir filling and irrigation, while drain flow capture is influenced by seepage between the end of the growing season and following inflows.

Of the four crop coefficient inputs evaluated, coefficients applicable to initial crop establishment (*kc_ini*) and mid-season crop growth periods (*kc_mid*) were the most sensitive. The effect of increasing crop coefficient values for the initial and mid-season crop growth periods lead to increased levels of crop evapotranspiration resulting in irrigation applications earlier in the growing season and of greater magnitude, but also a greater potential for the capture of tile drain flow during the growing season since reservoir water levels would be reduced to meet irrigation requirements. The crop coefficient for initial establishment showed a first-order sensitivity of 0.02 to 0.11 for applied irrigation but only 0.01 to 0.03 for captured tile drain flow, while total-order sensitivity was notably higher (applied irrigation: S_T = 0.16 to 0.32, captured tile drain flow: S_T = 0.15 to 0.30). The mid-season crop coefficient also showed low first-order sensitivity ($S \leq 0.01$) but indicated interaction effects for both model outputs with total order-sensitivities varying from 0.10 to 0.25. This showed that for initial and mid-season crop coefficients, the majority of their influence on model outputs were linked to interaction with other input parameters. The crop coefficients for end of crop growth (*kc_end*) and periods of frozen conditions (*kc_frz*) generally showed first-order sensitivities less than or equal to 0.01 for both model outputs and based on total-order sensitivities, both the end-of-season crop coefficient and coefficient for frozen conditions fell below the 0.05 screening threshold identifying these input parameters as low-sensitivity parameters.

Satti et al. (2004) and Linhoss et al. (2017) found similar results showing that changes in crop coefficients were influential in affecting irrigation estimates. This emphasizes the importance of using regionally developed crop coefficients in the estimation of crop evapotranspiration for specific crop varieties and climates. The most widely available resources for crop coefficients have largely been focused on arid to subhumid climates where irrigation has traditionally been required to support crop production, and specifically pertain to crops managed under stress-free conditions (Allen et al., 1998; Jensen and Allen, 2016). Application of these coefficient values outside of their original context can create sizeable errors in estimating crop evapotranspiration and subsequent irrigation demand (Jagtap and Jones, 1989).

Given greater depths of the soil evaporation zone (*ze*) or values for readily evaporable water (*rew*), estimates of evaporative loss from the field will be greater, which when combined with estimates of transpiration that are based on chosen values for crop coefficients, can contribute to increased levels evapotranspiration, greater amounts of water depletion from the soil water balance, and increased irrigation requirements. Individually, evaporation-related input parameters including the depth of the soil evaporation zone and readily evaporable water exhibited low first-order sensitivity ($S \leq 0.05$) for both model outputs and across all reservoir sizes. However, similar to the response shown by initial and mid-season crop coefficients, these input parameters were involved in interaction effects with other parameters and these effects were more pronounced for the applied irrigation output. The total-order sensitivity for the depth of the soil evaporation zone varied from 0.16 to 0.24 and for readily evaporable water from 0.07

to 0.13 across all reservoir sizes. Interaction effects are likely greatest in combination with initial and mid-season crop coefficient input parameters as, collectively, these parameters represent the foundation of the dual-crop coefficient approach utilized by the model.

Irrigation application depth (*irr*) exhibited a negative relationship with reservoir size for both model outputs. First-order and total-order sensitivity values were greatest at a reservoir size of 2% for applied irrigation ($S = 0.12$, $S_T = 0.30$) and captured tiled drain flow ($S = 0.06$, $S_T = 0.20$), but values fell to ≤ 0.05 as reservoir size increased. This negative relationship between total-order sensitivity values for applied irrigation and reservoir size was also apparent for the depth of root zone and water depletion fraction input parameters which highlights their collective role in influencing the overall demand for irrigation but also the mitigating effect that reservoir size has on estimating applied irrigation amounts. As was discussed previously, small values for root zone depths (i.e., less total available water) or water depletion fraction result in increases in irrigation requirement leading to greater amounts of applied irrigation. Conversely, greater irrigation application depths result in more water withdrawn from the reservoir during a single irrigation event, potentially reducing reservoir water supplies for future periods and leading to less applied irrigation throughout the year. However, given a large enough reservoir size, the total amount of water stored may exceed the demand for irrigation regardless of the chosen values for depth of root zone, water depletion fraction, or irrigation application depth, resulting in lower sensitivity values for the applied irrigation output at these large reservoir sizes.

Curve number (*cn*), fraction of wetted surface (*fw*), and the non-growing season residue amount (*residue*) were identified as low-sensitivity parameters with average total-order sensitivity values less than or equal to the screening threshold (0.05) for both model outputs across all reservoir sizes.

3.4.3 Online tool

Results from the sensitivity analysis were used to guide the development of the user interface for an online tool, Evaluating Drainage Water Recycling Decisions (EDWRD). Each of the input parameters showing average total-order sensitivity values above the screening threshold were incorporated into the user interface (Table 3.5). This ensures that user interaction is focused on the most influential input parameters and gives users the opportunity to represent specific site conditions within the model.

Table 3.5 Input parameter total-order sensitivity (S_T) for applied irrigation and captured tile drain flow across a range of reservoir sizes.

	S_T – Applied irrigation						S_T – Captured tile drain flow					
	Reservoir size						Reservoir size					
Input parameter	2%	4%	6%	8%	10%	Average	2%	4%	6%	8%	10%	Average
zr	0.66	0.60	0.54	0.50	0.48	0.56	0.64	0.52	0.63	0.61	0.50	0.58
pfract	0.32	0.35	0.32	0.25	0.21	0.29	0.29	0.28	0.34	0.33	0.26	0.30
kc_ini	0.16	0.30	0.32	0.29	0.26	0.27	0.15	0.23	0.30	0.26	0.18	0.22
ze	0.23	0.24	0.24	0.23	0.22	0.23	0.21	0.18	0.23	0.21	0.16	0.20
kc_mid	0.10	0.20	0.22	0.20	0.17	0.18	0.10	0.17	0.25	0.21	0.14	0.17
irr	0.30	0.20	0.11	0.06	0.04	0.14	0.20	0.09	0.05	0.05	0.05	0.09
rew	0.10	0.12	0.13	0.13	0.12	0.12	0.09	0.10	0.11	0.10	0.07	0.09
rseep	0.06	0.07	0.07	0.06	0.05	0.06	0.11	0.23	0.18	0.32	0.51	0.27
kc_frz	0.10	0.06	0.03	0.01	0.01	0.04[a]	0.08	0.05	0.06	0.08	0.08	0.07
cn	0.06	0.05	0.05	0.05	0.05	0.05[a]	0.05	0.04	0.05	0.05	0.04	0.05[a]
fw	0.00	0.01	0.02	0.02	0.02	0.01[a]	0.00	0.01	0.01	0.01	0.00	0.01[a]
kc_end	0.00	0.00	0.01	0.01	0.01	0.00[a]	0.00	0.00	0.01	0.00	0.00	0.00[a]
residue	0.00	0.00	0.00	0.00	0.00	0.00[a]	0.00	0.00	0.00	0.00	0.00	0.00[a]

[a] Low-sensitivity input parameters, average $S_T \leq 0.05$ screening threshold

Low-sensitivity input parameters (*kc_frz, cn, fw, kc_end, residue*) are not directly included as part of the user interface given the minimal influence they have on model outputs. Instead, default values are assigned within the source code. This reduces the number of input parameter selections that is required to be made by the user with little risk of impacting the final model outputs by selections that may not exactly match site conditions. However, advanced users are still provided the functionality of being able to upload their own site-specific values as part of a custom input parameter file upload. This maintains the ability for advanced users who wish to model highly specific scenarios to control the entire input parameter space for the model while maintaining a simplified user interface for more basic users.

EDWRD includes internal checks and message interaction with the user to ensure validity in daily time-series data, input parameters, and outputs (Figure 3.8). Errors in daily time-series data, such as negative or missing values, result in detailed error messages informing users of invalid values and where these errors occur prior to tool execution. Input parameter errors are handled within the user interface and result in error messages for invalid values, such as incompatible date assignments or coefficient values outside of their realistic range, as well as warning messages to inform users when input parameter values fall outside of typical ranges, such as atypical estimates of monthly average wind speed and minimum relative humidity. During tool execution, error messages are delivered to the user whenever calculated variables are inconsistent with expected algorithm behavior (e.g., negative values, captured tile drain flow exceeds total daily drain flow, applied irrigation values inconsistent with user-selected irrigation options). This integrated checking functionality serves as a benefit to users in preparing and testing time-series data and input parameter selections, evaluating results, and communicating errors or suggesting tool improvements to tool developers.

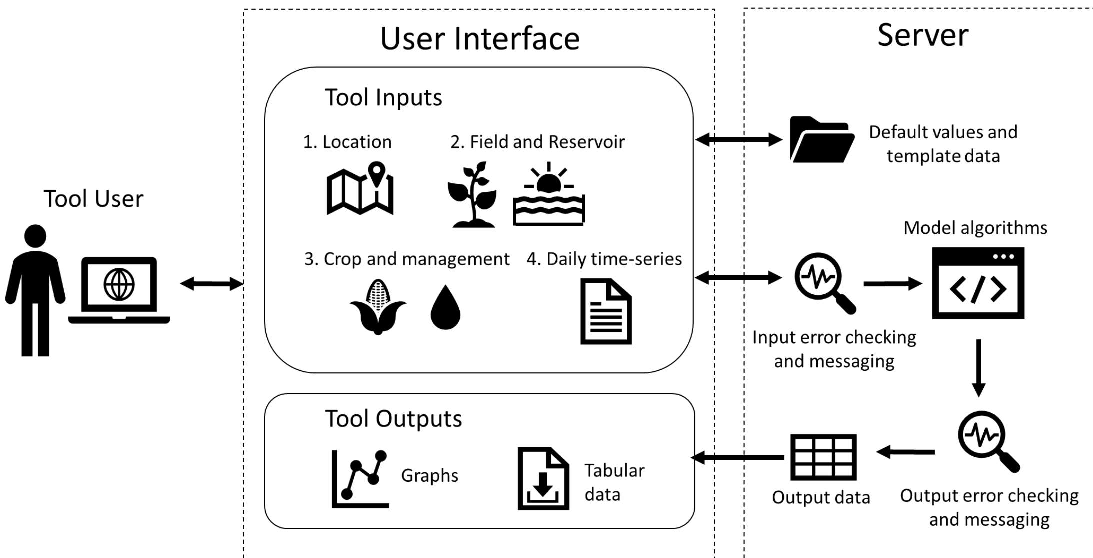

Fig. 3.8 Schematic overview of the tool, Evaluating Drainage Water Recycling Decisions (EDWRD)

The initial user interaction is focused on four main sets of tool inputs: location, field and reservoir, crop and management, and daily time series. For all inputs, default values are provided to represent typical soil and weather conditions in the U.S. Midwest and assign values to low-sensitivity inputs that are not included directly in the user interface. This approach also provides a simple method for users to generate initial estimates with EDWRD for the purpose of learning more about DWR systems and their potential benefits.

Tool users specify their location by placing a pin on a map. This information is passed to the server and used to lookup monthly average wind and relative humidity from the closest NOAA weather station (National Climatic Data Center, 2018). Soil freeze and thaw dates are based on an interpolation of soil surface temperatures from the NOAA Climate Reference Network stations (Diamond et al., 2013).

Within the field and reservoir inputs, users select a soil texture, average tile drain depth, drained and irrigated field areas, and reservoir area and average depth. Soil type selections are passed to the server to assign typical values for field capacity and wilting point based on values published in Allen et al. (1998). The average tile drain depth is used to describe the overall depth of the soil profile, and together with the soil properties assigned by soil type define the total available water for field water balance calculations. Users have the option to vary the drained and irrigated field areas separately such as in the case where fields contributing water to the reservoir are not the same fields being irrigated. The maximum storage capacity of the reservoir is calculated based on a user-supplied surface area and average depth.

For crop and management inputs, users can select corn or soybeans, which make up the majority of planted acreage in the tile-drained U.S. Midwest. Crop selections are passed to the server where typical planting and harvest dates are assigned based on data from the USDA National Agricultural Statistics Service (National Agricultural Statistics Service, 2010), and crop coefficients, growing periods, crop heights, and water depletion fraction are populated based on Allen et al. (1998). Tool users specify the target irrigation amount for each irrigation event to define their irrigation management approach. Users may choose a fixed irrigation amount or a variable irrigation approach where irrigation amounts are set equal to the daily soil water deficit amounts.

Daily time-series data for precipitation, reference crop evapotranspiration and open water evaporation, tile drain flow and nutrient concentrations, and water table depth are required for the time period being evaluated. Users may choose to upload their own data as a tab-delimited text file or select precompiled datasets from various sites across the U.S. Midwest. Datasets are available for several research sites across the U.S. Midwest as part of the USDA-NIFA funded Transforming Drainage Project (Reinhart et al., 2016). Users wishing to use these datasets are presented with a map showing sites with available data. Users may select a site to view a data summary and have the option to populate these data from the server. These example datasets are also available to users for download to be used as template files for formatting their own files for later upload.

In order to make EDWRD fully customizable, an option for modifying detailed input parameter selections including those inferred by soil type and crop selections is provided to the user through a modal window. Within this window, advanced users may customize input parameter settings for soil properties, planting and harvest dates, soil freeze and thaw dates, and crop characteristics. For full control of EDWRD users may upload an input parameter file defining values for all input parameters, including low-sensitivity input parameters which are not included in the user interface. A template input parameter file is available for download to facilitate the development of these custom input parameter files.

After finalizing input parameter selections and running EDWRD, users are presented with options to view model results for the estimated irrigation and water quality benefits from the DWR system and download tabular results. Users may choose to visualize output as average annual values across the time-series date range or may choose to also include the distribution of annual output values to identify years which fall outside the 10^{th} and 90^{th} percentiles. Choosing to include output distributions allows users to identify years where irrigation and water quality benefits were outside of the normal range of values, and these years may be further evaluated to explore what conditions led to these output values.

