

Assessing the hydrologic and water quality impacts of biofuel-induced changes in land use and management

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Abstract

The Southern High Plains (SHP) of Texas, where cotton (*Gossypium hirsutum* L.) is grown in vast acreage, and the Texas Rolling Plains (TRP), which is dominated by an invasive brush, honey mesquite (*Prosopis glandulosa*) have the potential for biofuel production for meeting the U.S. bioenergy target of 2022. However, a shift in land use from cotton to perennial grasses and a change in land management such as the harvesting of mesquite for biofuel production can significantly affect regional hydrology and water quality. In this study, APEX and SWAT models were integrated to assess the impacts of replacing cotton with Alamo switchgrass (*Panicum virgatum* L.) and *Miscanthus* × *giganteus* in the upstream subwatershed and harvesting mesquite in the downstream subwatershed on water and nitrogen balances in the Double Mountain Fork Brazos watershed in the SHP and TRP regions. Simulated average (1994–2009) annual surface runoff from the baseline cotton areas decreased significantly ($P < 0.05$) by 88%, and percolation increased by 28% under the perennial grasses scenario compared to the baseline cotton scenario. The soil water content enhanced significantly under the irrigated switchgrass scenario compared to the baseline irrigated cotton scenario from January to April and August to October. However, the soil water content was depleted significantly under the dryland *Miscanthus* scenario from April to July relative to the baseline dryland cotton scenario. The nitrate-nitrogen ($\text{NO}_3\text{-N}$) and organic-N loads in surface runoff and $\text{NO}_3\text{-N}$ leaching to groundwater reduced significantly by 86%, 98%, and 100%, respectively, under the perennial grasses scenario. Similarly, surface runoff, and $\text{NO}_3\text{-N}$ and organic-N loads through surface runoff reduced significantly by 98.9%, 99.9%, and 99.5%, respectively, under the post-mesquite-harvest scenario. Perennial grasses exhibited superior ethanol production potential compared to mesquite. However, mesquite is an appropriate supplementary bioenergy source in the TRP region because of its standing biomass and rapid regrowth characteristics.

Keywords: Agricultural Policy/Environmental eXtender, biomass, honey mesquite, *Miscanthus*, Soil and Water Assessment Tool, Southern High Plains of Texas, switchgrass, Texas Rolling Plains

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Introduction

The U.S. agriculture is facing an unprecedented challenge in securing the nation's energy future in addition to meeting the traditional goal of food security. According to the current Renewable Fuels Standard Program (RFS2), the volume of renewable fuel required to be blended into transportation fuel will be 136 million m^3 by 2022 (U.S. Department of Agriculture; USDA, 2010). As one of the world's largest food producer, exporter, and donor, the U.S. plays a vital role in addressing these challenges. Further increase in crop production or change in land use will be needed for meeting these

challenges in the coming years. Since the industrial revolution, human actions (including agriculture) have become a major driving factor for global environmental change, land and water degradation, and biodiversity loss (Rockström *et al.*, 2009; Foley *et al.*, 2011). As a result, agriculture must address its environmental consequences as it seeks to meet the aforementioned food security and renewable fuel challenges.

There are two general types of renewable biofuels. First-generation biofuels are usually produced through intensive agricultural activities, which are similar to those used in growing primary food crops such as maize (*Zea mays* L.) and grain sorghum (*Sorghum bicolor* (L.) Moench). Production of first-generation biofuels potentially competes with the production of food. Thus, if the production of first-generation biofuels rises to certain levels, there can be detrimental social consequences

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in the form of reduced food supplies and associated increases in commodity prices that can be passed on to consumers. As intensive agricultural activities typically utilize more resources (prime farmland, irrigation water, fertilizers and pesticides, and fuel for farming operations), there can be increased negative environmental effects associated with the production of first-generation biofuels. To address these concerns, the USDA recommended that of the targeted production of 136 million m³ of biofuels by 2022, 76 million m³ should be produced from cellulosic and other advanced biofuel feedstocks (USDA, 2010). Cellulosic biofuels, which are also called second-generation biofuels, are primarily made from the by-products of intensive agricultural activities or from less-intensive agricultural activities performed on nonfood croplands using substantially reduced resource inputs.

The Southern High Plains (SHP) of Texas in the United States is one of the most intensively managed cotton-growing regions in the world. The cotton planting area in the SHP accounted for approximately 31% of the entire U.S. cotton acreage in 2015 (National Agricultural Statistics Service; NASS, 2015). The Ogallala Aquifer is the primary source of irrigation water for this region. Intensive agricultural production in the SHP since 1950s has resulted in a continuous decline of groundwater levels and deterioration of groundwater quality, mainly due to high concentrations of nitrate nitrogen (NO₃-N) (Chaudhuri & Ale, 2014a,b). The land use change from high water- and N-consuming crops such as cotton to more water- and nitrogen-use-efficient perennial grasses such as Alamo switchgrass (*Panicum virgatum* L.) and *Miscanthus × giganteus* may benefit this region by prolonging the availability of groundwater and improving groundwater quality. Using the Soil and Water Assessment Tool (SWAT), Cibirin *et al.* (2016) simulated a reduction in annual surface runoff by about 12% and 15% under the *Miscanthus* and switchgrass land use scenarios, respectively, compared to the baseline corn/soybean land use in the Wildcat Creek watershed in Indiana. In another SWAT simulation study, Ng *et al.* (2010) showed that a 10% change in land use from cropland to *Miscanthus* would decrease the NO₃-N load in streamflow by about 6.4% at the outlet of the Salt Creek watershed in Illinois. Sarkar & Miller (2014) also predicted from a SWAT modeling study that the loss of N to surface runoff from switchgrass systems was approximately 73% lower than that from cotton systems in the Black Creek watershed in South Carolina. Through a GIS-based approach, Rao & Yang (2010) predicted that the increase in the extent of grassland could significantly increase groundwater recharge and thereby decrease the groundwater level decline rates, especially in the environmentally sensitive Texas High Plains (THP) region.

Honey mesquite (*Prosopis glandulosa*) is a polymorphic woody legume that invaded grasslands and rangelands in the Southwestern United States, and it is spread over 21 million ha in Texas alone (SCS, 1988; Asner *et al.*, 2003). It has been recognized as a bioenergy feedstock (Padron & Navarro, 2004; Singh *et al.*, 2007; Ansley *et al.*, 2010; Wang *et al.*, 2014), and it is grown under a vast acreage in the Texas Rolling Plains (TRP), which is adjacent to the SHP. The invasion of honey mesquite on grasslands of the TRP caused several negative impacts such as increasing the extent of bare ground and thereby increasing erosion potential, and reducing herbaceous production, which is harmful to the livestock industry and grassland ecosystems (Teague & Dowhower, 2003; Ansley *et al.*, 2010; Wang *et al.*, 2014). Mesquite harvest may not only supply feedstock for biofuel production, but also help in the recovery of grassland functions. Park *et al.* (2012) also reported that honey mesquite has the potential for use as bioenergy feedstock given its high density and presence in large extent of area in the TRP.

