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## Research papers



# New insights on evapotranspiration and water yield in crop and forest lands under changing climate

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#### ABSTRACT

Forest lands are sometimes thought to increase evapotranspiration (ET) and decrease water yield (WYLD) more than those of croplands, especially in the semi-arid subtropical and tropical regions. Using the US-EPA (Environmental Protection Agency)'s Hydrologic and Water Quality System (HAWQS) model along with Mann Kendall statistics ( $\tau$ ) and Kolmogorov-Smirnov test, I compared ET and WLYD between a cropland and a forest land in a humid subtropical region - Yazoo River basin (YRB), Mississippi, USA - under the changing climate. Results show that no temporal trend of ET was found over the past 50-year (1966 to 2015) and future 50-year (2021 to 2070) climate conditions, but a significant increasing trend ( $\tau = 0.403$ , p < 0.01) of ET was observed in the recent 20 years (1997 to 2017) in both the crop and forest lands. The simulation further reveals that the annual average air temperature over the past and future 50 years was about 1  $^{\circ}$ C cooler in the forest land than in the cropland. During the past 50 years, there was 10.8% more water lost from ET in the cropland (656 mm/year) than in the forest land (592 mm/year), while there was 17.3% less WYLD in the cropland (711 mm/year) than in the forest land (834 mm/year). Similar results were also obtained for the future 50 years, i.e., there were 42.0% more ET and 20.7% less WYLD in the cropland than in the forest land. Results show that over a long-range, the forest land reduced ET and increased WYLD as compared to those of the cropland in the YRB (a humid subtropical region). These new insights change the traditional views on how forests and crops affect ET and WYLD in the humid subtropical regions around the world and provide useful information to farmers and foresters for effective water resource management

## 1. Introduction

Evapotranspiration (ET) is the sum of land surface evaporations and plant transpirations. Water yield (WYLD) is the water production from the sum of surface water runoff to reach, lateral flow contribution to reach, and vadose zone groundwater recharge subtracting the sum of the transmission loss of water from ET and soil storage. Evapotranspiration contributes a large amount of water loss and plays an essential role in reducing WYLD in watersheds (Calder, 1998; Oren et al., 2001; Wilcox et al., 2003). Numerous studies reported that forest lands increase water losses from ET and decrease WYLD more than those of croplands (Allison et al., 1990; Calder, 1998; Scanlon et al., 2007; Owuor et al., 2016). Hornbeck et al. (1993) investigated the long-term change of annual WYLD for 11 catchments in northeastern US and found that WYLD increases substantially with a maximum of 350 mm  $y^{-1}$  in the first year of forest cutting but declines quickly after the cutting. Scanlon et al (2007) evaluated the global impacts of native vegetation conversion to

agricultural land on water quantity and concluded that the increase of crop and pasture lands during the past 300 years from forest lands decreases ET, increases groundwater recharge by two orders of magnitude, and raises streamflow by one order of magnitude. Owuor et al. (2016) performed a literature review of land use and land cover effects on groundwater recharge in the semi-arid tropical and subtropical regions. They argued that forests increase ET and decrease WYLD in the semi-arid tropical and subtropical regions.

In contrast, forest ET may decrease with tree age, and at certain age, forests increase WYLD (Murakami et al., 2000; Van Dijk and Keenan, 2007). Some forests can decrease ET during the periods with limited water availability through the reduction of leaf stomatal conductance (Oren et al., 1998; Bréda et al., 2006). Additionally, forest managements such as thinning to an intermediate tree density could increase groundwater recharge and therefore WYLD (Ilstedt et al., 2016). Murakami et al. (2000) measured the ET variations in the young (age 4–7) and mature (age 62–66) Japanese cypress (*Chamaecyparisobtusa*)

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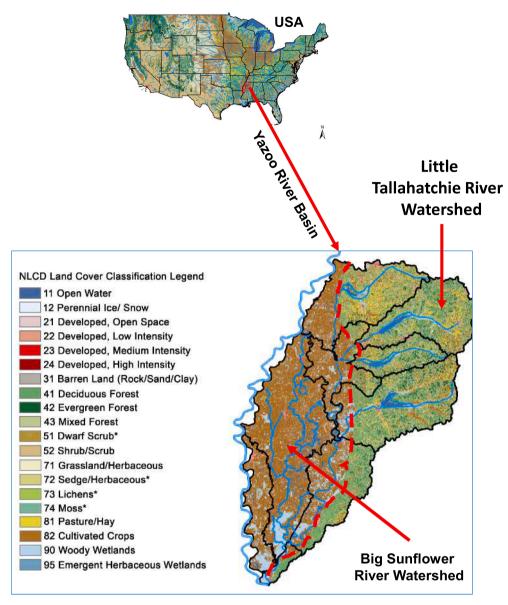


Fig. 1. Location of the Yazoo River basin (YRB) in Mississippi, USA.

catchments in Japan. These authors reported that annual ET increases in the young forests but decrease in the mature forests. McLaughlin et al. (2013) developed a statistical model to estimate water yield under different forest management strategies. These authors found that slash pine stands managed at lower basal areas can increase 64% more cumulative water yield over a 25-year rotation as compared to systems managed for high-density timber production. Ilstedt et al. (2016) reported that groundwater recharge and WYLD are maximized or increase at the intermediate tree densities. Recently, Ouyang et al. (2019) predicted the impact of forest lands on groundwater in a watershed of Mississippi, USA and cited that the average annual aquifer recharge in the forest land is slightly higher than that of the cropland, and thereby increasing WYLD.