Model outputs are presented to the user directly on the screen through a series of interactive visualizations. Since optimum reservoir size is an unknown during the initial phase of evaluating DWR systems, output visualizations summarize irrigation and water quality benefits across a range of reservoir sizes with the midpoint of this range being set equal to the user-specified reservoir size. Users may hover over graphical elements to see their numerical value or click on the value to explore results for specific scenarios. For example, by clicking on a point on the average line users can visualize the soil and reservoir water balance components for a specific reservoir size on a monthly basis across all years described in the location file. Alternatively, by clicking on a point outside of the 10^{th} and 90^{th} percentile users can visualize the soil and reservoir water balance components for a specific reservoir size on a monthly basis for a particular year.

3.5 Conclusion

This paper introduces an open-source modeling framework that combines water balances for a tile-drained field and water storage reservoir to simulate the potential benefits of drainage water recycling (DWR) systems, a novel practice providing irrigation and water quality benefits in tile-drained agricultural landscapes. A sensitivity analysis of 13 model input parameters showed that parameters controlling the total available water of the soil profile and total evaporable water from the soil surface were the most influential in estimating the potential irrigation and water quality benefits of DWR systems. Other influential parameters for determining irrigation and water quality benefits were the water depletion fraction, which describes how much of the available water in the soil profile may be depleted by evapotranspiration before the crop experiences deficit water stress, and crop coefficients for the growing season periods describing water use during initial crop establishment and mid-season development. Irrigation application depth was a sensitive input parameter for estimating the amount of applied irrigation while the daily reservoir seepage rate was sensitive when estimating the amount of tile drain flow that can be captured by DWR systems. Model outputs were insensitive to changes in parameter values for curve number, fraction of wetted surface, crop coefficients for the end of crop growth and frozen conditions, and the non-growing season residue amount.

The online tool, Evaluating Drainage Water Recycling Decisions (EDWRD) was developed based on the modeling framework. The user interface incorporates results from the sensitivity analysis and makes available pre-defined data files and default settings to develop a simple, accessible tool for a variety of potential users. Results on the potential irrigation and water quality benefits are displayed using interactive visualizations to help users evaluate DWR systems with various reservoir sizes and across multiple years. EDWRD is accessible via any standard web-browser at https://transformingdrainage.org/tools/edwrd and source code for EDWRD may be found at https://github.com/TransformingDrainageProject/edwrd.

3.6 Acknowledgements

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"Managing Water for Increased Resiliency of Drained Agricultural Landscapes", http://transformingdrainage.org.

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4. CONCLUSIONS AND FUTURE RESEARCH

4.1 Conclusions

The goal of this study was to increase our understanding of the potential benefits provided by DWR systems to water quality and crop production within the tiled-drained U.S. Midwest and develop a resource to support the evaluation and planning of DWR systems throughout the region. To address this goal, this study developed a modeling framework that established interconnected water balances for a water storage reservoir and a drained and irrigated field area. This modeling framework allowed for the daily simulation and quantification of water flows within a DWR system. Ten years of measured weather, soils, water table, and tile drain flow and nutrient concentration data were used to evaluate DWR at two tile-drained sites in the U.S. Midwest. From the developed modeling framework, an online tool was developed that allows users to evaluate a range of reservoir, field, and crop conditions across various reservoir sizes.

Overall, this study showed that DWR is a practice capable of capturing and storing adequate drainage to support supplemental irrigation and reduce the amount of drainage and nutrient loads that are delivered to downstream waters from tile-drained fields. Specific conclusions are listed below by study objective.

1. Quantify the amount of tile drainage that can be captured, stored, and utilized as supplemental irrigation at two measured field sites to estimate the potential nutrient reductions and irrigation benefits.
    a) Determine the amount of tile drainage that can be captured, stored, and utilized as supplemental irrigation by drainage water recycling systems.

        Simulated results from 10 years of measured data at a site in east-central Indiana and southeast Iowa showed that a reservoir size representing 6% to 8% of the irrigated field area with an average depth of 3.05 m would have been sufficient to capture and store enough tile drainage to satisfy the demand for irrigation across all years. In certain years smaller reservoir sizes would have been sufficient but this was dependent on the variability in annual precipitation within and across years, as well as inherent soil characteristics at each site. For example, in southeast Iowa, a 3-year dry period resulted in a high demand for irrigation thereby requiring a reservoir size of 8%. Outside of this 3-year period, there was little to no need for irrigation given the fact that a higher proportion of annual precipitation occurred during the growing season and soils at the site were able to store more water within the profile, so a small reservoir size was sufficient. Conversely, in east-central Indiana, soil water holding capacities were lower, and less of the annual precipitation occurred during the growing season resulting in a demand for irrigation in each of the ten years. However, the magnitude of these irrigation demands was smaller and a reservoir size of 6% was sufficient.

Conclusion:

The practice of DWR is capable of capturing and storing enough tile drainage to fully meet the demand for irrigation at tile-drained sites in the U.S. Midwest provided an adequate reservoir size is established. Important factors that will influence the decision as to what reservoir size is adequate include the variability and distribution in annual precipitation and the water holding capacity of the soil.

b) Estimate the corresponding reductions in nitrate-N and soluble reactive phosphorus (SRP) loads.

Given a reservoir size of 6% at the sites in east-central Indiana and southeast Iowa, average annual nitrate-N loads were reduced by 20% to 37% and soluble reactive phosphorus loads were reduced by 17% to 39%. The annual reduction in nutrient loads showed a positive relationship with annual applied irrigation. For example, in southeast Iowa, reservoirs were drawn down following irrigation in 2013. This resulted in greater capacity to capture and store water during 2014 and nutrient load reductions were as high as 47% to 54% for a reservoir size of 6%.

Conclusion:

DWR can reduce both nitrate and SRP loads in tile-drained landscapes. This characteristic adds considerable value to DWR as a water quality practice considering that often multiple different practices are required to address nitrogen and phosphorus loadings given their differences in travel pathways in agricultural settings. The water quality performance of DWR systems may be improved by increasing the amount of water use from the reservoir in order to create additional capacity to capture and store tile drainage.

2. Develop an online tool for evaluating drainage water recycling decisions that meets the needs of target users.
   a) Describe a modeling framework to simulate the field and reservoir water balance of DWR systems.

      This study established a modeling framework that consisted of interconnected water balances for a reservoir and a drained and irrigated field area. Inputs to this model are daily time-series data for precipitation, reference crop evapotranspiration and open water evaporation, water table depth, and tile drain flow and nutrient concentrations. Tile drain flow and precipitation are represented as water inflows to the reservoir, and outflows are withdrawals for irrigation and losses due to seepage and evaporation. The field water balance utilizes the FAO-56 dual crop coefficient approach to estimate crop evapotranspiration, and together with runoff losses and drainage, represent the depletion of water from the soil profile. Precipitation, applied irrigation, and upward flux from a shallow water table serve to reduce soil water depletion. The demand for irrigation, defined as the amount of water below a crop-specific depletion threshold, connects the reservoir and field water balance.

      Conclusion:

      DWR systems can be modeled following the framework that was developed in this study. Model outputs may be used to evaluate seasonal and annual patterns in water flows within the system and annual metrics of irrigation and water quality performance are provided.
   b) Conduct a global sensitivity analysis to determine influential and low-sensitivity input parameters to better understand the potential variability in model outputs.

      Sensitivity analysis was completed to quantify the level of influence model input parameters had on the outputs, applied irrigation and captured tile drain flow. A variance-based, global sensitivity analysis was chosen for this study with the objectives of prioritizing the most influential input parameters and identifying those which had little to no influence on outputs. Based on this analysis, the depth of the root zone for the field water balance, which is defined by the average tile drain depth and utilized in estimating the total available water for the soil profile, showed an average total-order sensitivity of 0.56 to 0.58 across a range of reservoir sizes. This meant that over half of the overall variance in model outputs could be explained by the variability in the depth of the zone parameter alone or in interactions this parameters and others. Crop coefficients for the initial establishment and mid-season growth period were also influential with average total-order sensitivity values between 0.17 to 0.27 across reservoir sizes. Irrigation management decisions (i.e., water depletion fraction, irrigation application depth) were also influential in determining irrigation outputs, particularly at small reservoir sizes, and reservoir seepage rates were influential in determining captured tile drain flow outputs with greater influence at large reservoir sizes.

Conclusion:

Soil characteristics that influence the estimation of total available water are critical in determining the model outputs and should ideally be measured for the specific site being evaluated. The development of localized crop coefficient values will improve the performance of the model for a given crop at the site. Irrigation management decisions and reservoir seepage rates should be carefully evaluated by model users, as these input parameters do influence model outputs but also represent management or design variables that may be adjusted by the user based on the irrigation or water quality objectives of the DWR evaluation scenario.

c) Develop an openly distributed online tool for evaluating DWR systems in applied settings.

The modeling framework of this study was adapted for use as an online tool. The development of the tool user interface incorporated results from the sensitivity analysis to focus user interaction on the most influential input parameters while also simplifying the input parameter selection process by removing parameters that were identified as having low-sensitivity. Default values and template time-series data are made available to users to ensure applicability to a wide range of users, even those who may not have their own measured data. Dynamic error checking of both inputs and outputs provide users with information and guidance on input selections and the interpretation of outputs. Interactive graphs and file download capabilities present outputs to the user and provide value to the tool.

Conclusion:

The online tool, Evaluating Drainage Water Recycling Decisions (EDWRD), can be used by multiple different audiences to simulate DWR systems under a variety of conditions. EDWRD provides users with graphs and output data that increase their awareness and understanding of the potential benefits of the practice.

4.2 Recommendations for future research

The DWR practice represents a novel approach to managing water in tile-drained landscapes, and there are few systems that have been constructed within the U.S. Midwest that allow for the direct, continuous measurements of water flows and conditions. This, combined with the knowledge gaps surrounding the response of modern crop varieties to irrigation on poorly drained soils and the influence of shallow groundwater in contributing to crop water needs, represents an obstacle to describing the potential benefits of DWR systems in the U.S. Midwest. More measured systems, including those which measure crop growth and development, are needed throughout the region to provide insights into how DWR systems perform in different landscapes within the region. These measurements could then be used to support the calibration and validation of models such as those used in this study, and guide the development of decision tools and frameworks for designing and managing DWR systems. Key measurements from a DWR system are listed in Table 4.1

Table 4.1 Recommended measurements for a drainage water recycling system

DWR System Component	Measurement
Reservoir	Water depth, Irrigation withdrawals, Evaporation, Overflow volume
Field	Surface runoff, Tile drain flow, Water table, Applied irrigation, Nutrient concentrations in surface runoff and tile drain flow
Crop	Evapotranspiration, Leaf area index, Growth stage and development, Yield, Biomass, Agronomic management (planting/harvest, field operations, inputs)
Soil[1]	Texture, Bulk density, Soil moisture, Impermeable layer depth, Water retention curves, Saturated hydraulic conductivity
Weather	Precipitation, Temperature, Maximum and Minimum, Wind speed, Relative humidity, Solar radiation

[1] For layers extending from the soil surface to below the tile drain depth

Results from this study suggest that there may be multiple avenues for managing DWR systems to achieve certain objectives. Future research on the potential impact of different irrigation management strategies and technologies within a DWR system will help shed light on how these decisions may influence system performance. For example, the use of precision irrigation systems may reduce the overall irrigation water use and thereby require smaller reservoir sizes within a DWR system or allow for increased acreage to be irrigated from a given reservoir size. Likewise, decisions on when and how much to irrigate can influence the overall irrigation water use, such as with deficit irrigation strategies that are common in more traditionally irrigated, arid landscapes.

Alternatively, reservoir water supplies may be managed to achieve greater water quality benefits. As was noted in Chapter 2, water use resulted in an increased capacity to capture and store tile drainage and nutrients that would otherwise be lost downstream. More intensive cropping systems, such as the practice of double-cropping, relay cropping, perennial crops, and cover crops, have the potential to show greater water quality benefits given higher demands for water that are associated with the increase in biomass production throughout the year. Active management of reservoir water supplies may also be used to target specific periods of the year to capture and store drainage water. For example, reservoir water levels may be lowered prior to anticipated periods of high drain flow or nutrient loads to improve the water quality performance of DWR systems. Research on reservoir management approaches would help inform potential management schedules for DWR systems where water quality performance is a main objective.

A significant obstacle to the adoption and implementation of DWR systems is the large capital costs associated with the drainage, irrigation, and water storage infrastructure. Research should include an analysis of the costs and benefits associated with the DWR system. Costs and benefits should include those tied directly to the agricultural operation (e.g., cost of removing land from production, benefits from increased crop yield), as well as societal costs and benefits (e.g., costs of supporting incentive programs to encourage DWR adoption, benefits that come from reduced nutrient loads).

Climate change stands to alter many facets of the current agricultural landscape. Future research on how the performance of DWR systems may change in the face of climate change is needed. Practices such as DWR that are capable of managing water during more intense periods of precipitation and drought are likely to be beneficial in supporting a more resilient agricultural landscape. However, the design of these systems will need to anticipate future changes in climate in order to carry the most benefits for agricultural producers and society.

Finally, the tool Evaluating Drainage Water Recycling Decisions (EDWRD) that was developed as part of this study represents a valuable resource for increasing the awareness and understanding of the practice of DWR. Research and user testing will be beneficial to ensure that EDWRD is used and remains useful into the future.