The SWAT model (Arnold *et al.*, 1998) and the Agricultural Policy/Environmental eXtender (APEX) model (Williams, 1995), which are widely used across the world, have demonstrated potential to satisfactorily predict long-term impacts of land use change and land management practices on hydrologic processes and water quality in complex watersheds (Ko *et al.*, 2009; Gassman *et al.*, 2010; Ghaffari *et al.*, 2010; Srinivasan *et al.*, 2010; Tuppad *et al.*, 2010; Powers *et al.*, 2011; Wu & Liu, 2012). Specifically, the APEX model has the capability to accurately predict hydrology and water quality in intensively managed agricultural watersheds with large extents of irrigated areas (Saleh & Gallego, 2007; Wang *et al.*, 2011; Jung *et al.*, 2014). The auto-irrigation function included in the APEX model simulates irrigation water as the precipitation, which results in a realistic simulation of percolation during the irrigation process. In contrast, auto-irrigation feature in the SWAT model applies irrigation water until the soil moisture content reaches the field capacity level, and hence, the model, in general, simulates negligible percolation during irrigation events. In addition, the APEX model includes detailed cotton growth parameters, which are very useful for accurate prediction of cotton growth. Furthermore, APEX outputs both cotton lint and seed yields, and it permits specifying disease severity and plant population. As for the SWAT model, it provides reasonable crop management functions for satisfactorily simulating range grass and honey mesquite land uses. For example, the SWAT model allows users to input initial biomass for honey mesquite (tree crop in the crop database), which eliminates the need to grow honey mesquite from seed at the beginning of the simulation.

The SWAT model also simulates reservoir operations accurately using four different methods when compared to the APEX model. While the SWAT model allows users to input daily observed reservoir releases, the APEX model allows inputting an average annual reservoir release only. Therefore, the APEX and SWAT models were integrated in this study (hereafter referred as 'Integrated APEX-SWAT model') to make use of the strengths of both models.

A majority of the published biofuel-induced water quantity and quality studies were conducted in the watersheds located in the humid regions of the United States such as the Upper Mississippi River Basin (Daloğlu *et al.*, 2012; Demissie *et al.*, 2012; Scherer *et al.*, 2015). However, such assessments are limited in the semi-arid SHP and TRP regions. The objectives of this study were: (1) to assess the impacts of biofuel-induced land use change from cotton to perennial bioenergy crops such as switchgrass and *Miscanthus*, and the harvest of mesquite for biofuel use on hydrology and water quality in the semi-arid Double Mountain Fork Brazos watershed that spans across the SHP and TRP regions using the Integrated APEX-SWAT model; (2) to estimate the biomass and biofuel production potential of three bioenergy crops considered in this study; and (3) to compare and contrast the effects of the proposed changes in land use on water and N balances under irrigated and dryland conditions.

Materials and methods

Study watershed

The delineated area of the Double Mountain Fork Brazos watershed is about 6000 km² (Fig. S1). The areas of the upstream subwatershed (upstream of Gauge I) and the downstream subwatershed (downstream of Gauge I and upstream of Gauge II) are about 3297 and 2703 km², respectively. The upstream subwatershed is located in the Hockley, Lynn, and Garza counties (Fig. S1), where cotton is the dominant land use (Fig. 1). The downstream subwatershed, which is primarily composed of rangelands (Fig. 1), is situated in Scurry, Kent, and Stonewall counties. The long-term (1981–2010) average annual rainfall across the watershed varies between 457 and 559 mm, and the long-term average annual maximum and minimum temperatures are about 24 °C and 9 °C, respectively. The topography of the watershed is relatively flat. The major soil types in the watershed are classified as Amarillo sandy loam, Acuff sandy clay loam, and Olton clay loam (Soil Survey Staff, 2010).

Description of SWAT and APEX models

SWAT is a continuous-time, semidistributed, process-based, river basin scale model (Arnold *et al.*, 2012). It divides a

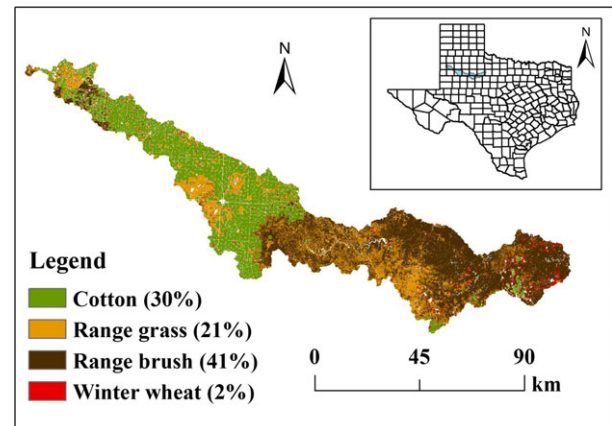


Fig. 1 Major land uses in the study watershed according to the 2008 National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL).

watershed into a number of subwatersheds, which are further divided into several hydrologic response units (HRUs). HRUs are the basic building blocks of the SWAT model from which all landscape processes are computed. They consist of homogeneous land use, soil characteristics, and soil slope. SWAT is operated on a daily time step, and it is widely proven to be a feasible tool to predict the impact of land use management on water, sediment, and agricultural chemical yields (Gassman *et al.*, 2014). A large number of input parameters are needed for SWAT to evaluate the effects of land use change or management practices on hydrology and water quality. The primary model components in SWAT relate to hydrology, water quality, and crop growth (Knisel, 1980; Leonard *et al.*, 1987; Williams *et al.*, 2008). Major model inputs are related to hydrography, terrain, land use, soil, tile drainage, weather, and management practices (Srinivasan *et al.*, 2010). Additional details about the SWAT model can be found in Arnold *et al.* (2012).

In this study, ArcSWAT 2012.10_2.16 (Revision 627) for ArcGIS 10.2.2 platform was used. The SWAT Calibration and Uncertainty Procedures (SWAT-CUP) tool (Abbaspour *et al.*, 2007) was used for the sensitivity analysis, and calibration and validation of the SWAT model. The Sequential Uncertainty Fitting version-2 (SUFI-2) procedure (Abbaspour *et al.*, 2007) available in SWAT-CUP 2012 was used to estimate various SWAT parameters related to streamflow and N load.

APEX model is a flexible and dynamic tool that is used for simulating management and land use change impacts on hydrology and water quality for whole farms and small watersheds (Williams, 1995; Williams *et al.*, 2008). The APEX model divides a watershed into a number of subareas, which have the same function as the SWAT HRUs. The APEX model consists of 12 major components: climate, hydrology, crop growth, pesticide fate, nutrient cycling, erosion–sedimentation, carbon cycling, management practices, soil temperature, plant environment control, economic budgets, and subarea/routing (Golmohammadi *et al.*, 2014). More details about the APEX model components can be found in Williams (1995), Tuppad *et al.* (2009), and Wang *et al.* (2012). The ArcAPEX model (version

0806), which was interfaced with ArcGIS 10.2.2 platform, was used in this study.