Climate change is a naturally occurring phenomenon while human activities result in extreme climate change patterns (IPCC, 2012). Evapotranspiration and WYLD are vulnerable to climate change because this change influences precipitation and air temperature and thereby the ET and WYLD. Stone et al (2001) applied the Soil and Water Assessment Tool (SWAT) model to investigate impacts of climate change on WYLD in the Missouri River basin, US and found that overall WYLD at the

outlet of the basin decreases during spring and summer but increases during fall and winter. Chien et al. (2013) studied the potential impacts of climate change on streamflow in agricultural watersheds of the midwestern US using the SWAT model. They projected the annual streamflows from 2051 to 2095 decrease in a range of 44.1 to 61.3%. Caldwell et al. (2016) estimated climate change impacts on WYLD from the forest mountain watersheds of the southern Appalachian Mountains in North Carolina, US. These authors cited that the annual WYLD increases up to 55% in some watersheds from 1938 to mid-1970 and then decreases up to 22% by 2013, whereas the opposite is true for forest ET with a decrease up to 31% in the mid-1970 followed by an increase up to 29% in 2013.

A literature review reveals that our understanding of ET and WYLD in crop and forest lands under the changing climate conditions is still fragmented. To mitigate future climate impacts on ET and WYLD in watersheds, water resource managers, farmers and foresters need to understand the potential threats and develop the watershed-specific strategies. The goal of this study was to compare ET and WYLD between croplands and forest lands under the changing climate, using the US Environmental Protection Agency (US-EPA)'s Hydrologic and Water

Quality System (HAWQS) model. The Yazoo River basin (YRB), a humid subtropical region, in Mississippi, USA was selected as a study site. Specific objectives were to: (1) create a model (or a project) for the YRB using the HAWQS model; (2) calibrate and validate the model using field measured data; (3) apply the model to compare ET and WYLD between the crop and forest lands over the past and future 50 years; and (4) detect the temporal trends of ET and WYLD using the Mann Kendall statistics.

## 2. Materials and methods

#### 2.1. HAWOS model

The US-EPA's HAWQS model is public available for simulating water quantity and quality in watersheds of the continental USA (HAWQS, 2020). The model used the SWAT model as the core simulation engine with many user-friendly features such as web interfaces, pre-loaded past and future climate datasets, online project development and execution, and tabular and chart format outputs. Currently, a couple of studies are performed using HAWQS (Yen et al., 2016; Fant et al., 2017). Yen et al. (2016) applied HAWQS to predict large-scale water quantity and quality in the Illinois River watershed, USA. These authors argued that with the help of HAWQS, scientists can simulate a large-scale watershed with minimum efforts without tedious procedures in a timesaving and cost-effective manner. Fant et al. (2017) employed HAWQS to predict future water quality conditions and economic impact in USA. They concluded that under the business-as-usual greenhouse gas emissions scenario, climate change is likely to have negative economic impacts.

#### 2.2. Site description

The YRB is the largest river basin in Mississippi (Fig. 1) and is one of the highest crop productive regions in midsouth US (MDEQ (Mississippi Department of Environmental Quality), 2008). Human activities such as forest clear-cuttings for croplands, stream channel alterations for navigations and recreations, and groundwater pumpage for crop irrigation in the past decades resulted in frequent river flooding, low streamflow, wetland loss and groundwater level decline in the YRB (Little et al., 1982; Clark and Hart, 2009; MSU Extension Service, 2014; Ouyang et al., 2019). The YRB has two distinct topographic regions (Guedon and Thomas, 2004): one is the bluff hills (16,600 km<sup>2</sup>) in the east and the other is the Mississippi alluvial delta (about 18,200 km<sup>2</sup>) in the west, which is separated by a dashed line in Fig. 1. The bluff hills region situates in the upland of the YRB, which is primarily occupied by forests with loess and loess-derived alluvium. The delta region places in the lowland of the YRB with clay and fine sand from alluvial deposition of the ancestral Mississippi and Ohio Rivers (Guedon and Thomas, 2004). The YRB has nine watersheds with a total drainage area of about 34,800 km<sup>2</sup> and consists of 35.54% cropland, 36.7% forestland, 18% grassland and wetland, 5.81% residential, and 3.95% water. The average annual temperature is 18 °C with a mean minimum of 5.5 °C in winter and a mean maximum of 32 °C in summer (Southern Regional Climate Center, 1998). Long-term average precipitation is 1290 mm/year with 120 mm/ month from December to April and 80 mm/month from August to October (Berkowitz et al., 2020). Of the nine watersheds in the YRB, the Little Tallahatchie River watershed (LTRW, 4,271 km<sup>2</sup> with about 66% forest and wetlands) was chosen as the forest dominated watershed and the Big Sunflower River watershed (BSRW, 8,171 km<sup>2</sup> with about 88% croplands) was selected as the crop dominated watershed in this study (Fig. 1). The rest of seven watersheds were not selected in this study because most of them are the mixture of forests and crops.

## 2.3. Model creation

Followed the HAWQS (Version 1.2) model's instructions (https://hawqs.tamu.edu/content/docs/HAWQS-1.2-Whats-New.pdf), the web-based YRB model was developed and executed using the

following four steps: (1) Create a project. Choosing the catchment resolution of HUC 8 (Hydrologic Unit Code 8), selecting the HUC ID of 08030208 and setting the HRU (Hydrologic Response Units) to 1%, the YRB model with nine watersheds was created in HAWQS (Fig. 1). A threshold level of 1% for HRUs was used to remove the areas of land uses < 1%; (2) Create scenarios and customize inputs. Two simulation scenarios were chosen in this study: the first assessed the past climate change impacts on ET and WYLD for the period from 1966 to 2015 (50 years), whereas the second estimated the future climate change impacts on ET and WYLD for the period from 2021 to 2070 (50 years). The future weather dataset generated from the CCSM4 (Community Climate System Model 4) with the RCP45 (Representative Concentration Pathway 45) was used for the second scenario, which is readily available in HAWQS; (3) Run the model; and (4) Analyze the simulation outputs.