APPENDICES

APPENDIX A: CHAPTER 2 SUPPLEMENTARY DATA

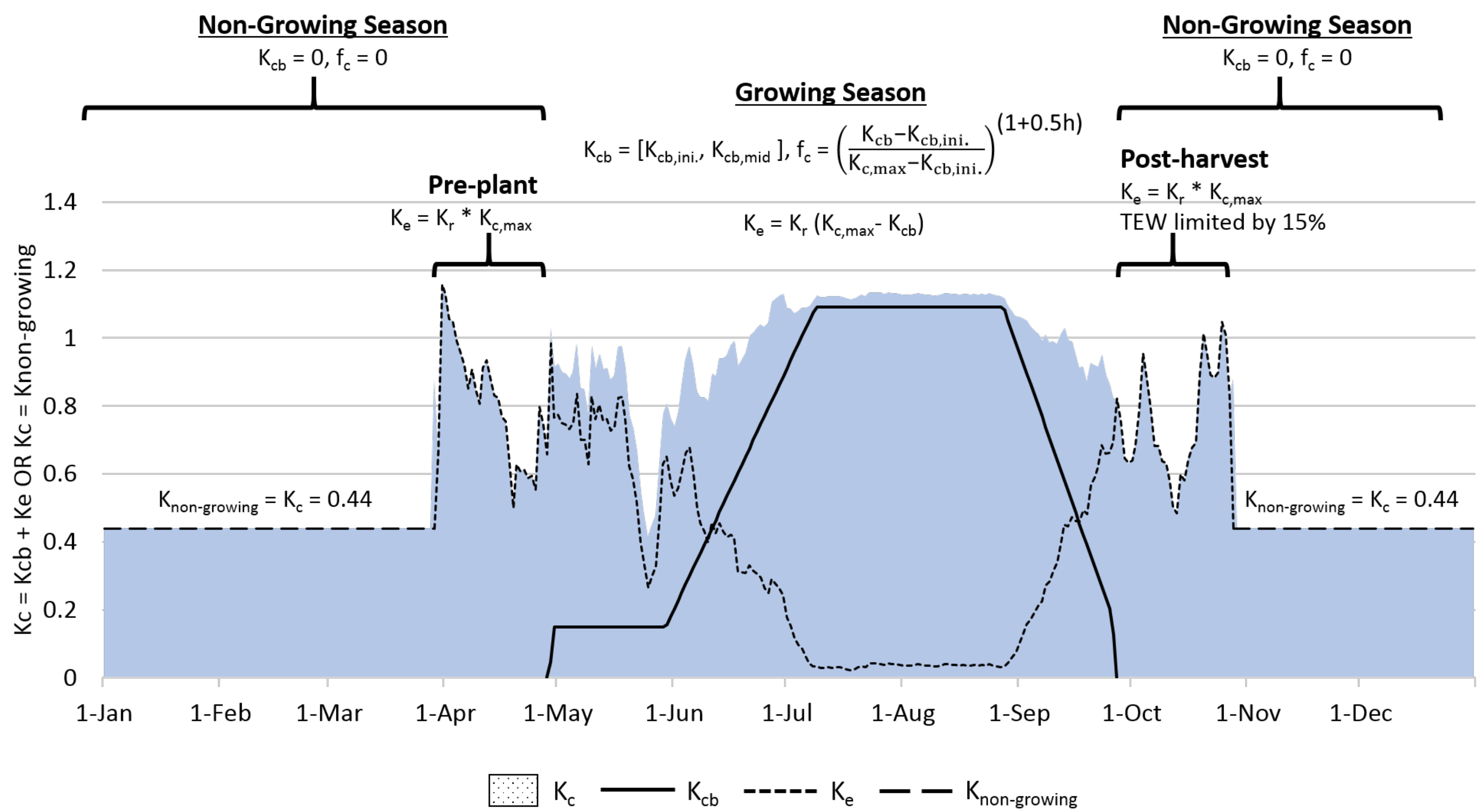


Fig. A.1 10-year average of daily basal crop coefficient (K_{cb}) and soil evaporation coefficient (K_e) at DPAC (IN) calculated based on the FAO-56 dual crop coefficient approach (Allen et al., 1998). The crop coefficient (K_c) is the summation of K_{cb} and K_e. Outside of the pre-plant, growing season, and post-harvest periods, K_c is set equal to an average non-growing season crop coefficient value ($K_{non-growing}$)

Table A.1 Total annual applied irrigation amounts from reservoir sizes representing between 2% to 10% of field area at DPAC and SERF between 2007 and 2016 (Reservoir depth = 3.05 m; UNL = unlimited water supply = irrigation requirement)

	Reservoir size	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
DPAC	2%	55.8	51.1	50.6	77.4	54.9	55.0	57.2	45.5	17.8	58.2
	4%	111.9	110.7	105.4	96.9	109.0	112.3	109.6	45.5	17.8	78.7
	6%	131.8	110.7	153.5	96.9	138.5	141.1	109.6	45.5	17.8	78.7
	8%	131.8	110.7	153.5	96.9	138.5	141.1	109.6	45.5	17.8	78.7
	10%	131.8	110.7	153.5	96.9	138.5	141.1	109.6	45.5	17.8	78.7
	UNL	131.8	110.7	153.5	96.9	138.5	141.1	109.6	45.5	17.8	78.7
SERF	2%	0.0	0.0	0.0	0.0	90.9	52.6	58.0	0.0	0.0	0.0
	4%	0.0	0.0	0.0	0.0	111.5	114.7	113.8	0.0	0.0	0.0
	6%	0.0	0.0	0.0	0.0	111.5	160.5	165.4	0.0	0.0	0.0
	8%	0.0	0.0	0.0	0.0	111.5	191.0	207.4	0.0	0.0	0.0
	10%	0.0	0.0	0.0	0.0	111.5	191.0	207.4	0.0	0.0	0.0
	UNL	0.0	0.0	0.0	0.0	111.5	191.0	207.4	0.0	0.0	0.0

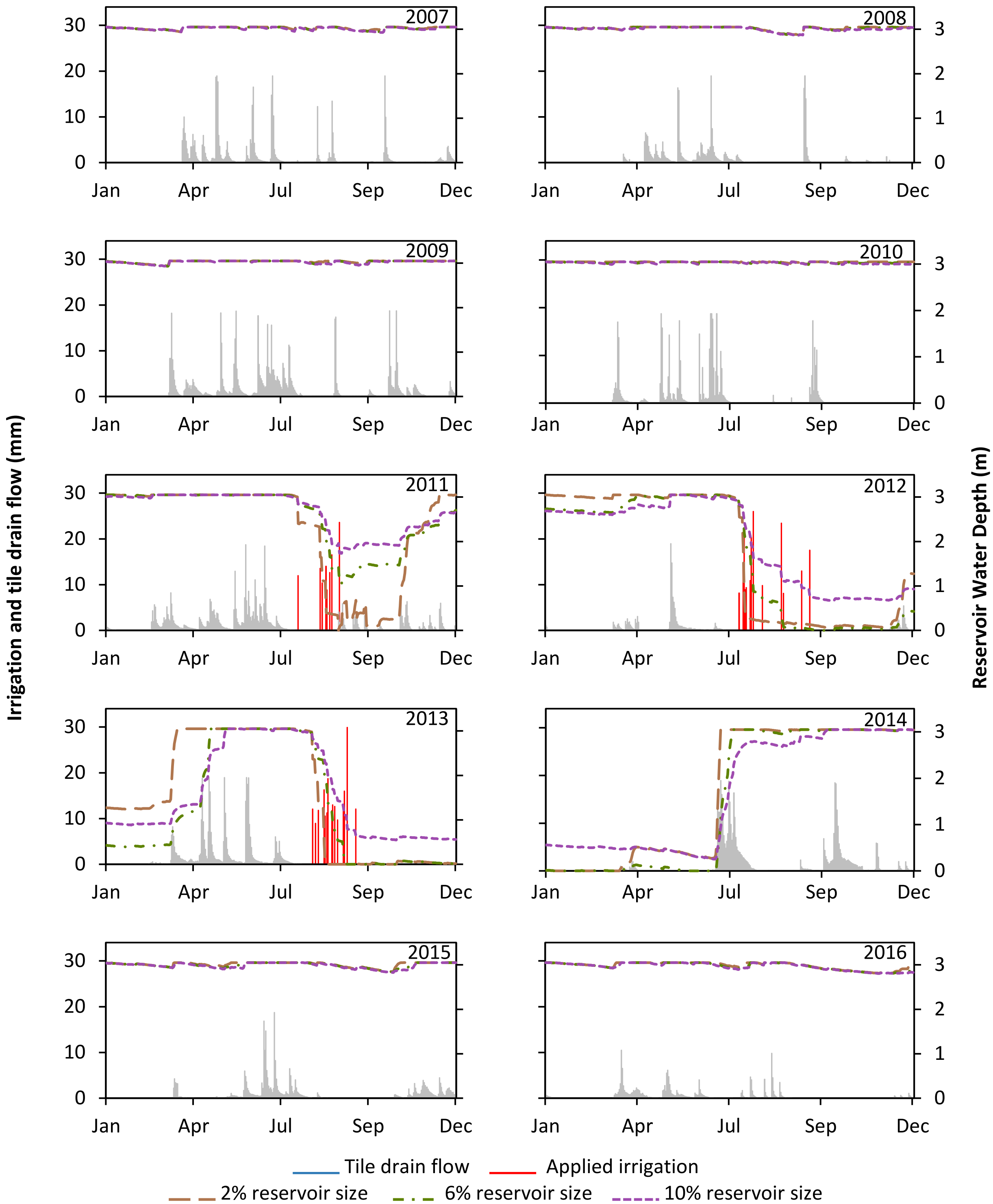


Fig. A.2 Simulated reservoir water depth, irrigation, and measured tile drain flow for reservoir sizes representing 2%, 6%, and 10% of field area between 2007 and 2016 at SERF.

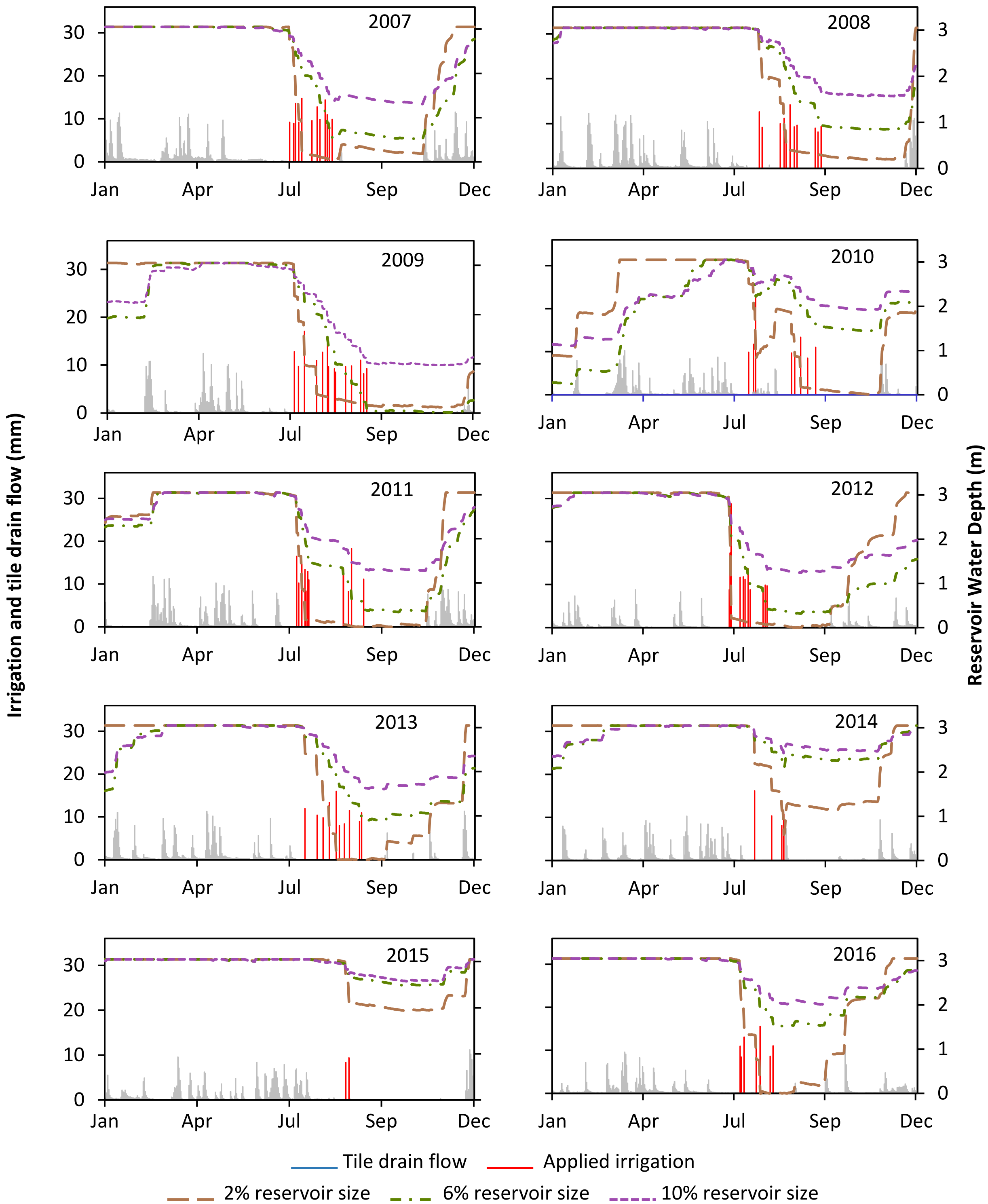


Fig. A.3 Simulated reservoir water depth, irrigation, and measured tile drain flow for reservoir sizes representing 2%, 6%, and 10% of field area between 2007 and 2016 at DPAC.