SWAT and APEX models' setup and integration

The DEM (30 × 30 m) of the study watershed was downloaded from the U.S. Geological Survey (<http://viewer.nationalmap.gov/viewer/#>) and input to the Integrated APEX-SWAT model. The 2008 NASS Cropland Data Layer (CDL) (<http://na.ssgeddata.gmu.edu/CropScape/>) was used to represent the prevalent land use conditions during the period of model simulations (1994 to 2009). The dominant agricultural land use in the watershed in 2008 was cotton, which occupied about 30% of the entire watershed area, and about 52% of the upstream subwatershed (Fig. 1). About 41% and 21% of the entire watershed area were covered by range brush and range grass, respectively. The soil data were obtained from the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff, 2014), which was compatible with the Integrated APEX-SWAT model. Four soil slopes were considered: ≤1%, 1–3%, 3–5%, and >5%. Daily weather data from a total of seven weather stations for the period from 1992 to 2009 were obtained from the National Climatic Data Center (NCDC) and used in this study (Fig. S1) (NOAA-NCDC, 2014). The missing weather data for a weather station were filled with the average value of weather parameter for two adjacent weather stations (Ale *et al.*, 2009). More detailed information for the model setup can be found in Chen *et al.* (2016a,b). For the HRU and subarea definitions, thresholds of 5%, 5%, and 10% were used for land use, soil type, and slope, respectively. A total of 25 APEX subareas were delineated in the upstream subwatershed, and 35 SWAT subbasins and 1417 HRUs were identified in the downstream subwatershed.

The Alan Henry Reservoir (storage capacity: $4882 \times 10^4 \text{ m}^3$) exists in the downstream subwatershed. The SWAT parameters related to the operation of this reservoir were obtained from the Texas Water Development Board's report on 'Volumetric Survey of Alan Henry Reservoir' (Texas Water Development Board, 2005). The 'Measured Daily Outflow' method available in the SWAT model was used to estimate the reservoir discharge based on the reservoir storage levels recorded by the

USGS gauge. More details about the parameters used for reservoir simulation are provided in Chen *et al.* (2016a).

As described earlier, the APEX model is capable of simulating croplands better when compared to the SWAT model, and on the other hand, SWAT performs better in simulating non-croplands and transport of flow, sediment, and nutrients through detailed in-stream channel and reservoir processes (Santhi *et al.*, 2014). To take advantage of the strengths of APEX and SWAT models, the APEX model was integrated with SWAT model in this study. Initially, the APEX model was set up for the upstream subwatershed (Fig. 2), where cotton was the dominant land use. The SWAT model was then set up for the entire watershed, and the upstream subwatershed was simulated as one subbasin in the SWAT model. The APEX-simulated net flows, and sediment and nutrient loads were then input as a point source to the SWAT model at Gauge I (outlet of the upstream subwatershed). The downstream subwatershed, which is dominated by the range land use and contains the Alan Henry Reservoir, was therefore essentially modeled using the SWAT model. Although measured streamflow data were available at both Gauge I and Gauge II in the watershed, measured data on N concentration in streamflow were available at Gauge II (watershed outlet) only, and hence, this integration of two models enabled assessment of water quality effects of proposed land use change and mesquite harvest from the entire 6000-km² watershed.

Management practices of crops in the study watershed

The management-related parameters for cotton were specified based on the locally followed practices. Spring tillage was implemented for cotton (Table S1). About 138 and 69 kg N ha⁻¹ were applied to the irrigated and dryland cotton, respectively. According to the NASS county-wise cotton acreage estimates over the period from 1994 to 2009 (NASS, 2015), about 39% of the cotton acreage in the watershed was irrigated. Remote sensing images were used to identify irrigated subareas. Subareas that contain large number of circular fields, which represent center pivot irrigated areas, were considered as irrigated subareas. It was also made sure that the total extent of irrigated cotton area was about 39% of the entire

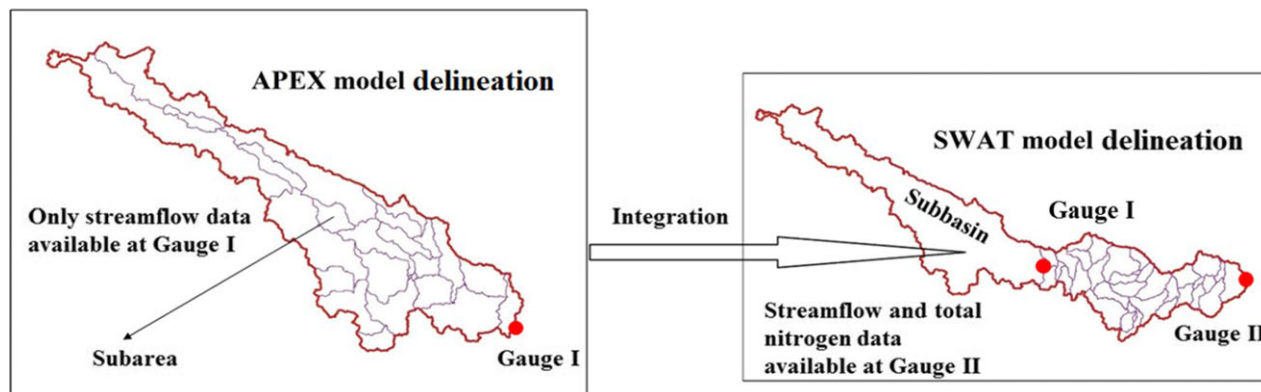


Fig. 2 Illustration showing the APEX model integration with the SWAT model.

cotton-growing areas in the watershed. Auto-irrigation was therefore simulated in about 39% of cotton planting area in the watershed based on plant water stress.

The land uses of range grass and range brush were simulated as Southwestern U.S. range and honey mesquite, respectively. The most commonly adopted heavy continuous grazing management practice was simulated on the range grassland (Park *et al.*, 2017). The detailed management-related parameters for the range grass were set up according to Park *et al.* (2017) (Table S1). Biomass of honey mesquite at the beginning of the simulation was assumed as 19.4 Mg ha⁻¹ (Whisenant & Burzlaff, 1978) (Table S1).

Observed streamflow, cotton lint yield, and water quality data used for model calibration

Observed daily streamflow recorded at Gauge I and Gauge II during the period from 1994 to 2009 was obtained from the USGS National Water Information System (<http://waterdata.usgs.gov/nwis/sw>). The observed dryland and irrigated cotton lint yield data over the period from 1994 to 2009 for Lynn County, the county with the highest cotton acreage in the study area, were obtained from the NASS reports (<http://quickstats.nass.usda.gov/>). The instantaneous total nitrogen (TN) concentration data measured at the watershed outlet at Gauge II on some specific days (from a total of 39 grab samples) (Fig. S2) were used for model water quality calibration. These concentrations were used to estimate continuous daily TN loads using the USGS Load Estimator (LOADEST) regression model (Runkel *et al.*, 2004). A detailed description of LOADEST can be found in Jha *et al.* (2007). The estimated daily TN load data were distributed over 1995–2000 period.