## 2.4. Trend analysis and statistical test

The temporal trends of the predicted ET and WYLD due to the past and future climate change impacts are detected using the Mann-Kendall analysis. Mann-Kendall statistics is a nonparametric trend test, does not require normally distributed data, and is calculated as (Kendall and Stuart, 1976; Gilbert, 1987):

$$S = \sum_{k=1}^{n-1} \sum_{i=k+1}^{n} sgn(X_{i} - X_{k})$$
 (1)

with

$$sgn(x) = \begin{cases} 1 & \text{if} & x > 0 \\ 0 & \text{if} & x = 0 \\ -1 & \text{if} & x < 0 \end{cases}$$
 (2)

The mean of S is zero and the variance is

$$\sigma = \frac{1}{18} \left\{ n(n-1)(2n+5) - \sum_{j=1}^{m} t_j(t_j-1)(2t_j+5) \right\}$$
 (3)

where n is the number of times of measurements, m is the number of the tied groups in the data set, and  $t_j$  is the number of data points in the  $j^{th}$  tied group. The Kendall's S statistic is approximately normal distributed if the following Z-transformation is valid:

$$Z = \begin{cases} \frac{s-1}{\sigma} & \text{if} \quad S > 0\\ 0 & \text{if} \quad S = 0\\ \frac{s+1}{\sigma} & \text{if} \quad S < 0 \end{cases}$$
 (4)

The statistic S is closely related to Kendall's  $\tau$  as:

$$\tau = \frac{S}{D} \tag{5}$$

with

$$D = \left[\frac{1}{2}n(n-1) - \frac{1}{2}\sum_{j=1}^{p} t_j(t_j - 1)\right]^{1/2} \left[\frac{1}{2}n(n-1)\right]^{1/2}$$
 (6)

In this study, the Mann Kendall analysis is implemented with Kendall's package in R-Statistics (Pohlert, 2018).

The differences between the crop-dominated and forest-dominated watersheds as well as the past and future climate impacts among the hydrological variables such as PET, ET, surface runoff, and WLYD are estimated using the Kolmogorov-Smirnov (K-S) test. The K-S test is based on the empirical cumulative distribution function (ECDF). Given N ordered data points  $Y_1, Y_2, ..., Y_N$ , the ECDF can be defined as (Chakravarti et al., 1967):

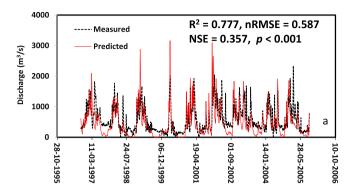
$$E_N = \frac{n(i)}{N} \tag{7}$$

Table 1
Major input parameter values used for the YRB-HAWQS model.

Input				
variable	Definition	Value	Unit/ method/ Explanation	Reference
Water balance				
SFTMP	Snowfall	1	°C	Local
	temperature			observation
SMTMP	Snow melt base	0.5	°C	Local
0	temperature	0.0	G	observation
SMFMX	Melt factor for snow	4.5	mm H <sub>2</sub> O/°C-	Local
	on June 21		day	observation
SMFMN	Melt factor for snow	4.5	mm H <sub>2</sub> O/°C-	Local
	on December 21		day	observation
TIMP	TIMP: Snow pack	1		Local
	temperature lag			observation
	factor			
IPET	Potential	1	Penman/	
	evapotranspiration		Monteith	
	(PET) method		method	
ESCO	Soil evaporation	0.95		Calibrated
	compensation factor			
EPCO	EPCO: Plant uptake	1		Calibrated
21 00	compensation factor	-		Gambratea
Surface Runof	-			
ICN	Daily curve number	1	Calculate as a	Calibrated
1011	calculation method	-	function of	Gambratea
	careameron memoa		plant	
			evaporation	
ICRK	Crack flow code	0	Do not model	Local
TOTAL	Grack now code	Ü	crack flow in	observation
			soil	ODSCI VALIOII
SURLAG	Surface runoff lag	14	5011	Calibrated
0010210	time			Gambratea
CN2	Subbasins curve	-8%	CN2	calibrated
GIVE	number	070	decreased 8%	canbratea
	number		for all	
			subbasins	
Reaches			Subbusins	
IRTE	Channel water	1	Muskimgum	Calibrated
IKIL	routing method	1	method	Gilibratea
MSK_COL1	Calibration	0	incurou	Calibrated
MSK_COLI	coefficient used to	O		Cambrated
	control impact of the			
	storage time			
	constant for normal			
	flow			
MSK_COL2	Calibration	0.5		
				Calibrated
WISK_COL2		3.5		Calibrated
WISK_COLZ	coefficient used to	3.5		Calibrated
WOK_COL2	coefficient used to control impact of the	3.5		Calibrated
MBR_GGEZ	coefficient used to control impact of the storage time	3.5		Calibrated
MBK_COLZ	coefficient used to control impact of the storage time constant for low	3.5		Calibrated
	coefficient used to control impact of the storage time constant for low flow			
MSK_X	coefficient used to control impact of the storage time constant for low flow Weighting factor	0.2		Calibrated  Calibrated
	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative			
	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow			
	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate			
	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining			
	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in			
MSK_X	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment	0.2		Calibrated
	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of			
MSK_X	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses	0.2		Calibrated
MSK_X	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel	0.2		Calibrated
MSK_X	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep	0.2		Calibrated
MSK_X TRNSRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer	0.2		Calibrated
MSK_X	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation	0.2		Calibrated
MSK_X TRNSRCH EVRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor	0.2		Calibrated  Calibrated
MSK_X TRNSRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation	0.2	Channel	Calibrated  Calibrated
MSK_X TRNSRCH EVRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor	0.2	dimention is	Calibrated  Calibrated
MSK_X TRNSRCH EVRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation	0.2	dimention is not updated	Calibrated  Calibrated
MSK_X TRNSRCH EVRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation	0.2	dimention is	Calibrated  Calibrated
MSK_X TRNSRCH EVRCH	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation	0.2	dimention is not updated	Calibrated  Calibrated
MSK_X TRNSRCH EVRCH IDEG	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation	0.2 0.1 1 0	dimention is not updated as a result of degradation	Calibrated  Calibrated  Local observation
MSK_X TRNSRCH EVRCH IDEG	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation	0.2	dimention is not updated as a result of	Calibrated  Calibrated  Local observation
MSK_X  TRNSRCH  EVRCH IDEG	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation code	0.2 0.1 1 0	dimention is not updated as a result of degradation	Calibrated  Calibrated  Local observation
MSK_X  TRNSRCH  EVRCH IDEG	coefficient used to control impact of the storage time constant for low flow Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment Fraction of transmission losses from main channel that enter deep aquifer Reach evaporation adjustment factor Channel degradation code	0.2 0.1 1 0	dimention is not updated as a result of degradation	Calibrated  Calibrated  Local observation