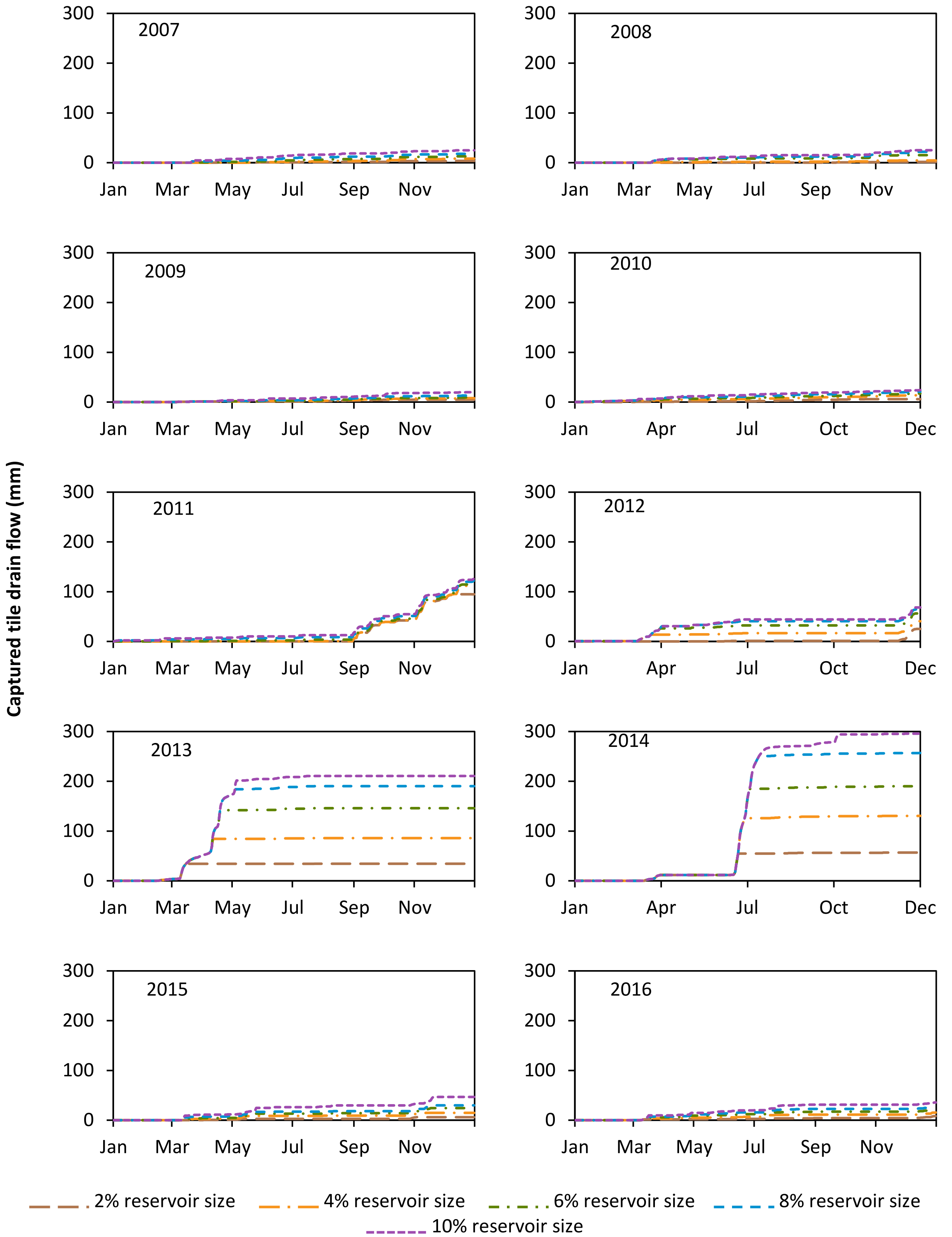


Fig. A.4 Estimated cumulative captured tile drain flow given reservoir sizes of 2%, 4%, 6%, 8%, and 10% between 2007 and 2016 at SERF (IA).

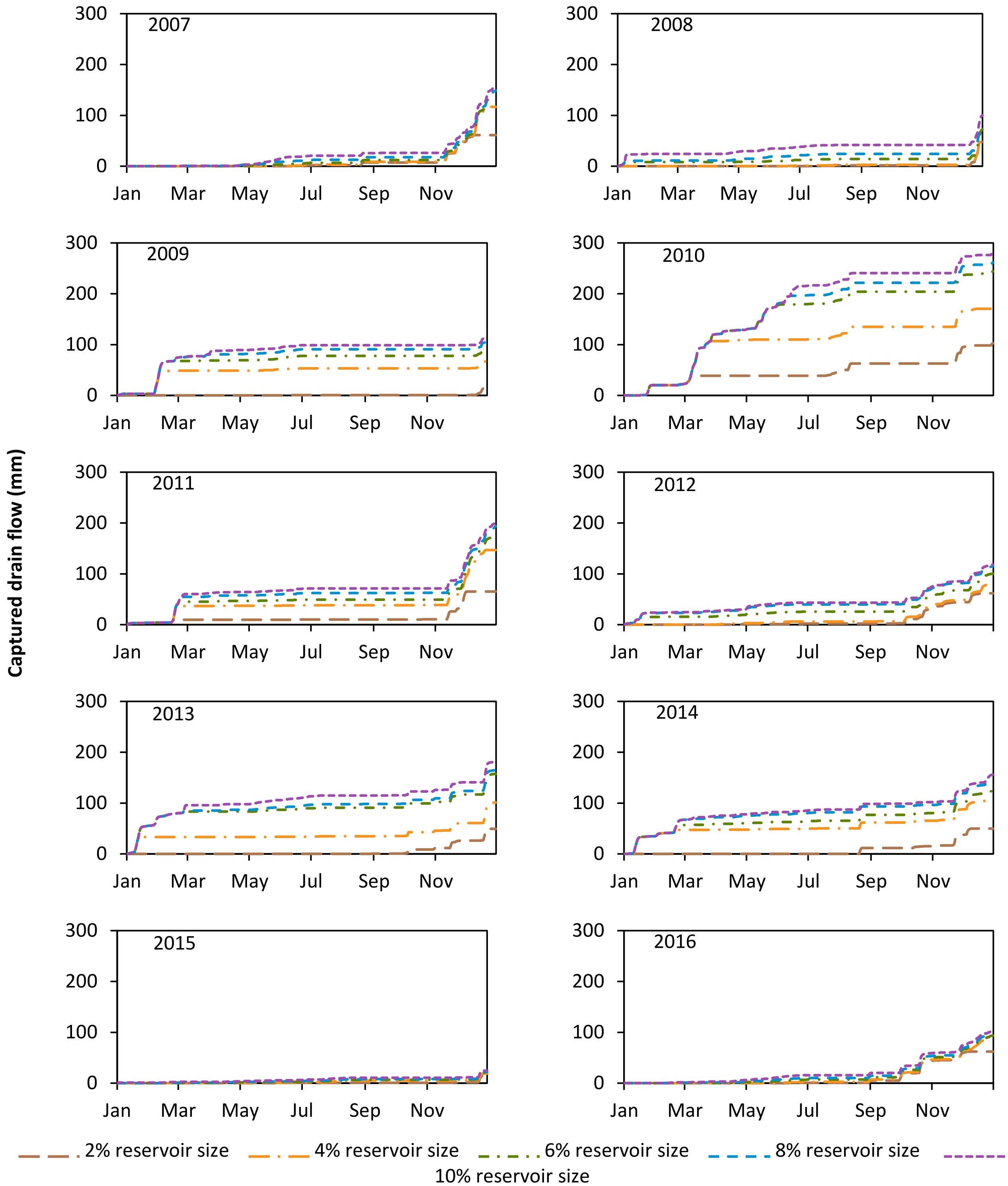


Fig. A.5 Estimated cumulative captured drain flow given reservoir sizes of 2%, 4%, 6%, 8%, and 10% between 2007 and 2016 at DPAC (IN).

Table A.2 Absolute and percent of annual drain flow captured by reservoir sizes representing 2% to 10% of field area (depth = 3.05 m) for DPAC (IN) and SERF (IA).

	Reservoir size	2007		2008		2009		2010		2011		2012		2013		2014		2015		2016	
		mm	%	mm	%	mm	%	mm	%	mm	%	mm	%	mm	%	mm	%	mm	%	mm	%
DPAC	2%	61.2	14%	47.7	11%	14.9	6%	103.6	35%	70.8	17%	61.7	27%	49.3	14%	49.7	14%	14.7	4%	62.1	21%
	4%	116.8	27%	60.9	13%	68.2	27%	175.5	59%	152.5	36%	81.5	35%	101.9	28%	104.4	29%	18.8	5%	89.1	31%
	6%	143.0	33%	73.6	16%	92.7	37%	245.0	82%	186.5	43%	102.1	44%	158.1	43%	123.4	34%	20.4	6%	93.5	32%
	8%	148.7	35%	83.6	18%	105.6	42%	262.5	88%	199.7	47%	116.5	50%	165.2	45%	147.2	41%	21.9	6%	96.5	33%
	10%	157.0	36%	101.1	22%	113.9	46%	281.2	94%	208.3	49%	119.8	52%	182.1	50%	156.3	43%	25.1	7%	102.2	35%
SERF	2%	3.6	1%	1.5	1%	4.7	1%	5.8	1%	94.7	20%	25.2	19%	34.3	9%	56.8	13%	6.0	2%	8.3	5%
	4%	8.2	2%	4.5	2%	7.9	1%	13.7	3%	114.7	24%	41.7	31%	85.8	23%	130.6	29%	14.7	5%	15.5	9%
	6%	12.7	3%	15.2	6%	9.3	2%	17.2	4%	117.5	25%	57.5	43%	145.9	40%	190.2	43%	24.3	8%	21.4	13%
	8%	17.8	5%	21.9	8%	13.1	2%	20.8	5%	124.0	26%	65.8	49%	190.2	52%	256.9	58%	29.8	10%	27.1	16%
	10%	24.8	6%	25.1	9%	19.8	3%	24.0	6%	127.9	27%	69.6	52%	210.6	57%	295.7	66%	46.7	16%	35.6	21%

Table A.3 Absolute and percent of annual nitrate-nitrogen load captured by reservoir sizes representing 2% to 10% of field area (depth = 3.05 m) for DPAC (IN) and SERF (IA).

	Reservoir	2007		2008		2009		2010		2011		2012		2013		2014		2015		2016	
	Size	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%
DPAC	2%	9.4	30%	4.5	9%	1.7	8%	8.1	25%	3.3	14%	8.3	44%	5.07	13%	3.4	8%	0.3	2%	5.5	24%
	4%	17.8	56%	5.6	11%	5.6	25%	13.3	41%	7.3	31%	10.3	54%	11.0	28%	6.8	17%	0.2	1%	8.0	35%
	6%	19.8	62%	6.9	14%	7.4	33%	22.7	69%	8.6	37%	11.5	61%	14.9	39%	7.5	19%	0.0	0%	8.2	36%
	8%	20.0	63%	7.7	16%	8.5	38%	25.3	77%	9.2	39%	11.9	63%	16.9	43%	8.1	20%	0.0	0%	8.3	36%
	10%	20.2	64%	8.9	18%	8.9	40%	29.5	90%	9.8	42%	12.0	63%	18.3	47%	8.4	21%	0.0	0%	9.0	39%
SERF	2%	0.4	1%	0.2	1%	0.3	1%	0.0	0%	10.5	27%	2.6	16%	3.7	11%	8.9	15%	0.9	3%	1.6	8%
	4%	0.5	1%	0.7	2%	0.4	1%	0.0	0%	13.3	34%	5.3	32%	9.3	27%	20.2	33%	1.7	5%	2.8	14%
	6%	0.7	1%	1.0	4%	0.2	1%	0.0	0%	13.7	35%	6.6	40%	15.3	45%	29.2	47%	2.5	7%	3.4	17%
	8%	0.4	1%	1.3	5%	0.6	1%	0.0	0%	14.0	36%	7.6	46%	19.0	55%	36.8	60%	3.6	11%	4.7	24%
	10%	0.8	2%	1.4	5%	0.5	1%	0.0	0%	14.5	37%	7.6	46%	20.6	60%	42.0	68%	4.9	15%	5.2	26%

Table A.4 Absolute and percent of annual soluble reactive phosphorus load captured by reservoir sizes representing 2% to 10% of field area (depth = 3.05 m) for DPAC (IN) and SERF (IA).