Integrated APEX-SWAT model calibration

The APEX model was initially calibrated against observed streamflow and cotton lint yield data for the upstream subwatershed (Chen *et al.*, 2016b). As the observed N load data were not available for this upstream subwatershed, the APEX model was integrated with the SWAT model and the net flow, and sediment and nutrient loads from the upstream subwatershed were input as a point source to the downstream subwatershed at Gauge I (Fig. 2). The Integrated APEX-SWAT model was then calibrated against the observed streamflow data at Gauge II by solely adjusting SWAT model parameters in the downstream subwatershed. The calibration and validation periods considered for streamflow prediction were 1994–2001 and 2002–2009, respectively. After achieving a satisfactory streamflow calibration, the Integrated APEX-SWAT model was calibrated for the TN load prediction by changing the water quality parameters of both APEX (in the upstream subwatershed) and the SWAT (in the downstream subwatershed) models. Based on the available data, 1995–1997 and 1998–2000 periods were considered as the calibration and validation periods for TN, respectively. The calibrated Integrated APEX-SWAT model was then used to simulate the impacts of land use change from cotton to perennial grasses, and mesquite harvest on water and N balances. The values of calibrated

parameters related to hydrology, crop growth, and water quality are shown in Table S2.

The performance of the Integrated APEX-SWAT model in predicting streamflow and water quality during the calibration and validation periods was evaluated using three different statistical measures: square of Pearson's product-moment correlation coefficient (R^2) (Legates & McCabe, 1999), Nash–Sutcliffe efficiency (NSE) (Nash & Sutcliffe, 1970), and percent bias ($PBIAS$). The goal of calibration for monthly streamflow and water quality predictions was to achieve all three objective functions: minimize $PBIAS$, maximize NSE , and maximize R^2 . We aimed to achieve $NSE \geq 0.60$, $R^2 \geq 0.65$, and $PBIAS$ within $\pm 15\%$ in monthly streamflow, and $NSE \geq 0.60$, $R^2 \geq 0.65$, and $PBIAS$ within $\pm 40\%$ in monthly TN load. The model performance in cotton lint yield prediction was assessed using R^2 and $PBIAS$ only, and we aimed to achieve a $PBIAS$ within $\pm 10\%$ in average annual cotton lint yield under both irrigated and dryland conditions. Statistical analyses of the scenario analysis results were carried out using the Statistical Package for Social Science (SPSS 19.0). Analysis of variance (ANOVA) was used to test the difference with significance levels set at $P < 0.05$ or $P < 0.1$. Microsoft Excel 2013 was used for other data analysis.

Scenario analysis

In this study, switchgrass and *Miscanthus*, which were identified as ideal bioenergy grasses for this study region (Chen *et al.*, 2016a), were selected to hypothetically replace irrigated and dryland cotton areas, respectively. Honey mesquite, which was dominant in the range brush areas, was also considered as the bioenergy crop. Although honey mesquite harvest was recommended at a ten-year interval (Wang *et al.*, 2014), a nine-year harvest interval was assumed in this study so that it could be harvested twice (in 2000 and 2009) over the total simulation period of 18 years. In addition, standing honey mesquite biomass of 19.4 Mg ha⁻¹ was harvested in 1992, at the beginning of the simulation period.

The Integrated APEX-SWAT model simulations were run from 1992 to 2009, and the 1992–1993 period was considered as the model warm-up period. The impacts of hypothetical biofuel-induced land use change and mesquite harvest on hydrology and water quality under simulated scenarios were evaluated over the remaining simulation period from 1994 to 2009. The land use change effects under both irrigated and dryland conditions were compared and contrasted.

Perennial grasses were planted on May 15, 1992, and harvested once every year on November 15 (Table S3). Irrigated switchgrass was assigned the same irrigation management practices as irrigated cotton. A recommended fertilizer application rate of about 124 kg N ha⁻¹ was applied for irrigated switchgrass (Yimam *et al.*, 2014). About 98 kg N ha⁻¹ was applied to dryland *Miscanthus* (Lewandowski & Schmidt, 2006; Danalatos *et al.*, 2007) (Table S3). No fertilizer was applied to honey mesquite. Tillage was not simulated under any of these hypothetical scenarios. Heat units to maturity of all simulated crops were estimated using the SWAT Potential Heat Unit (SWAT-PHU) program (<http://swat.tamu.edu/software/pote>

ntial-heat-unit-program/) (Tables S1 and S3). As crop growth parameter values for *Miscanthus* were not available in the models' crop database, the values from Trybula *et al.* (2015) field study were adopted.

Results

Integrated APEX-SWAT model calibration and validation results

The simulated monthly streamflow at the watershed outlet (Gauge II) during the calibration (1994–2001) and validation (2002–2009) periods closely matched with the observed streamflow (Fig. S3). The *NSE*, *R*², and *PBIAS* values for monthly predictions of streamflow were 0.64, 0.67, and 10.7%, respectively, during the calibration period, and they were 0.60, 0.65, and −9.3%, respectively, during the validation period. These values demonstrate a 'satisfactory' agreement between the simulated and observed streamflow according to the Moriasi *et al.* (2007) criteria. The *PBIAS* in predicting dryland and irrigated cotton lint yields over the entire simulation period (1994–2009) was about 0.1% and 0.7%, respectively, indicating a good overall match between the simulated and observed yields.

The simulated monthly TN load and the LOADEST estimated load during the calibration (1995–1997) and validation (1998–2000) periods also matched well as shown in Fig. S4. The *NSE* for monthly TN load prediction was 0.70 and 0.65 during the calibration and validation periods, respectively. The *PBIAS* in predicting TN load was −20.4% and 34.8% for the calibration and validation periods, respectively. The model performance ratings for the monthly TN load predictions were considered as 'satisfactory' for both the calibration and validation periods based on the *NSE* and *PBIAS* values, according to Moriasi *et al.* (2007) and Wang *et al.* (2012) criteria.

Simulated water and N mass balances in the upstream subwatershed under the baseline cotton scenario

The primary component of water balance in the upstream subwatershed, which is dominated by cropland, is the evapotranspiration (ET). Results showed that approximately 89% and 95% of the average annual (1994–2009) input water (precipitation + irrigation) was lost due to ET in the irrigated and dryland conditions, respectively, under the baseline cotton scenario (Table 1). Less than 1% of the input water yielded as surface runoff under the baseline cotton scenario in both the irrigated and dryland conditions (Table 1). Average annual percolation accounted for approximately 10% and 4% of the total water input under the baseline

Table 1 Hydrologic and water quality impacts of land use change from irrigated cotton to irrigated switchgrass, and dryland cotton to dryland *Miscanthus* in the upstream subwatershed