\*NCDC = National Climate Data Center, NWS = National Weather Service, and NOAA = National Oceanic and Atmospheric Administration.

\*\*MRI-CGCM3 = Meteorological Research Institute- Third Generation Coupled Global Climate Model, and CMIP 5 = Coupled Model Intercomparison Project Phase 5.



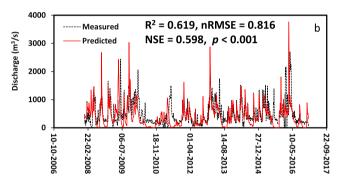


Fig. 2. Comparison of the observed and predicted daily discharges during model calibration (a) and validation (b).

where  $E_N$  is the ECDF, n(i) is the number of points less than  $Y_i$  and the  $Y_i$  are ordered from smallest to largest value. The K-S test statistic is given as (Chakravarti et al., 1967):

$$D = \max_{1 < i < N} [F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i)]$$
 (8)

where F is the theoretical cumulative distribution.

## 2.5. Model calibration and validation

The YRB model was calibrated and validated using field measured data prior to its applications. The model calibration was accomplished by adjusting some key input parameter values such as curve number, plant uptake compensation factor, and soil evaporation compensation factor within an acceptable range so that the model predictions match the field observations closely. Table 1 lists the input parameter values used during the model calibration. After calibration, the model was validated by comparing the model predictions to an independent dataset of field observations without adjusting any input parameter values. In this study, the field observed stream discharge data were used for model calibration and validation, which were downloaded from the USGS Station # 07288955 in Yazoo River BL Steele Bayou near Long Lake, MS.

The statistical measures of the model calibration and validation are shown in Fig. 2. The observed daily discharges from October 1, 1996 to December 31, 2005 were used for model calibration, while the observed daily discharges from January 1, 2008 to December 31, 2016 were chosen for model validation. With the values of  $R^2 = 0.777$ , nRMSE (normalized root mean square error) = 0.587 m<sup>3</sup>/s, NSE (Nash-Sutcliffe Efficiency) = 0.357 and p < 0.001, a good agreement was obtained

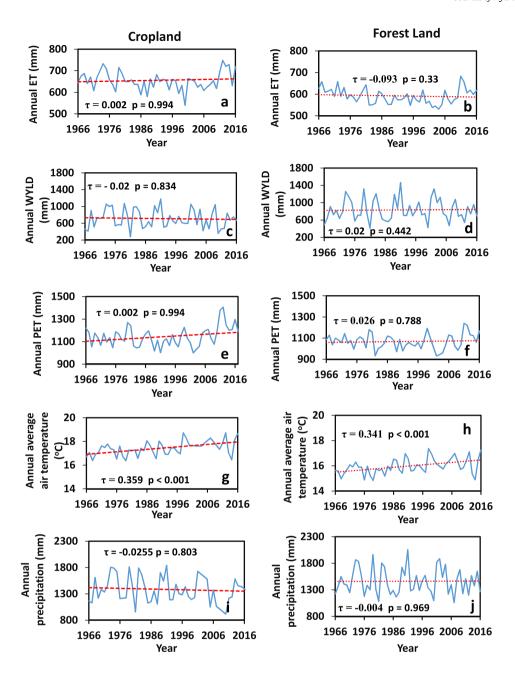


Fig. 3. Annual ET, WYLD, PET, and precipitation over the past 50-year period from 1966 to 2015 in the cropland (BSRW) and forest land (LTRW) along with Mann Kendall analysis.

between the predicted and observed daily discharge during the model calibration (Fig. 2a). Analogous to the case of the model calibration, the values of  $\mathbb{R}^2$ , nRMSE, NSE and p were statistically significant (Fig. 2b) during the model validation, which confirmed the model predictions matched the field observations reasonably well.