	Reservoir Size	2007		2008		2009		2010		2011		2012		2013		2014		2015		2016	
		kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%	kg ha^{-1}	%
DPAC	2%	0.023	17%	0.019	13%	0.007	9%	0.038	34%	0.022	17%	0.024	21%	0.052	48%	0.053	29%	0.001	0%	0.010	16%
	4%	0.044	34%	0.023	16%	0.018	23%	0.054	48%	0.045	34%	0.030	26%	0.079	73%	0.086	47%	0.000	0%	0.015	22%
	6%	0.050	38%	0.029	20%	0.023	29%	0.087	77%	0.054	40%	0.041	36%	0.085	79%	0.089	48%	0.000	0%	0.015	23%
	8%	0.052	40%	0.034	23%	0.025	32%	0.095	84%	0.055	42%	0.046	40%	0.086	80%	0.091	49%	0.000	0%	0.015	23%
	10%	0.053	41%	0.038	26%	0.027	34%	0.105	93%	0.057	43%	0.048	42%	0.088	81%	0.091	50%	0.000	0%	0.016	24%
SERF	2%	0.001	1%	0.001	1%	0.001	1%	0.000	0%	0.025	25%	0.003	14%	0.003	3%	0.027	32%	0.004	3%	0.006	7%
	4%	0.001	1%	0.002	3%	0.001	1%	0.000	0%	0.032	31%	0.007	32%	0.007	7%	0.038	45%	0.007	6%	0.013	13%
	6%	0.003	3%	0.004	4%	0.000	0%	0.000	0%	0.034	33%	0.009	42%	0.010	11%	0.046	54%	0.009	8%	0.017	17%
	8%	0.003	2%	0.005	6%	0.002	1%	0.000	0%	0.035	35%	0.011	49%	0.017	17%	0.053	62%	0.012	10%	0.024	25%
	10%	0.004	3%	0.005	6%	0.001	1%	0.000	0%	0.037	37%	0.011	49%	0.020	21%	0.064	75%	0.018	16%	0.027	28%

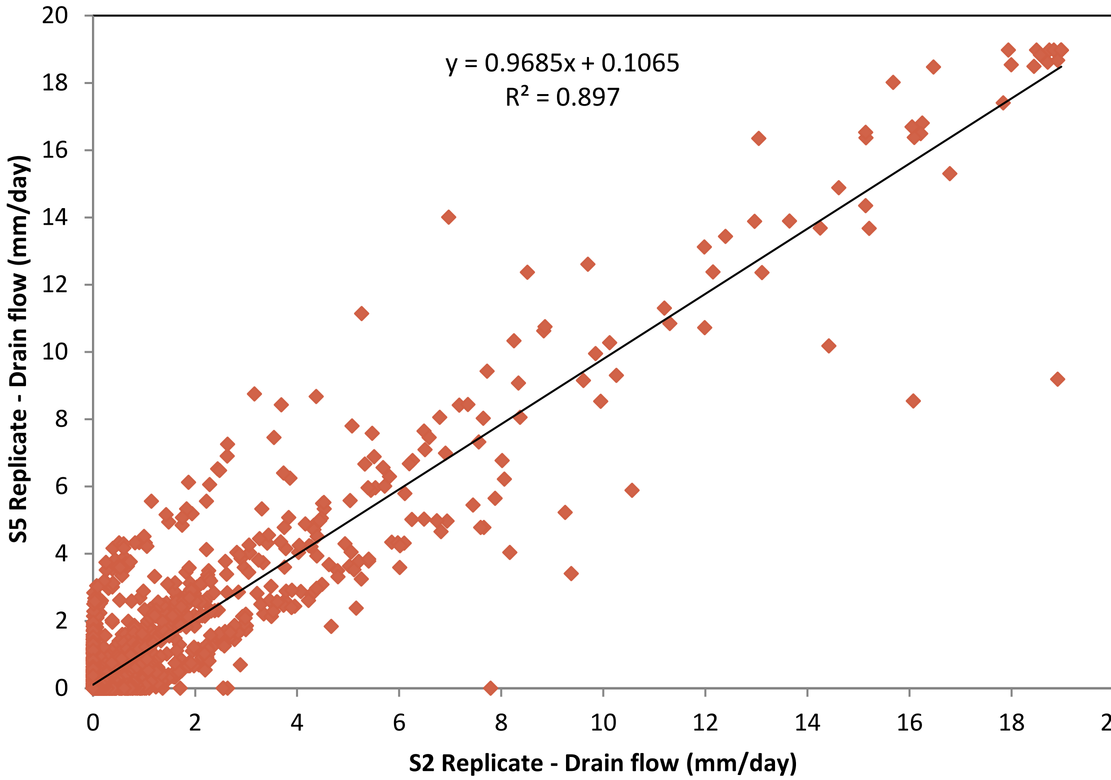


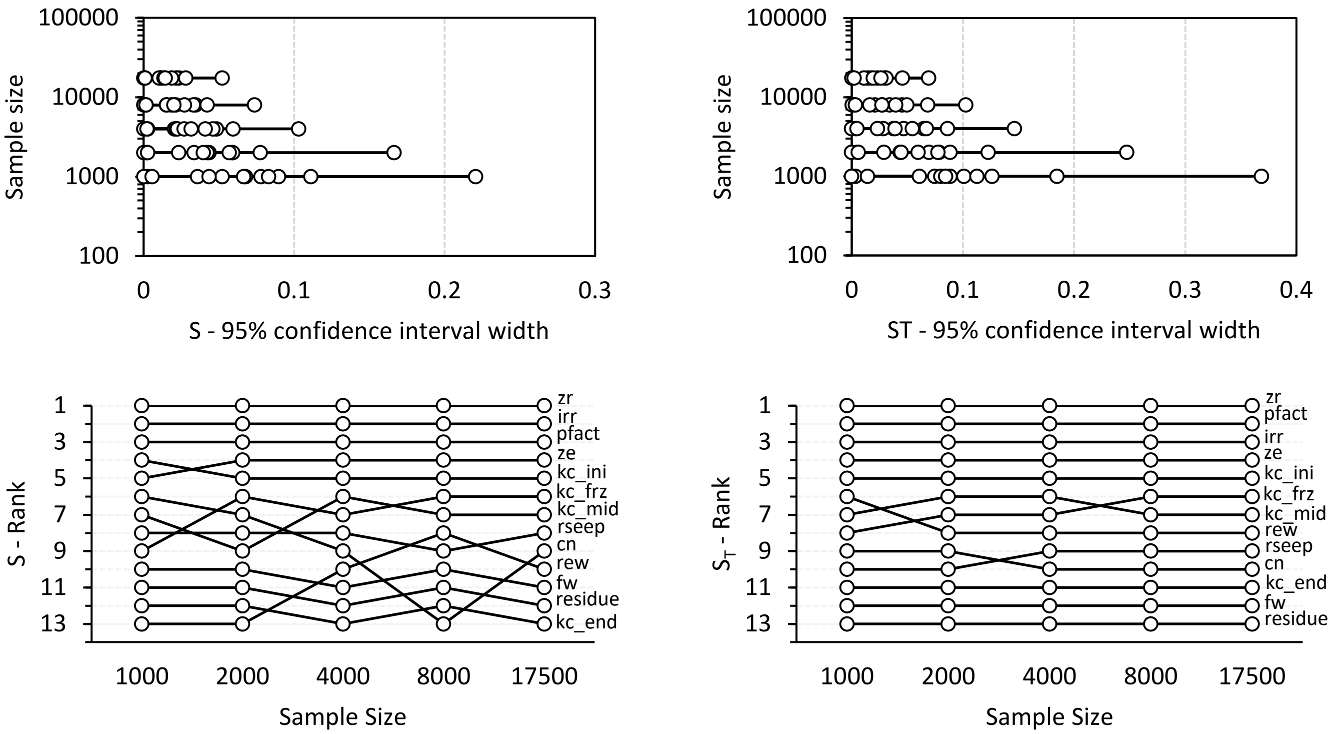
Fig. A.6 Linear regression relationship between free drainage treatment replicate plots at SERF (2007–2016). Regression relationships between drainage treatment replicate plots at DPAC are provided in Saadat et al. (2018a).

Table A.5 Seasonal (Winter = Jan-Mar, Spring = Apr-Jun, Summer = Jul-Sep, Fall = Oct-Dec) linear regression relationships between daily tile drain flow and 3-day cumulative precipitation at DPAC and SERF. Days where precipitation was greater than zero and drain flow exceeded the average daily drain flow during the summer were used in the regression analysis. This minimum drain flow threshold removed days with very small drain flow amounts, which can be common during the late growing season in the Corn Belt due to higher levels of evapotranspiration and improved the regression relationship. The minimum drain flow threshold for DPAC and SERF was 0.1 mm and 0.6 mm, respectively. Three-day average precipitation was used to account for the influence of multiday precipitation events on drain flow and resulted in the highest R^2 values for each season when compared to daily and other multiday estimates. If precipitation did not occur, but drain flow on the previous day was present, the drain flow was estimated from the previous day using seasonal recession slope constants (DPAC: Winter = -0.68, Spring = -0.63, Summer = -1.42, Fall = -0.66; SERF: Winter = -0.45, Spring = -0.54, Summer = -0.83, Fall = -0.69).

	Season	Intercept	Slope	r2
DPAC	Winter	0.82	0.35	0.41
	Spring	-0.04	0.38	0.51
	Summer	0.52	0.13	0.30
	Fall	1.06	0.29	0.36
SERF	Winter	0.59	0.57	0.70
	Spring	1.33	0.44	0.42
	Summer	2.64	0.24	0.19
	Fall	-0.08	0.49	0.41

APPENDIX B: CHAPTER 3 SUPPLEMENTARY DATA

Applied irrigation



Captured tile drain flow

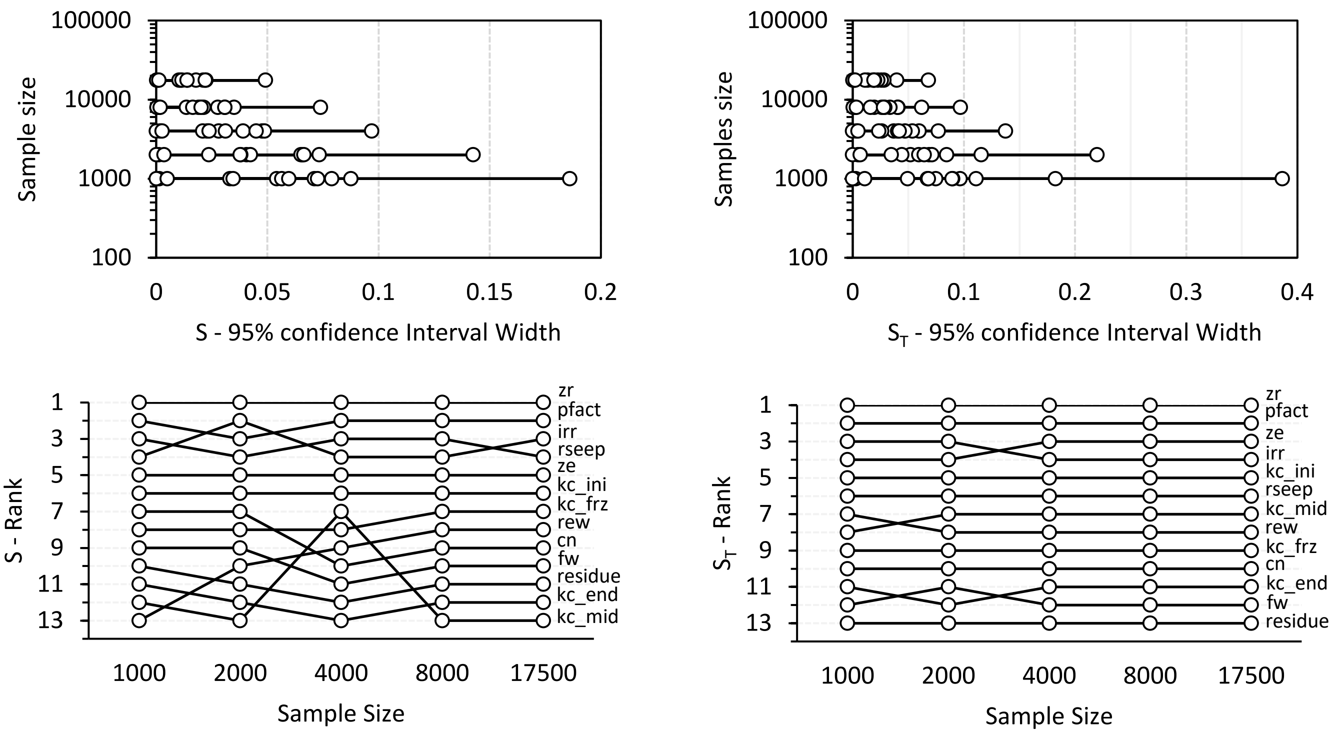


Fig. B.1 Convergence and rank analysis of first-order (S) and total-order (ST) sensitivity values for a reservoir size representing 2% of the irrigated area with an average depth of 3.05 m (10 ft)

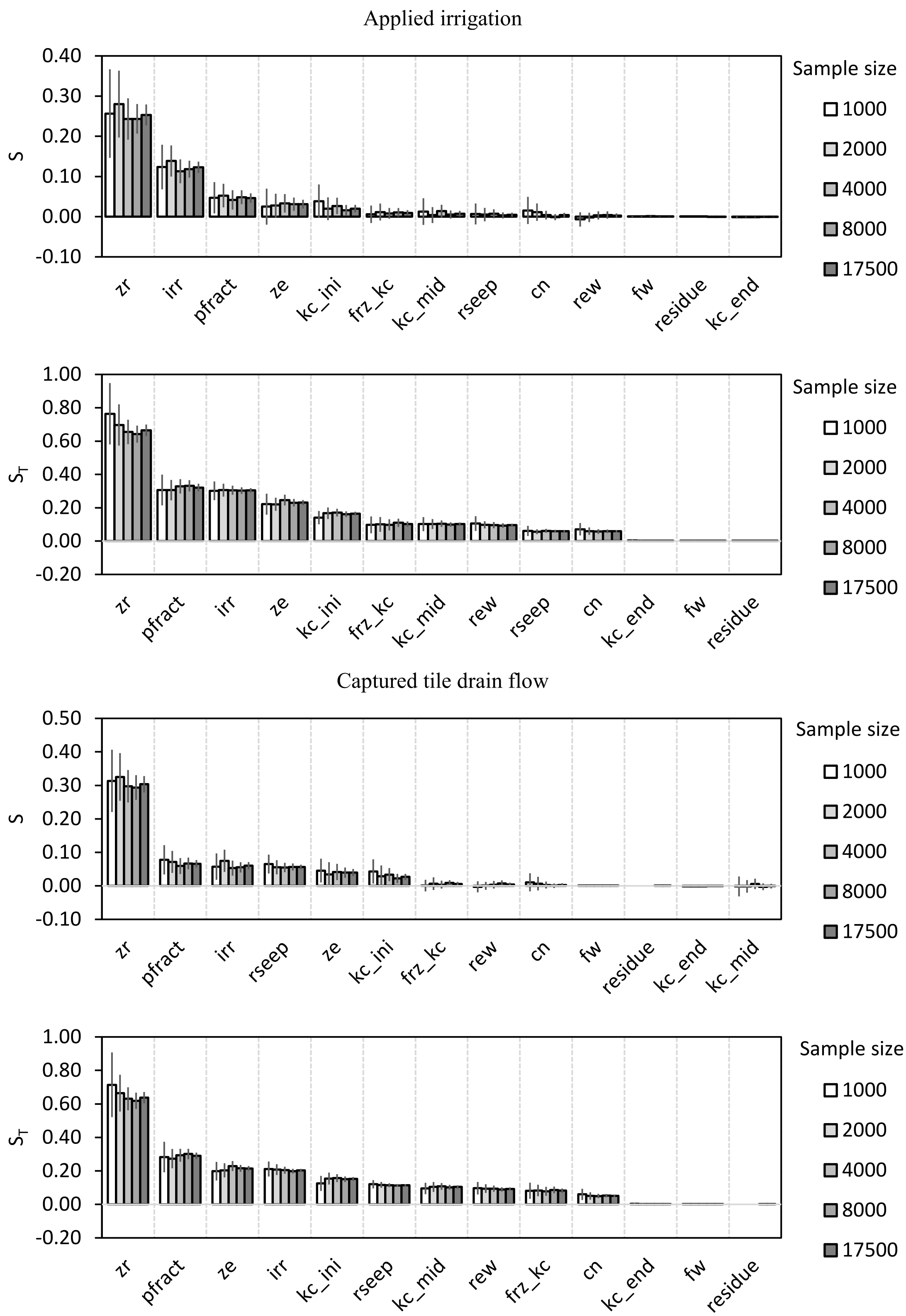


Fig. B.2 First-order (S) and total-order (S_T) sensitivity values for a reservoir size representing 2% of the irrigated area with an average depth of 3.05 m (10 ft). Bars indicate the 95% confidence interval.