Irrigated and dryland areas combined	Cotton (baseline)	Perennial grasses	Change (%)
Precipitation (mm)	490.4	490.4	–
Irrigation (mm)	189.0	198.9	5.2
ET (mm)	624.1	626.0	0.3
Surface runoff (mm)	6.1	0.7	−88.1**
Percolation (mm)	47.0	60.3	28.1
NO ₃ -N load in surface runoff (kg ha ^{−1})	0.11	0.01	−86.3**
Organic-N load in surface runoff (kg ha ^{−1})	0.21	0.003	−98.4**
NO ₃ -N leaching (kg ha ^{−1})	9.43	0.05	−99.5**
Irrigated areas	Irrigated cotton	Irrigated switchgrass	Change (%)
Precipitation (mm)	481.2	481.2	–
Irrigation (mm)	484.5	509.9	5.2
ET (mm)	863.7	841.3	−2.6
Surface runoff (mm)	8.2	1.0	−87.3**
Percolation (mm)	92.3	147.6	59.9*
NO ₃ -N load in surface runoff (kg ha ^{−1})	0.16	0.04	−77.5**
Organic-N load in surface runoff (kg ha ^{−1})	0.26	0.001	−99.5**
NO ₃ -N leaching (kg ha ^{−1})	21.03	0.12	−99.4**
Dryland areas	Dryland cotton	Dryland <i>Miscanthus</i>	Change (%)
Precipitation (mm)	496.3	496.3	–
ET (mm)	472.5	489.6	3.6
Surface runoff (mm)	4.7	0.5	−88.9**
Percolation (mm)	18.4	4.9	−73.1
NO ₃ -N load in surface runoff (kg ha ^{−1})	0.08	0.002	−97.7**
Organic-N load in surface runoff (kg ha ^{−1})	0.18	0.005	−97.4**
NO ₃ -N leaching (kg ha ^{−1})	2.08	0.01	−99.7*

**A significant difference at *P* < 0.05; *A significant difference at *P* < 0.1.

cotton scenario in the irrigated and dryland conditions, respectively (Table 1).

The simulated N mass balance under the baseline cotton scenario is shown in Table 2. On average, approximately 48% of the N inputs remained in soil under the baseline irrigated cotton scenario with 27% of N inputs taken up by the harvested portion of cotton and 13% leached to groundwater. Bronson *et al.* (2004) reported that the TN content of surface soil (0 to 10 cm) in some fields within our study watershed in 2001 was about 479 kg ha^{−1} under the long-term irrigated cotton land

Table 2 Simulated average (1994–2009) annual nitrogen mass balances (kg N ha^{-1}) of the upstream subwatershed under cotton and perennial grass land uses

Land use	Nitrogen (N) inputs		Nitrogen outputs							Change in soil N
	N fertilizer	N in rainfall	N in runoff	N in return flow	N in sediment	N leaching	Denitrification	Volatilization	N uptake by harvested portion	
Irrigated cotton	138	4.0	0.15 (0.11)*	6.2 (4.4)	0.25 (0.2)	18.8 (13.2)	0.49 (0.3)	9.36 (6.6)	38.34 (27.0)	68.28 (48.1)
Dryland cotton	69	4.0	0.08 (0.11)	0.62 (0.8)	0.18 (0.2)	1.9 (2.6)	0.09 (0.1)	5.32 (7.3)	18.18 (24.9)	46.37 (63.5)
Irrigated switchgrass	124	4.0	0.03 (0.02)	0.09 (0.1)	0.001 (0.001)	0.28 (0.2)	2.50 (2.0)	5.98 (4.7)	122.14 (95.4)	-3.02 (-2.4)
Dryland <i>Miscanthus</i>	98	4.0	0.002 (0.002)	0.009 (0.004)	0.004 (0.004)	0.026 (0.03)	0.74 (0.7)	4.57 (4.5)	58.52 (57.4)	38.13 (37.4)

*The numbers in the parentheses indicate the percentages of total nitrogen inputs that were either lost in different pathways or accumulated in soil.

use. At the same sampling locations, Zobeck *et al.* (2007) further documented that the soil TN content in 0–10 cm soil profile in 2003 was about 590 kg ha^{-1} under the long-term irrigated cotton land use. They found that about 56 kg ha^{-1} TN was accumulated in the soil each year under the irrigated cotton production. The simulated annual soil TN accumulation under the baseline irrigated cotton scenario in our study (about 68 kg ha^{-1} ; Table 2) was comparable to the value reported in the above studies. The simulated average annual total N uptake by the irrigated cotton in our study (about 189 kg ha^{-1} ; Table 2) was also comparable to the measured N uptake of 168 kg ha^{-1} by cotton, which was irrigated at 75% ET replacement in a field study by Li & Lascano (2011) in the SHP. Under the baseline dryland cotton scenario, approximately 64%, 25%, and 3% of N inputs were accumulated in soil, taken up by the harvested portion of cotton, and leached to groundwater, respectively (Table 2). The simulated total N uptake during the period of simulation (1994–2009) ranged from 56 to 152 kg ha^{-1} under the baseline dryland cotton scenario. Mullins & Burmester (1990) also documented that the total N uptake by dryland cotton ranged from 127 to 155 kg ha^{-1} in their field experiments conducted in Alabama in 1986 and 1987.

Biomass and biofuel availability from the changes in watershed land use and management

The simulated average annual harvestable biomass under the irrigated switchgrass, dryland *Miscanthus*, and honey mesquite scenarios was 17.3, 15.7, and 4.0 Mg ha^{-1} , respectively (Table 3). The APEX-simulated annual irrigated switchgrass and dryland *Miscanthus* biomass yields in this study were similar to those simulated by the SWAT model (17.5 and 15.6 Mg ha^{-1} biomass of irrigated switchgrass and dryland *Miscanthus*, respectively) in this watershed (Chen *et al.*, 2016a). The predicted annual *Miscanthus* biomass yield under the dryland conditions in this study was also within the range of reported *Miscanthus* biomass yield (9.8 – 17.8 Mg ha^{-1}) in the dryland production conditions in the U.K. (Christian *et al.*, 2008).

The crop database of honey mesquite was adjusted based on the studies of Kiniry (1998) and Ansley *et al.* (2010) in Texas to match the simulated biomass with the observed biomass in the TRP region (Table S2). The simulated total tree biomass of a 30-year-old honey mesquite plant in this study was about 40 Mg ha^{-1} , which was comparable to the measured biomass of 43 Mg ha^{-1} in a field study in the TRP (Ansley *et al.*, 2010). In addition, the predicted total tree biomass of a nine-year-old regrown honey mesquite was the same (28 Mg ha^{-1}) as that reported in Ansley *et al.* (2010).

Table 3 Average (1994–2009) annual biomass and biofuel production of irrigated switchgrass, dryland *Miscanthus*, and honey mesquite

Annual production	Harvestable biomass (Mg ha ⁻¹)	Biofuel conversion efficiency (liters ethanol Mg ⁻¹ biomass)*	Biofuel production (liters ethanol ha ⁻¹)
Irrigated switchgrass	17.3	366	6332
Dryland <i>Miscanthus</i>	15.7	366	5746
Honey mesquite	4.0	309	1246

*The theoretical ethanol yield data was taken from http://www.afdc.energy.gov/fuels/ethanol_feedstocks.html.