#### 3. Results and discussion

## 3.1. Past climate change impacts

Annual variations of the predicted ET and WYLD associated with their highly relevant variables such as PET (potential ET), air temperature, and precipitation in the cropland (BSRW) and forest land (LTRW) over the past 50-year simulation period from 1966 to 2015 are shown in Fig. 3. The annual PET was calculated using the Penman-Monteith

method, the annual air temperature and precipitation were the model input data, and the dashed lines in the figure were the trend lines. In general, the annual ET and WYLD varied with times and land uses over the past 50 years (Fig. 3a-3d). For example, the annual ETs for the cropland and forest land were, respectively, 709.14 and 577.85 mm in 1975 but 539.75 and 558.24 mm in 2000, while the annual WYLDs for the cropland and forest land were, respectively, 1029.19 and 1008.77 mm in 1975 but 595.67 and 425.97 mm in 2000. This happened because PET, air temperature and precipitation are, among others, the major factors controlling the ET and WYLD. As these factors varied with times and land uses (Fig. 3e-3 h), so did the ET and WYLD.

What is more interesting are the annual trends of ET, WYLD, PET, air temperature and precipitation (Fig. 3), which were obtained with Mann Kendall analysis. In Mann Kendall statistics, the value  $\tau$  ranges from -1 to 1 and measures the relationships between variables and times. If  $\tau=$ 

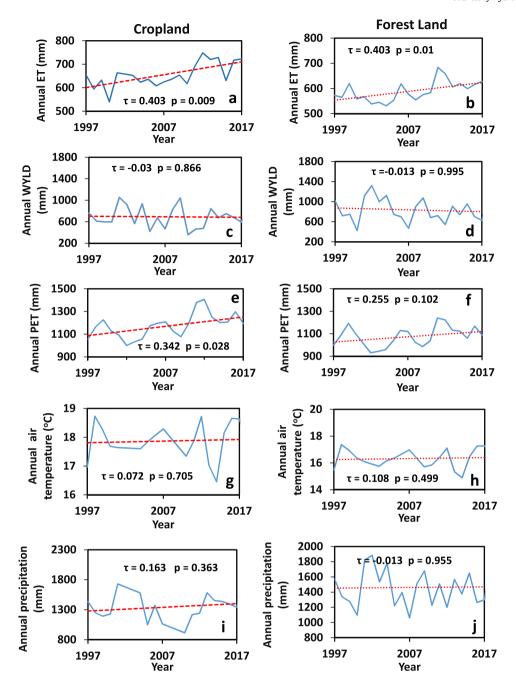
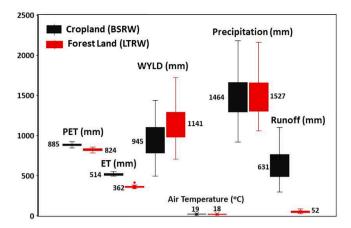


Fig. 4. Annual ET, WYLD, PET, and precipitation over a 20-year period from 1997 to 2017 in the cropland (BSRW) and forest land (LTRW) along with Mann Kendall analysis.

0, no relationship exists, while  $\tau=1$  (or -1) is a perfect relationship (with positive  $\tau$  for an increasing trend and negative  $\tau$  for a decreasing trend). The p value is a statistical measure of a trend, and if  $p \leq 0.05$  there is a monotonic trend (Mangiafico, 2016). Over the past 50 years from 1966 to 2015, only the annual average air temperature had a significant increasing trend (p < 0.001) in both the crop and forest lands (Fig. 3g) and 3 h, while the annual precipitation decreased very slightly (small negative  $\tau$ ) but was not significant statistically (p > 0.05) in the same land uses (Fig. 3i and 3j). Results indicate that the past climate conditions had no discernable impacts on ET and WYLD in both the crop and forest lands.

It is reported that climate change has resulted in precipitation anomaly in the contiguous 48 States of US with more extreme wet than dry conditions since 1990 (US-EPA, 2021). Based on this report, a short-term analysis was performed to assess the past climate change impacts

on annual variations of ET and WYLD in the crop and forest lands over a recent 20-year simulation period from 1997 to 2017 (Fig. 4). This short-term period was selected according to Atlantic Multidecadal Oscillation (AMO), which is an index of the climate cycle that affects the sea surface temperature of the North Atlantic Ocean based on different modes on multi-decadal timescales. The negative AMO index is for a cooling cycle and the positive one is for a warming cycle (McCarthy, et al., 2015). The period from 1997 to 2017, selected in this analysis, has positive AMO index and belongs to a warming cycle (Ouyang et al., 2020). In the recent 20 years there were significant increasing trends of ET ( $\tau=0.403$  and p<0.05) and PET ( $\tau=0.342$  and p<0.05) in the cropland (Fig. 4a and 4e), while there was only a significant increasing trend of ET ( $\tau=0.403$  and p<0.05) in the forest land (Fig. 4b). The increasing trend of ET in both the crop and forest lands could be a result of a warming AMO cycle although the temporal trends of air temperature and precipitation



**Fig. 5.** Box plots for the past 50-year annual PET, ET, WYLD, air temperature, precipitation, and runoff in the cropland (BSRW) and forest land (LTRW). The numbers in the figure are the averages.

in these land uses were not statistically significant (Fig. 4g to 4j). Results show that a short-term climate impact on ET, especially in the recent 20 years, was discernable in the crop and forest lands of the YRB.