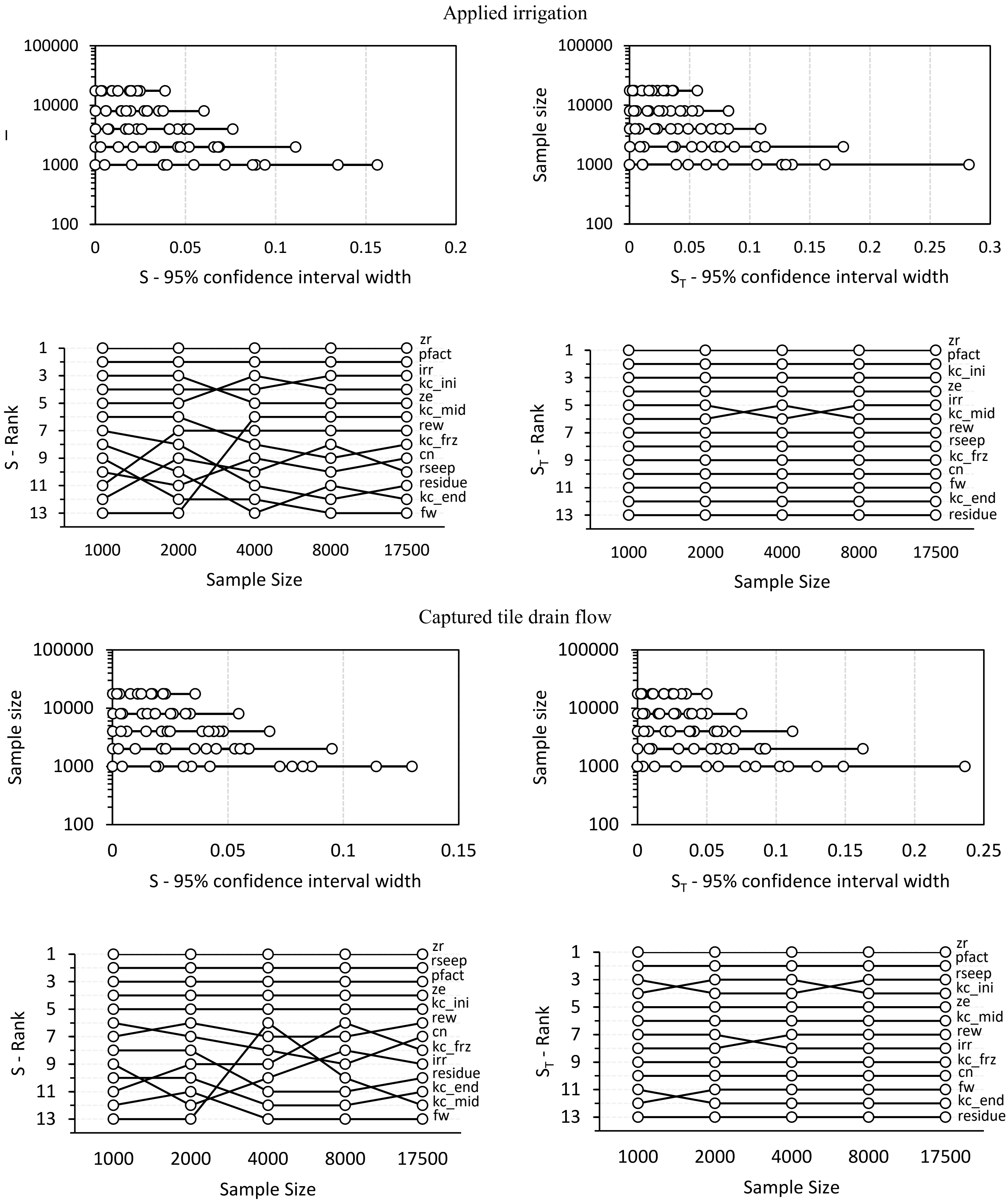


Fig. B.3 Convergence and rank analysis of first-order (S) and total-order (ST) sensitivity values for a reservoir size representing 4% of the irrigated area with an average depth of 3.05 m (10 ft)

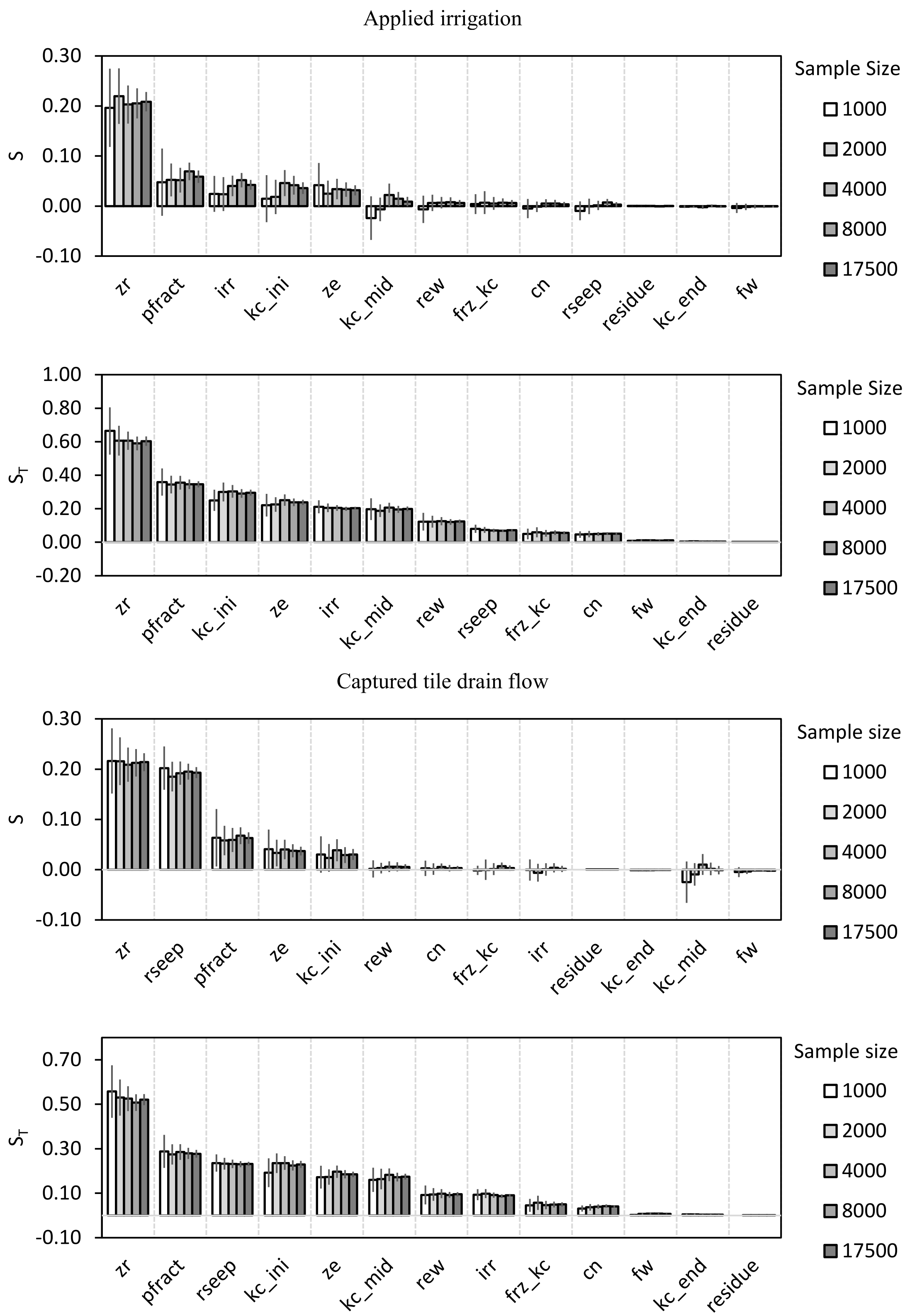
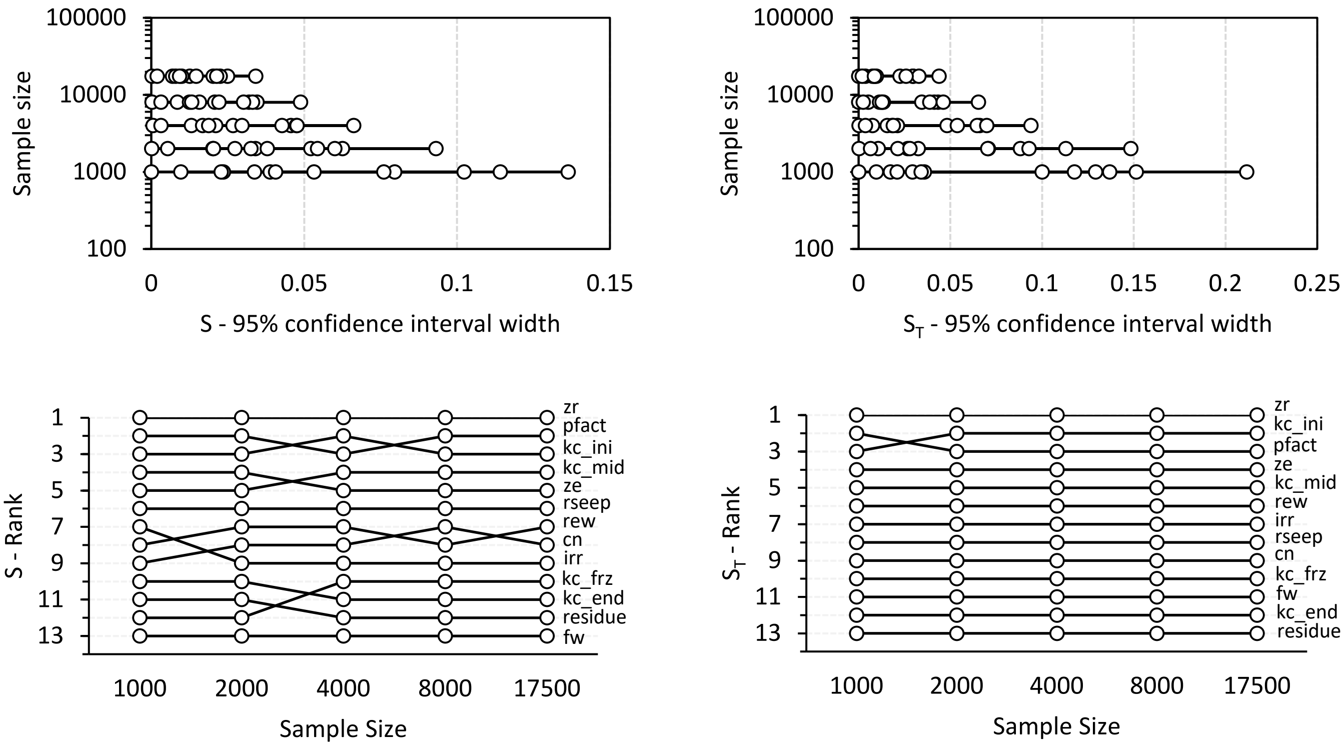


Fig. B.4 First-order (S) and total-order (S_T) sensitivity values for a reservoir size representing 4% of the irrigated area with an average depth of 3.05 m (10 ft). Bars indicate the 95% confidence interval.