The simulated annual regrowth rate was about 2.4 Mg ha⁻¹ for honey mesquite in this study. Ansley *et al.* (2010) and Wang *et al.* (2014) also documented a similar annual production rate of honey mesquite of 2.2 Mg ha⁻¹. According to the suggested theoretical ethanol yield (<http://www.afdc.energy.gov/fuels/ethanolfeedstocks.html>), the estimated average annual ethanol that could be produced with the simulated biomass of irrigated switchgrass, dryland *Miscanthus*, and honey mesquite was 6332, 5746, and 1246 L ha⁻¹, respectively (Table 3).

Impacts of biofuel-induced land use change and mesquite harvest on hydrology

The average (1994–2009) annual surface runoff from the upstream subwatershed decreased significantly ($P < 0.05$) by 88% under the perennial grasses scenario (i.e., irrigated cotton replaced by switchgrass and dryland cotton replaced by *Miscanthus*) compared to the baseline cotton scenario (Table 1). The annual percolation increased significantly ($P < 0.1$) by approximately 60% under the irrigated switchgrass scenario, and it decreased by approximately 73% under the dryland *Miscanthus* scenario relative to the baseline cotton scenario (Table 1). Overall, under the perennial grasses scenario, the average annual percolation in the upstream

subwatershed increased by 28% relative to the baseline cotton scenario. However, this trend was not statistically significant at the $P < 0.1$ level. The average annual ET of irrigated switchgrass decreased by approximately 2.6% (not significant at the $P < 0.1$ level) when compared to the irrigated cotton. In contrast, the annual ET increased by about 3.6% under the dryland *Miscanthus* scenario compared to that under the baseline dryland cotton scenario. Overall, there was a statistically insignificant small increase in annual ET (0.3%) under the perennial grasses scenario relative to the baseline cotton scenario.

In the case of downstream subwatershed, the simulated average annual ET increased by 8.4% under the post-mesquite-harvest scenario relative to the baseline mesquite scenario (Table 4). However, this difference was not statistically significant. Also, a considerable interannual variability was found in this trend. For example, under the post-mesquite-harvest scenario, the average annual ET increased by 11% during the normal and wet years (rainfall > 500 mm) and reduced by about 1% during the dry years when compared to the baseline mesquite scenario. The increase in ET in wet years might have been caused by a much higher increase in evaporation when compared to reduction in transpiration after the mesquite harvest. The increase in average annual ET caused a significant ($P < 0.05$)

Table 4 The changes in hydrologic and water quality variables due to the harvest of honey mesquite from the downstream watershed for bioenergy purposes

Variable	Mesquite (baseline)	Post-mesquite-harvest
Hydrologic variables		
ET (mm)	458.0	496.3 (8.4)†
Surface runoff (mm)	20.8	0.23 (−98.9**)
Percolation (mm)	43.4	27.0 (−37.7)
Water quality variables		
NO ₃ -N load in surface runoff (kg ha ⁻¹)	0.009	0.000007 (−99.9**)
Organic-N load in surface runoff (kg ha ⁻¹)	0.06	0.0009 (−99.5**)
NO ₃ -N leaching (kg ha ⁻¹)	0.12	0.18 (56.1)

†The numbers in the parentheses indicate the percent changes between the post-mesquite-harvest and baseline mesquite scenarios.

**Significant differences between the post-mesquite-harvest and baseline mesquite scenarios at $P < 0.05$.

decrease in surface runoff by about 98.9% and an insignificant (at $P < 0.1$ level) 37.7% reduction in percolation under the post-mesquite-harvest scenario when compared to the baseline mesquite scenario (Table 4).

A hypothetical change in land use from cotton to perennial grasses altered average (1994–2009) monthly ET and soil water content significantly ($P < 0.05$) under the irrigated switchgrass and dryland *Miscanthus* scenarios (Fig. 3a,b,g,h). Monthly ET under the irrigated switchgrass scenario was significantly ($P < 0.05$) higher than that under the baseline irrigated cotton scenario in the months of May to July and November (Fig. 3a). However, it was significantly ($P < 0.05$) lower relative to the baseline irrigated cotton scenario in other months. Under the dryland *Miscanthus* scenario, monthly ET increased significantly ($P < 0.05$) in April, May, and November, but it decreased significantly ($P < 0.05$) in months of January, February, July, and December compared to the baseline dryland cotton scenario.

The simulated soil water content enhanced significantly ($P < 0.05$) under the irrigated switchgrass scenario from January to April and from August to October compared to the baseline irrigated cotton scenario. A significant ($P < 0.05$) decrease in soil water content was found under the irrigated switchgrass scenario in May and June when the simulated ET was significantly ($P < 0.05$) higher under the irrigated switchgrass scenario than the baseline irrigated cotton scenario (Fig. 3a,g). The soil water content depleted significantly ($P < 0.05$) under the dryland *Miscanthus* scenario from April to July relative to the baseline dryland cotton scenario due to the increase in simulated ET during those months. In general, soil water content was enhanced under the irrigated switchgrass scenario relative to the baseline irrigated cotton scenario, while it was reduced under the dryland *Miscanthus* scenario when compared to the dryland cotton scenario.

Negligible surface runoff was generated under the perennial grass scenarios relative to the baseline cotton scenario (Fig. 3c,d). The surface runoff under the irrigated switchgrass scenario decreased significantly ($P < 0.05$) in March and August compared to the baseline irrigated cotton scenario. The percolation under the irrigated switchgrass scenario increased from February to May and from July to November relative to the baseline irrigated cotton scenario (Fig. 3e). However, this trend was not statistically significant (at the $P < 0.05$ level). The percolation was negligible under the dryland *Miscanthus* scenario, and it also corresponded well with the depletion of soil water content under this scenario (Fig. 3f,h). Even under the baseline dryland cotton scenario, notable percolation was simulated only in May and June when the precipitation was relatively high and the simulated ET was relatively low.

Effects of biofuel-induced land use change and mesquite harvest on N losses

The average (1994–2009) annual $\text{NO}_3\text{-N}$ and organic-N loads in the surface runoff and the $\text{NO}_3\text{-N}$ leaching to the groundwater decreased significantly ($P < 0.05$) by about 86%, 98%, and 100%, respectively, under the perennial grasses scenario compared to the baseline cotton scenario (Table 1). The N lost through leaching was much higher compared to that lost through surface runoff (Table 1). For example, the $\text{NO}_3\text{-N}$ leaching was about 20 times higher than the N lost through surface runoff under the baseline cotton land use. However, in the case of perennial grasses, $\text{NO}_3\text{-N}$ leaching was only about four times higher than the N lost through surface runoff because of the higher N use efficiency of perennial grasses (Table 1).