Fig. 5 shows that the 50-year (1966-2015) annual averages of PET, ET, and air temperature in the cropland were larger than those in the forest land. The averages in the crop and forest lands were, respectively, 1145 and 1068 mm for PET, 656 and 592 mm for ET, and 17 and 16  $^{\circ}$ C for air temperature. There were 7.21 and 10.81% more PET and ET, respectively, in the cropland than in the forest land. These differences were confirmed using the K-S test at a significant level of  $\alpha\,=\,0.05$ (Table 2). Results demonstrate that over the past 50 years, the cropland lost more water than that of the forest land through ET. This finding was contradicted to some consensuses that forest lands lost more water from ET than that of croplands (Allison et al., 1990; Calder, 1998; Owuor et al., 2016). Although the scientific reasons remain to be investigated, one possible explanation of the discrepancy would be the different weather conditions at different study locations. While most of their studies are focused on the semi-arid tropical and subtropical regions, this study was aimed at the humid subtropical region (i.e., YRB). In the semi-arid regions, the top-soil layers are drier and have lesser water available for crop ET, but forests have a much longer rooting-depth to uptake water from the deeper soil layers. As a result, the ET in the forest land was higher than in the cropland. In the humid subtropical regions, however, there are more amounts of precipitation and thereby more soil water available in the top-soil layers for ET. With the higher water content and air temperature in the cropland of the Mississippi alluvial plain, more ET could occur in the cropland than in the forest land.

Comparisons of the 50-year (1966 to 2015) annual averaged WYLD and precipitation between the crop and forest lands are also shown in Fig. 5. Unlike the cases of the PET, ET, and air temperature, the averaged WYLD and precipitation were smaller in the cropland than in the forest land. The averages in the crop and forest lands were, respectively, 711 and 834 mm for WYLD and 1386 and 1462 mm for precipitation. There were 17.3 and 5.481% lower WYLD and precipitation, respectively, in the cropland than in the forest land. The lower WYLD in the cropland was significant at  $\alpha = 0.05$  (Table 2) and occurred because of higher water loss from the crop ET although topography also played an important role. Additionally, the forest-dominated watershed received more precipitation than the cropland-dominated watershed (Fig. 5), which would reduce ET and increase WYLD in the forest-dominated watershed although the difference in precipitation between the cropland and forest land was statistically not significant based on the K-S test (Table 2).

**Table 2**Differences between the crop and forest lands as well as between the past and future climates for the selected hydrological variables based on the Kolmogorov-Smirnov test.

Parameter	Significance Level (α)	D Statistics	Critical Value (n-	p- value	Result	
			scaled)			
K-S test between cr	opland and forest	land for the p	eriod from 1	966 to 2015		
ET	0.05	1	0.264	0	Reject H <sub>o</sub>	
PET	0.05	0.396	0.264	4 x 10 <sup>-</sup>	Reject H <sub>o</sub>	
Air Temperature	0.05	0.717	0.264	2.065 x 10 <sup>-13</sup>	Reject H <sub>o</sub>	
Surface Runoff	0.05	1	0.264	0	Reject H <sub>o</sub>	
WYLD	0.05	0.283	0.264	0.028	Reject H <sub>o</sub>	
Precipitation	0.05	0.201	0.269	0.215	Accepted	
Number of Precipitation day	0.05	0.38	0.272	0.002	H <sub>o</sub> Reject H <sub>o</sub>	
Daily Average Solar Radiation	0.05	0.167	0.554	0.996	Accepted H <sub>o</sub>	
(MJ/m²/day) Daily Average Windspeed (m/s)	0.05	0.333	0.554	0.518	Accepted H <sub>o</sub>	
K-S test between cr	opland and forest	land for the p	eriod from 20	021 to 2070		
ET	0.05	1	0.272	0	Reject H <sub>o</sub>	
PET	0.05	0.96	0.272	0	Reject H <sub>o</sub>	
Air Temperature	0.05	0.72	0.272	8.756 x 10 <sup>-13</sup>	Reject H <sub>o</sub>	
Surface Runoff	0.05	1	0.272	0	Reject H <sub>o</sub>	
WYLD	0.05	0.4	0.272	6.0 x 10 <sup>-4</sup>	Reject H <sub>o</sub>	
Precipitation	0.05	0.16	0.272	0.549	Accepted H <sub>o</sub>	
Number of Precipitation day	0.05	0.62	0.272	8.99 x 10 <sup>-9</sup>	Reject H <sub>o</sub>	
Daily Average Solar Radiation (MJ/m²/day)	0.05	0.167	0.554	0.999	Accepted H <sub>o</sub>	
Daily Average Windspeed (m/s)	0.05	0.333	0.554	0.536	Accepted H <sub>o</sub>	
K-S test between th	e past (1966 to 2	015) and the t	future (2021	to 2070)		
ET in Cropland (BSRW)	0.05	0.981	0.268	0	Reject H <sub>o</sub>	
ET in Forest Land (LTRW)	0.05	1	0.268	0	Reject H <sub>o</sub>	
PET in Cropland (BSRW)	0.05	1	0.268	0	Reject Ho	
PET in Forest Land (LTRW)	0.05	1	0.268	0	Reject H <sub>o</sub>	
Air Temperature in Cropland	0.05	0.846	0.268	0	Reject H <sub>o</sub>	
(BSRW) Air Temperature in Forest Land	0.05	0.849	0.268	0	Reject H <sub>o</sub>	
(LTRW) Surface Runoff in cropland (BSRW)	0.05	0.286	0.268	0.018	Reject H <sub>o</sub>	
Surface Runoff in forest land (LTRW)	0.05	0.32	0.272	0.012	Reject H <sub>o</sub>	
WYLD in cropland (BSRW)	0.05	0.428	0.268	0.0001	Reject H <sub>o</sub>	
WYLD in Forest Land (LTRW)	0.05	0.487	0.268	4.254 x 10 <sup>-6</sup>	Reject H <sub>o</sub>	
	0.05	0.216	0.268	0.148 (continued of	on next page	

Table 2 (continued)