Applied irrigation



Captured tile drain flow

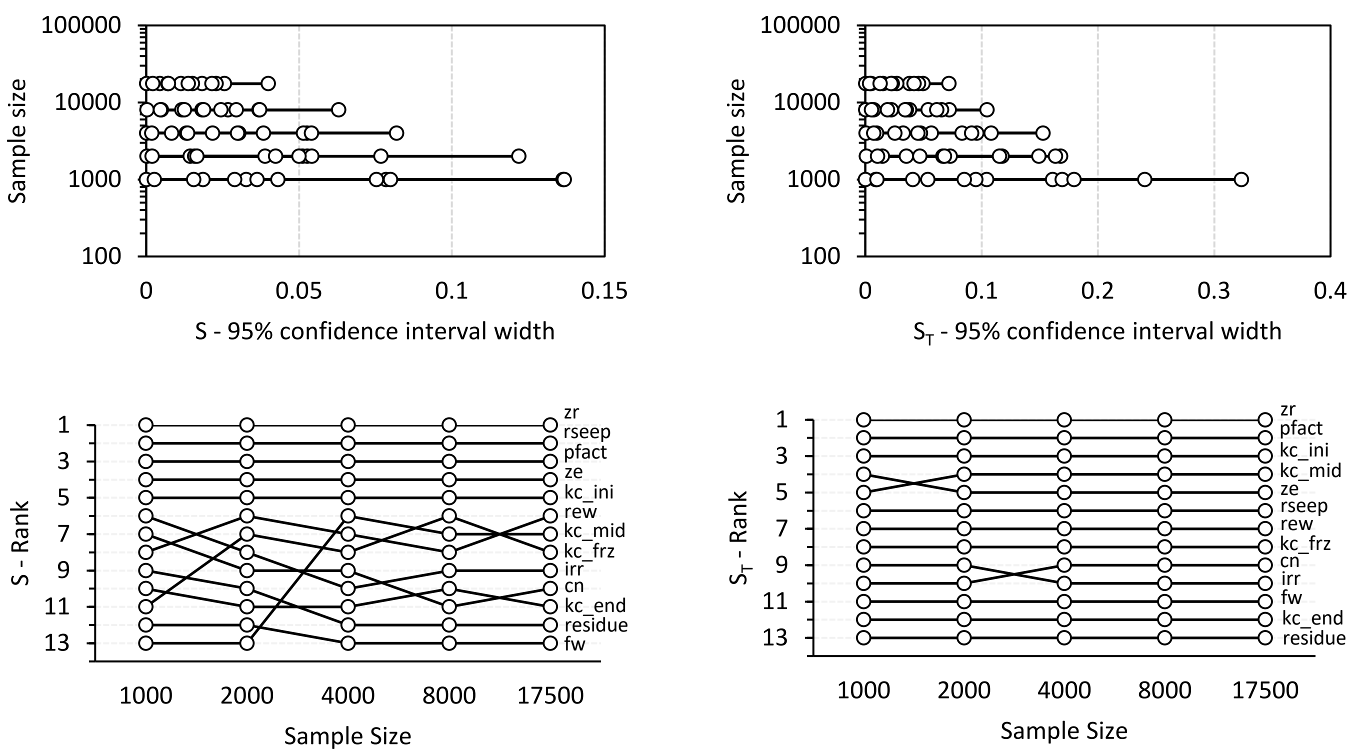


Fig. B.5 Convergence and rank analysis of first-order (S) and total-order (ST) sensitivity values for a reservoir size representing 6% of the irrigated area with an average depth of 3.05 m (10 ft)

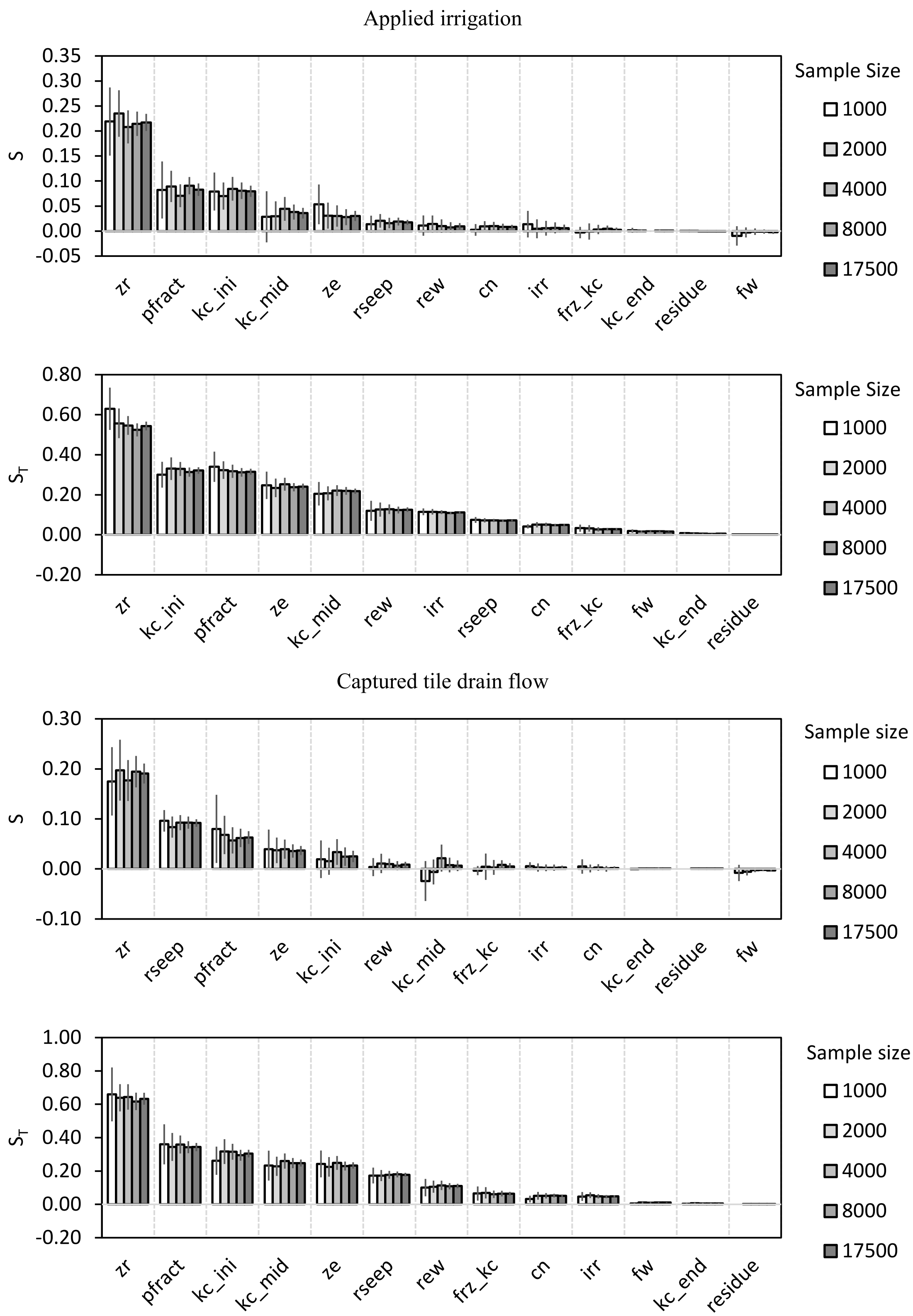
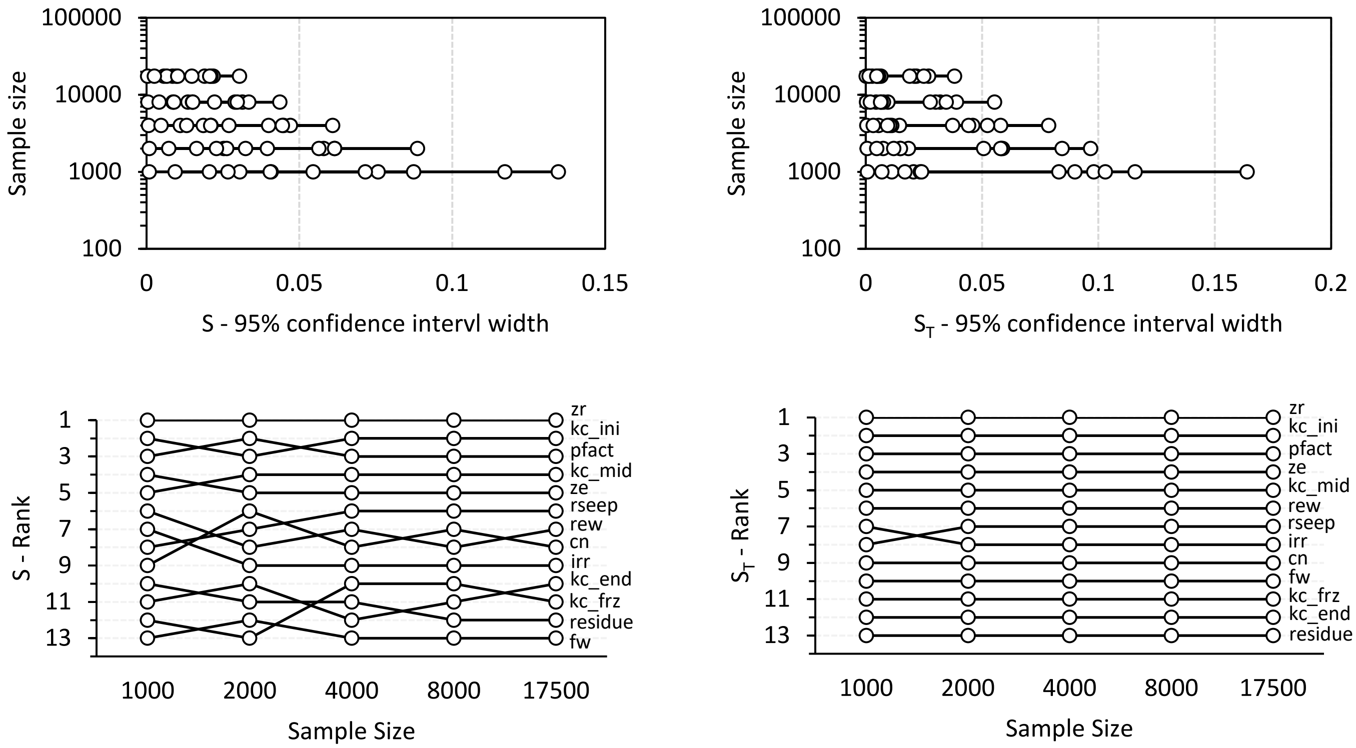


Fig. B.6 First-order (S) and total-order (S_T) sensitivity values for a reservoir size representing 6% of the irrigated area with an average depth of 3.05 m (10 ft). Bars indicate the 95% confidence interval.

Applied irrigation



Captured tile drain flow

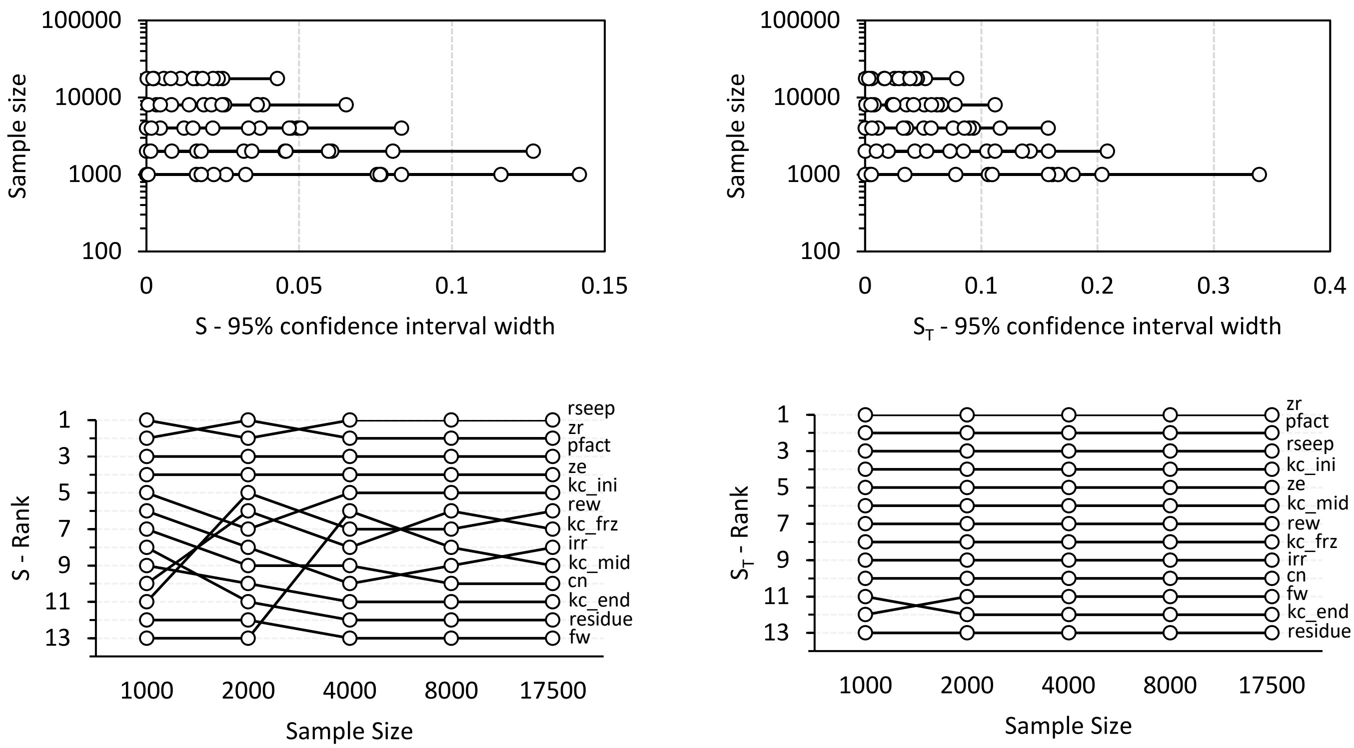


Fig. B.7 Convergence and rank analysis of first-order (S) and total-order (ST) sensitivity values for a reservoir size representing 8% of the irrigated area with an average depth of 3.05 m (10 ft)