A close look at the average annual N balances in irrigated conditions indicated that the $\text{NO}_3\text{-N}$ and organic-N losses in surface runoff and $\text{NO}_3\text{-N}$ leaching to groundwater were also significantly ($P < 0.05$) lower by about 78%, 100%, and 99%, respectively, under the irrigated switchgrass scenario than those under the baseline irrigated cotton scenario (Table 1). Although the average annual percolation increased by about 60% under the irrigated switchgrass scenario relative to the baseline irrigated cotton scenario (Table 1), the average annual $\text{NO}_3\text{-N}$ leaching reduced by approximately 99% under the irrigated switchgrass scenario due to higher N uptake by harvested switchgrass (95% N uptake for irrigated switchgrass vs. 27% for irrigated cotton) (Table 2) and lower amount of N fertilizer application (124 kg N ha^{-1} for irrigated switchgrass vs. 138 kg N ha^{-1} for irrigated cotton) (Table S3). Similar results were found in case of dryland *Miscanthus* scenario. The annual $\text{NO}_3\text{-N}$ load and organic-N load reduced significantly ($P < 0.05$) by about 98% and 97%, respectively, under the dryland *Miscanthus* scenario relative to the baseline dryland cotton scenario (Table 1). Ng *et al.* (2010) also predicted that a 50% change in land use from cropland to *Miscanthus* would result in a decrease in $\text{NO}_3\text{-N}$ load in streamflow by about 30% at the watershed outlet in the Salt Creek watershed in Illinois. The average annual $\text{NO}_3\text{-N}$ leaching also decreased significantly ($P < 0.1$) by about 100% under the dryland *Miscanthus* scenario compared to the baseline dryland cotton scenario. The N uptake by the dryland *Miscanthus* (167 kg N ha^{-1}) was also clearly higher than that of dryland cotton (92 kg N ha^{-1}) (Table 2).

The average annual $\text{NO}_3\text{-N}$ leaching increased from 0.12 to 0.18 kg ha^{-1} under the post-mesquite-harvest scenario compared to the baseline mesquite scenario (Table 4), but these differences were not significant. The $\text{NO}_3\text{-N}$ load and organic-N load through surface runoff

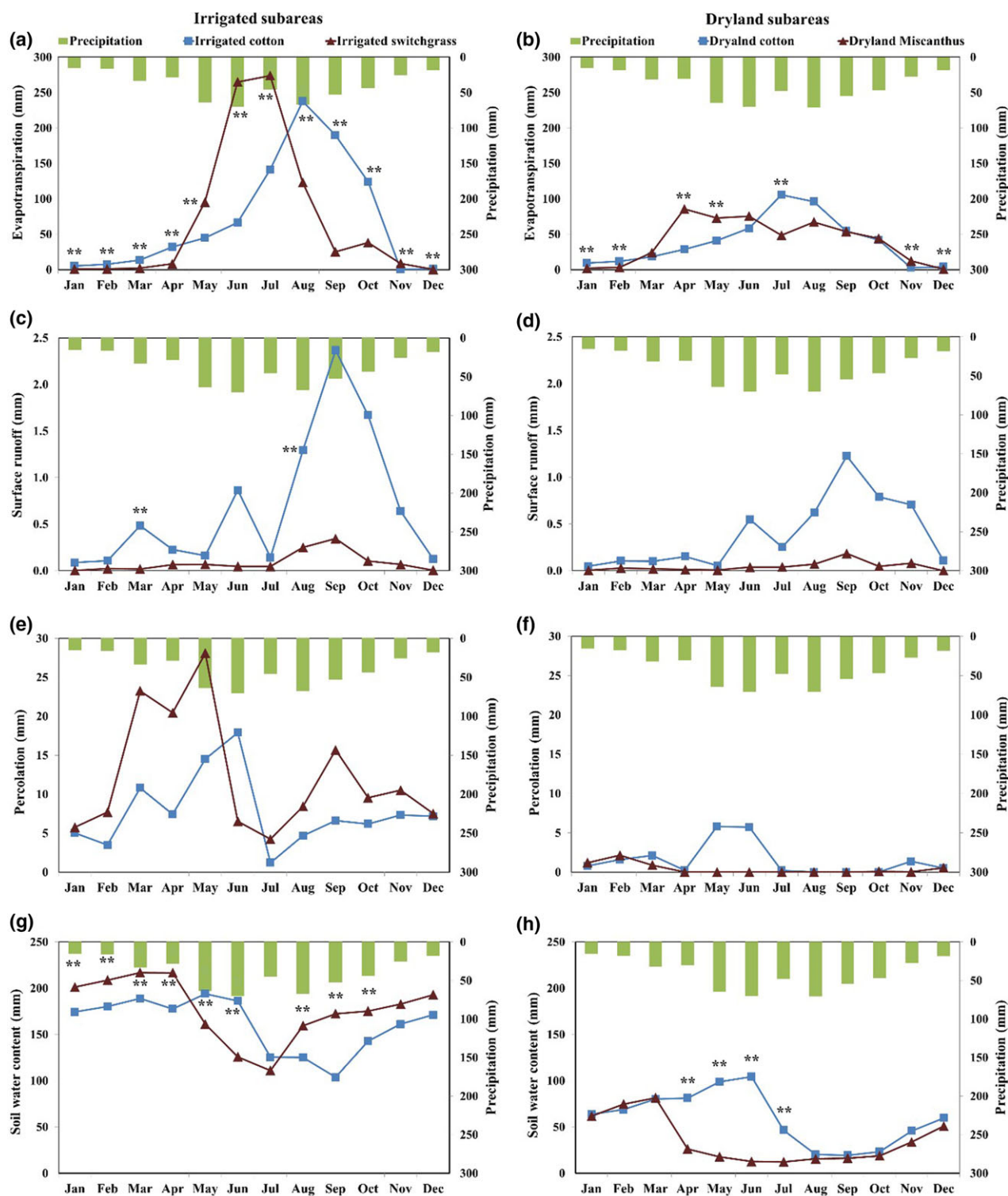


Fig. 3 Simulated average (1994–2009) monthly water fluxes in the irrigated and dryland areas under the baseline cotton and hypothetical perennial grass scenarios (** indicates a significant difference at $P < 0.05$).

were significantly reduced by about 99.9% and 99.5% under the post-mesquite-harvest scenario compared to the baseline mesquite scenario (at $P < 0.05$ level). The

significant decrease in surface runoff was the key reason for the associated significant reduction in N losses in surface runoff.