Parameter	Significance Level (α)	D Statistics	Critical Value (n- scaled)	p- value	Result
Precipitation in cropland (BSRW)					Accepted H <sub>o</sub>
Precipitation in Forest Land (LTRW)	0.05	0.195	0.268	0.24	Accepted H <sub>o</sub>
Number of Precipitation days in cropland (BSRW)	0.05	0.9	0.272	0	Reject H <sub>o</sub>
Number of Precipitation days in forest land (LTRW)	0.05	0.88	0.272	0	Reject H <sub>o</sub>
Monthly average daily solar radiation in cropland (BSRW)	0.05	0.25	0.554	0.869	Accepted H <sub>o</sub>
Monthly average daily solar radiation in forest land (LTRW)	0.05	0.25	0.554	0.869	Accepted H <sub>o</sub>
Monthly daily average windspeed in cropland (BSRW)	0.05	0.583	0.554	0.031	Reject H <sub>o</sub>
Monthly daily average windspeed in forest land (LTRW)	0.05	0.583	0.554	0.034	Reject H <sub>o</sub>

## 3.2. Future climate change impacts

Projected variations of the annual ET, WYLD, PET, air temperature and precipitation over the future 50-year simulation period from 2021 to 2070 are shown in Fig. 6. No significant temporal trend of ET was observed over the simulation period in both the crop and forest lands (Fig. 6a and 6b) although a significant increasing temporal trend of PET was found at the same simulation period and land uses (Fig. 6e and 6f). In general, PET is a measure of the atmospheric ability to remove water from a surface through the processes of evaporation and transpiration when water supply is not a limiting factor, which is positively correlated to air temperature. As the air temperature increased (Fig. 6g and 6 h), the PET in both the crop and forest lands increased. On the other hand, ET is the amount of water that is actual removed from the surface through the same processes that are controlled by water supply. As the precipitation (or water supply in this case) had no statistically significant trend (Fig. 6i and 6j), so did the ET in both the crop and forest lands. Results indicate that future climate change had a minimum effect on ET in the YRB.

Analogous to the case of ET, there was no significant temporal trend of WYLD in the crop and forest lands over the future 50 years (Fig. 6c and 5d). This occurred primarily because there were no significant temporal trends of ET (Fig. 6a and 6b) and precipitation (Fig. 6i and 6j) since the ET and precipitation are the two major factors governing the WYLD of watersheds. Results suggest that the future climate change would not affect annual WYLD in the YRB.

Fig. 6 further reveals that there was a similar annual variation pattern between the WYLD and the precipitation in the crop (Fig. 6c vs.

Fig. 6i) and forest (Fig. 6d vs. Fig. 6j) lands. A linear regression analysis shows the following two relationships:

WYLD = 
$$470 + 1.05*$$
Precipitation( $R^2 = 0.967, p < 0.001, cropland$ )
(9)

WYLD = 
$$330 + 1.04*$$
Precipitation (R<sup>2</sup> = 0.951,  $p < 0.001$ , forestland) (10

With the very good  $R^2$  and low p values, it is apparent that the annual WYLD can be approximated from the annual precipitation.

Comparisons of the future 50-year (2021–2070) annual averaged PET, ET, air temperature, WYLD and precipitation between the crop and forest lands are shown in Fig. 7. Similar to the case of the past 50-year annual averages (Fig. 5), the future averages of the PET, ET, and air temperature in the cropland were larger than those in the forest land (Fig. 7). The future averages in the cropland and forest land were, respectively, 885 and 824 mm for PET, 514 and 362 mm for ET, and 19 and 18 °C for air temperature. There were 7.4 and 41.99% more PET and ET, respectively, in the cropland than in the forest land. The differences between the cropland and forest land among the PET, ET, and air temperature were statistically significant based on the K-S test (Table 2). Results show that over the next 50 years, the cropland lost more water than that of the forest land through ET. This finding agreed to that of the past climate conditions due to the same reasons as described in Section 3.2.

Fig. 7 further reveals that the 50-year annual averaged WYLD and precipitation were smaller in the cropland than in the forest land over the future 50 years. More specifically, the averages in the crop and forest lands were, respectively, 945 and 1141 mm for WYLD and 1464 and 1527 mm for precipitation. There were 20.7% WYLD and 4.3% precipitation lower in the cropland than in the forest land although the difference was statistically significant for WYLD but not for precipitation (Table 2). The lower WYLD in the cropland primarily occurred because of higher ET.

#### 3.3. Past vs. Future climate impacts

Differences in 50-year annual averaged PET, ET, air temperatures, surface runoff, WYLD and precipitation between the past and future climate impacts can be inferred from Figs. 5 and 7. Overall, the averaged PET and ET were larger under the past climate conditions than under the future climate conditions for the same land uses. For example, the averaged ETs in the crop and forest lands were, respectively, 27.6% [(656-514)/514) = 0.276] and 63.5% [(592-362)/362) = 0.635] larger under the past climate than under the future climate conditions. The differences were statistically significant with the K-S test (Table 2). These findings contradicted to our consensus that the averaged ET and PET will increase in watersheds as the future averaged air temperature and precipitation increase. In this study, while future averaged precipitation in both the crop and forest lands increased as compared to those of the past (but not statistically significant, Table 2), the future averaged surface runoffs in both the crop and forest lands also increased as compared to those of the past (statistically significant, Table 2). The annual averaged surface runoffs in the cropland and forest land were, respectively, 27% [(631–499)/499) = 0.54] and 33% [(52–39)/39) = 0.33] larger under the future climate than under the past climate conditions. These larger future surface runoffs reduced soil water storage and provided less soil water for the future ET. The higher future surface runoffs in both the crop and forest lands could be the result of the larger number of precipitation days under the future climate than under the past climate conditions (Fig. 8). In this study, the number of precipitation days were the days when the precipitation events occurred regardless of their duration and intensity. There were 59 (i.e., 273 - 214 = 59) and 55 (i.e., 254 - 199 = 55) more precipitation days, respectively, in the crop and forest lands under the future climate than under