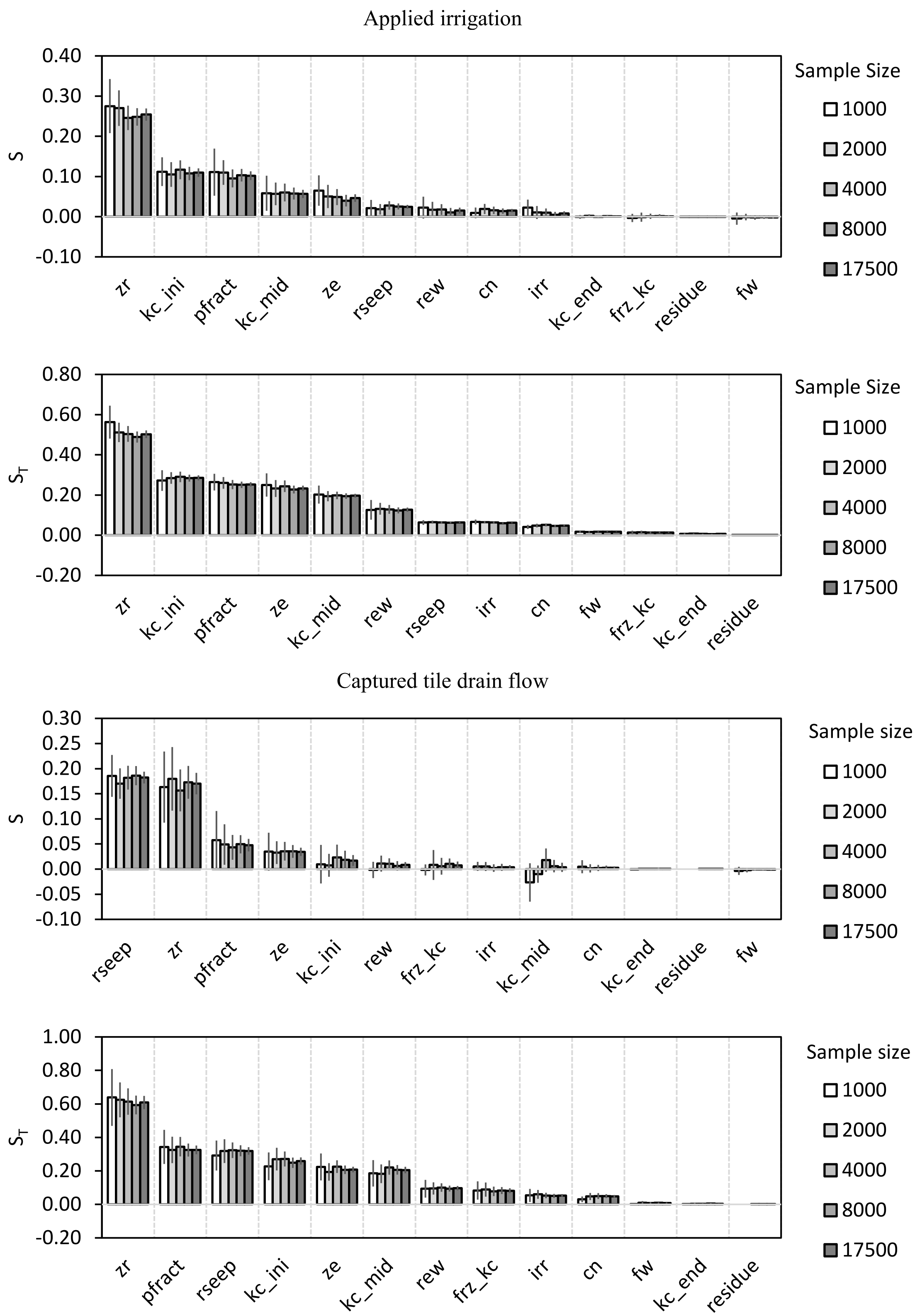
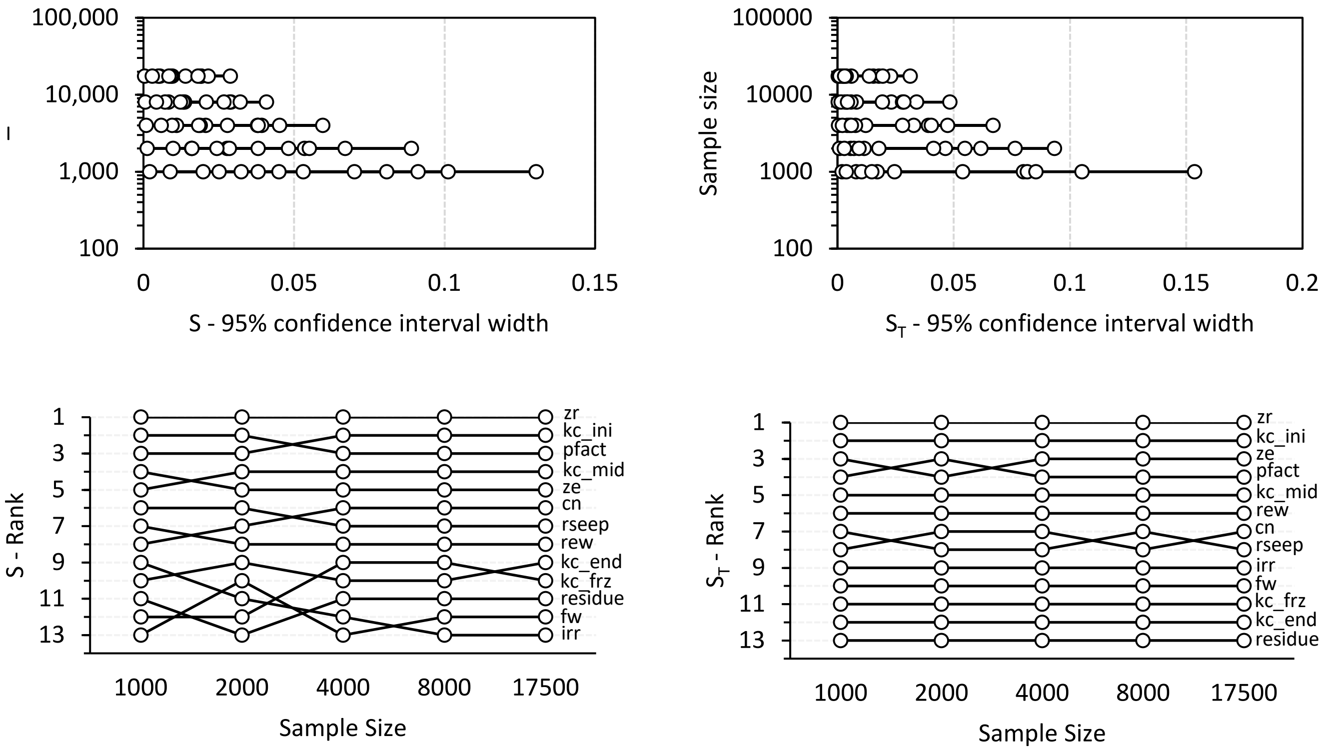


Fig. B.8 First-order (S) and total-order (S_T) sensitivity values for a reservoir size representing 8% of the irrigated area with an average depth of 3.05 m (10 ft). Bars indicate the 95% confidence interval.

Applied irrigation



Captured tile drain flow

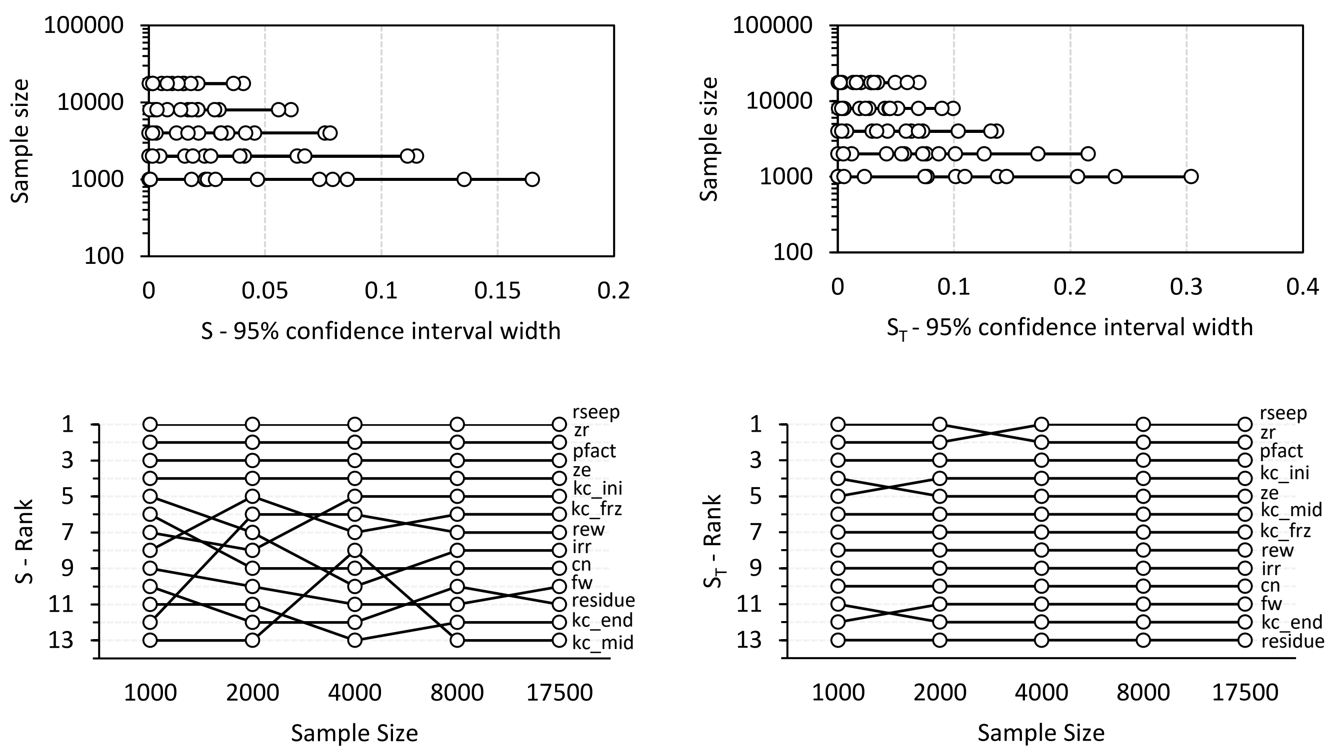


Fig. B.9 Convergence and rank analysis of first-order (S) and total-order (ST) sensitivity values for a reservoir size representing 10% of the irrigated area with an average depth of 3.05 m (10 ft)

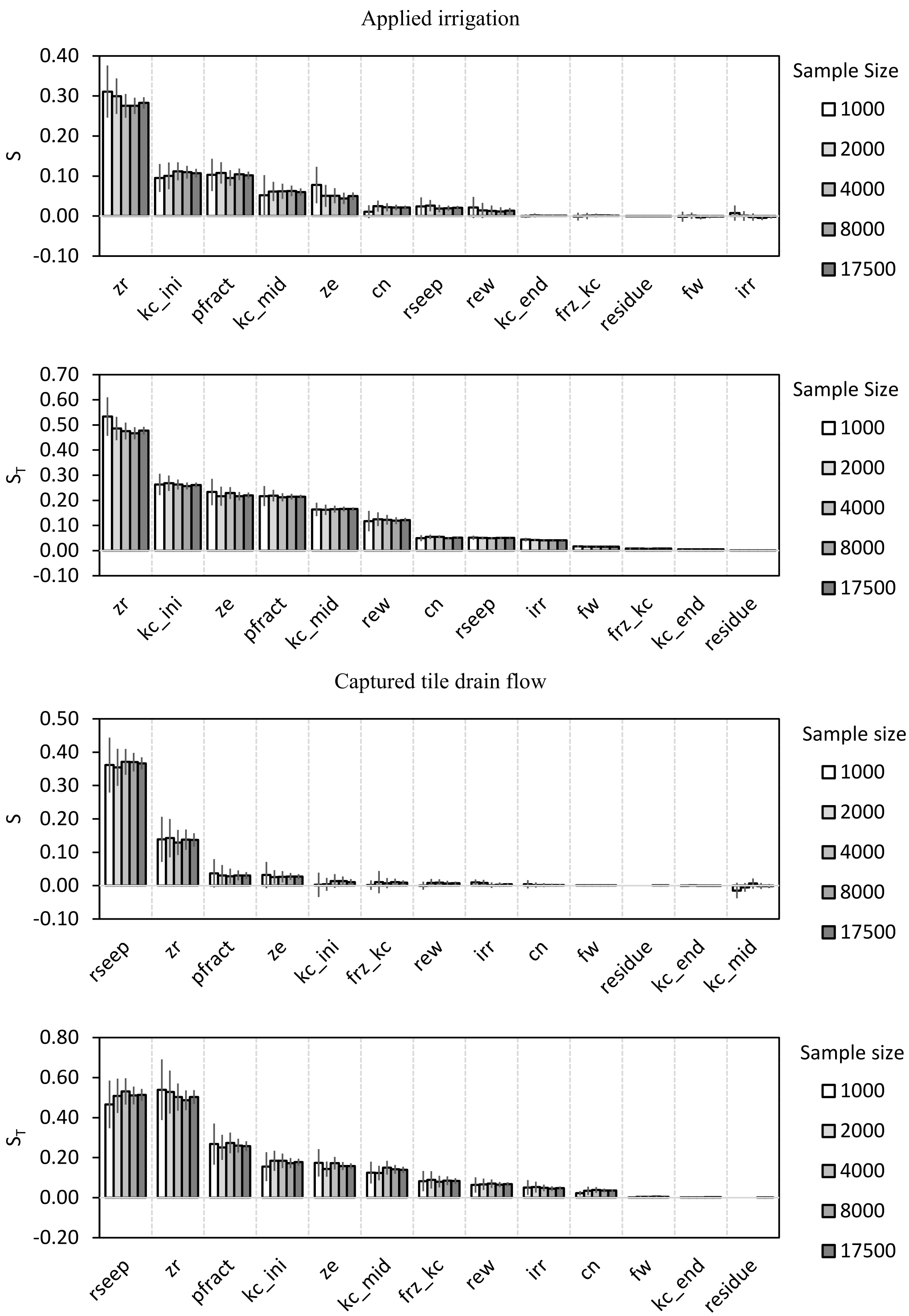


Fig. B.10 First-order (S) and total-order (S_T) sensitivity values for a reservoir size representing 10% of the irrigated area with an average depth of 3.05 m (10 ft). Bars indicate the 95% confidence interval.