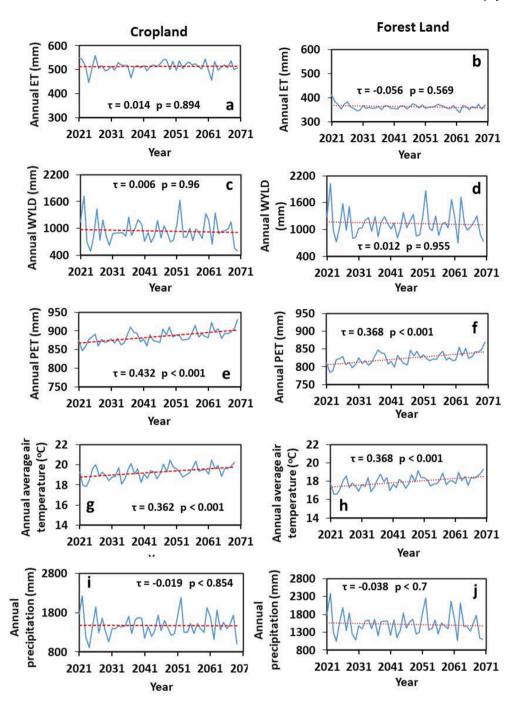


Fig. 6. Annual ET, WYLD, PET, and precipitation over the future 50-year period from 2021 to 2070 in the cropland (BSRW) and forest land (LTRW) along with Mann Kendall analysis.

the past climate conditions. Additionally, the lower monthly averaged solar radiation (not significant, Table 2) and windspeed (significant, Table 2) under the future climate conditions (Fig. 8b) also decreased the future PET and ET as compared to those of the past (Fig. 8a).

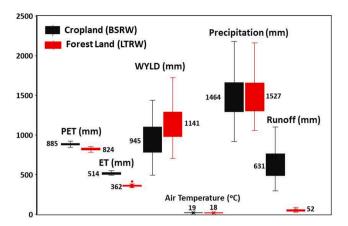
In contrast, the opposite was true for the WYLD and precipitation. That is, the 50-year annual averaged WYLD and precipitation were larger under the future climate than under the past climate conditions in the crop and forest lands. For instance, the averaged WYLDs in the crop and forest lands were, respectively, 32.9 and 26.9% larger under the future climate than under the past climate conditions. Parallel to the case of WYLD, the averaged precipitations in the crop and forest lands were, respectively, 5.6 and 4.3% larger under the future climate than under the past climate conditions. This finding was consistent with the

report that climate change resulted in precipitation anomaly in the contiguous 48 States of US with more extreme wet than dry conditions since 1990 (US-EPA, 2021). As the future precipitation increased and ET decreased, more WYLD was produced in the YRB.

## 4. Conclusions

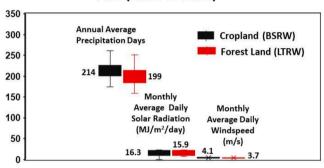
No temporal trend of ET was found under the long-term past and future climate conditions, but a significant increasing trend of ET was observed in the recent 20 years (1997 to 2017) in both the crop and forest lands.

There were more ET and less WYLD in the cropland than in the forest land over the past 50 years (1966-1985) and future 50 years



**Fig. 7.** Box plots for the future 50-year annual PET, ET, WYLD, air temperature, precipitation, and runoff in the cropland (BSRW) and forest land (LTRW). The numbers in the figure are the averages.

## Past (1966 to 2015)



## Future (2021 to 2070)

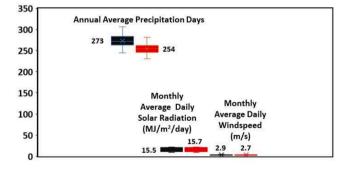


Fig. 8. Box plots of annual average number of precipitation days, and monthly average daily solar radiation and windspeed.

(2021–2070). In a long-range, the forest land reduced ET and increased WYLD as compared to those of the cropland in the Yazoo River Basin (a humid subtropical region).

There was a very good linear relationship between the annual WYLD and the annual precipitation in both the crop and forest lands and thus the annual WYLD can be approximated from the annual precipitation. The past and future annual average air temperatures were approximately 1  $^{\circ}\text{C}$  cooler in the forest land than in the cropland.

The 50-year annual averaged PET and ET were larger under the past climate than under the future climate conditions in both the crop and forest lands. The possible reasons of this phenomenon are: (1) the future number of precipitation days were larger than those of the past in the crop and forest lands, which created the larger future surface water runoff and provided less water for ET, and (2) the solar radiation and

windspeed under the future climate conditions were lower than those of the past, which reduced the future PET as compared to that of the past.

The Penman-Monteith method was used to estimate PET in this study. Recent reports show that this method may overestimate the ET because it neglects the impact of atmospheric  $\mathrm{CO}_2$  concentrations under the non-water stress conditions. A higher atmospheric  $\mathrm{CO}_2$  concentration decreases water loss by reducing plant stomatal conductance (Yang et al., 2019). Further study is therefore warranted to tackle on this issue. For a comprehensive understanding of land use impacts on ET and WYLD, further study is warranted to synthesize the past studies on these two variables at different geographical and climate regions.

#### CRediT authorship contribution statement

**Ying Ouyang:** Conceptualization, Methodology, Validation, Data curation, Writing – original draft, Writing – review & editing.

## **Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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