The average monthly $\text{NO}_3\text{-N}$ and organic-N loads in surface runoff and $\text{NO}_3\text{-N}$ leaching to groundwater were negligible under the perennial grass scenarios when compared to the baseline cotton scenario (Fig. 4). The $\text{NO}_3\text{-N}$ load in the surface runoff decreased

significantly ($P < 0.05$) under the irrigated switchgrass scenario in March (100%), August (89%), September (93%), November (99%), and December (99%) relative to the baseline irrigated cotton scenario. Under the dryland *Miscanthus* scenario, $\text{NO}_3\text{-N}$ load in surface runoff

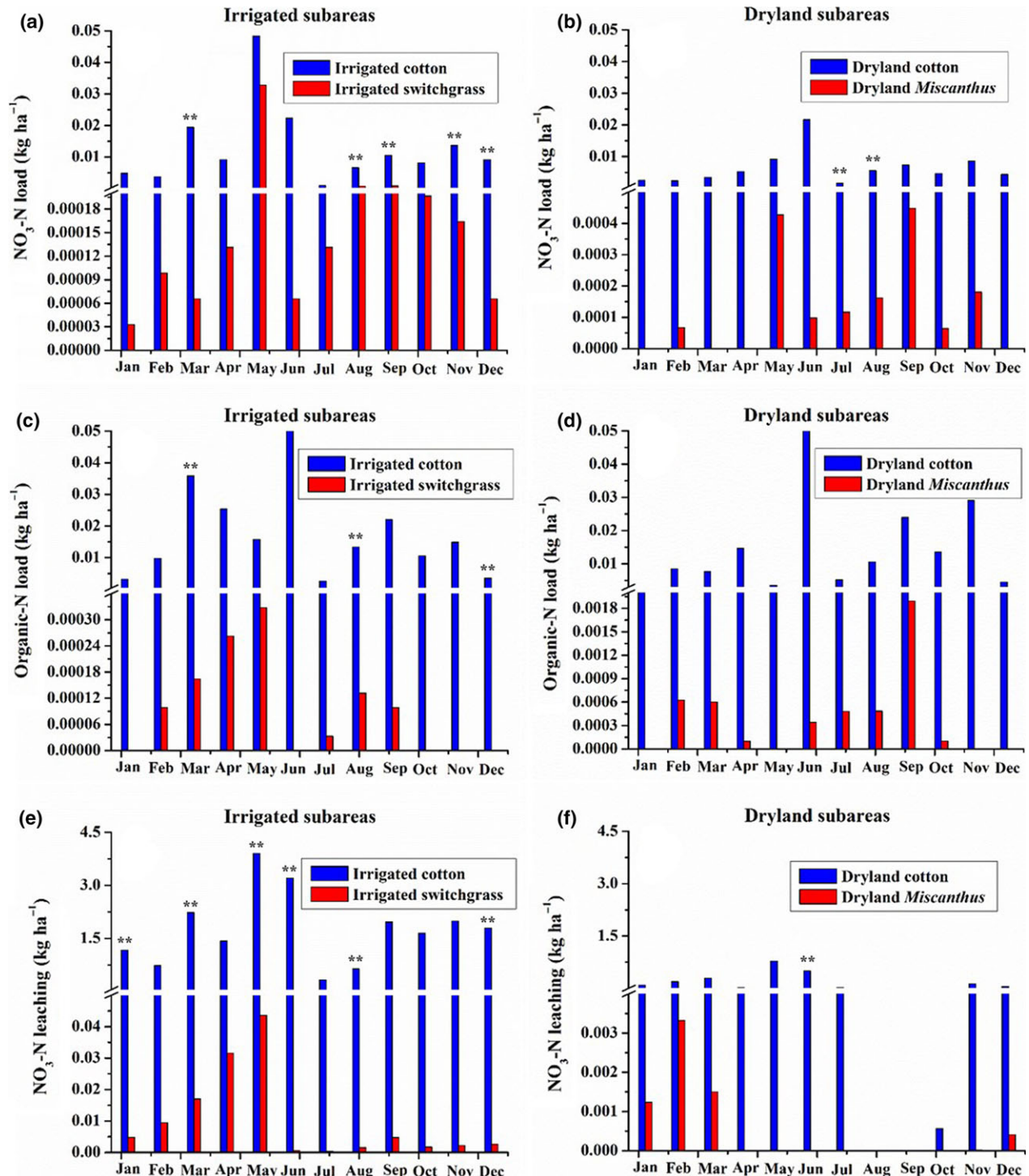


Fig. 4 Simulated average (1994–2009) monthly nitrogen loss through surface runoff and leaching under the irrigated and dryland areas under the baseline cotton and hypothetical perennial grass scenarios (** indicates a significant difference at $P < 0.05$).

decreased significantly ($P < 0.05$) in July (93%) and August (97%) compared to the baseline dryland cotton scenario. Using the APEX model, Feng *et al.* (2015) also found a significant ($P < 0.05$) reduction in N transported by surface water (91%) under the *Miscanthus* production scenario compared to the initial corn/soybean land use in the St. Joseph River watershed in Indiana. Generally, the organic-N load in surface runoff under the perennial grass scenarios was also much lower than that under the baseline cotton scenario (Fig. 4c,d). However, the differences in organic-N load between the dryland *Miscanthus* and baseline dryland cotton scenarios were not statistically significant (at $P < 0.1$ level). In contrast, the organic-N load in surface runoff under the irrigated switchgrass scenario reduced significantly ($P < 0.05$) in March (99.5%), August (99%), and December (100%) when compared to the baseline irrigated cotton scenario. The $\text{NO}_3\text{-N}$ leaching to groundwater also decreased significantly ($P < 0.05$) under the irrigated switchgrass scenario in January (99.6%), March (99.2%), May (98.9%), June (100%), August (99.8%), and December (99.9%) when compared to the baseline irrigated cotton scenario. When the irrigated cotton land use was changed to irrigated switchgrass, the $\text{NO}_3\text{-N}$ leaching decreased significantly ($P < 0.05$) during the high precipitation months such as May, June, and August. In this study, when compared to the baseline dryland cotton scenario, $\text{NO}_3\text{-N}$ leaching under the dryland *Miscanthus* scenario decreased significantly ($P < 0.05$) by about 100% in June. The highest percolation under the baseline dryland cotton scenario and the lowest percolation under the dryland *Miscanthus* scenario were both predicted in June (Fig. 3h), and this might have contributed for the significant ($P < 0.05$) reduction in $\text{NO}_3\text{-N}$ leaching under the dryland *Miscanthus* scenario in June compared to the baseline dryland cotton scenario.

Discussion

Impacts of biofuel-induced changes in land use and management on water and nitrogen balances

The average (1994–2009) annual surface runoff decreased significantly ($P < 0.05$) by 87% under the irrigated switchgrass scenario relative to the baseline irrigated cotton scenario in this study (Table 1). Using the SWAT model, Nelson *et al.* (2006) predicted a 55% decrease in surface runoff in the Delaware Basin in northeast Kansas due to the change in land use from the traditional corn–soybean cropping rotation to switchgrass. However, the average annual irrigation water requirement increased by approximately 5% (not significant at the $P < 0.1$ level) under the irrigated switchgrass

scenario when compared to the baseline irrigated cotton scenario (Table 1). It is interesting to find that the net groundwater use (irrigation water minus percolation) decreased by approximately 7.6% under the irrigated switchgrass scenario relative to the baseline irrigated cotton scenario. Monthly ET under the irrigated switchgrass scenario was significantly ($P < 0.05$) lower than that under the baseline irrigated cotton scenario in the months of January to April, August to October and December, while it was significantly higher in other months (Fig. 3a). This was primarily due to the simulated early initiation of regrowth of switchgrass in the study watershed in late April, and its late harvest in mid-November when compared to cotton. Cotton was planted in mid-May and harvested at the end of October. Yimam *et al.* (2015) also observed that the regrowth of switchgrass occurred around mid-April in a field experiment at Stillwater, Oklahoma. Also, the simulated peak ET occurred earlier in case of irrigated switchgrass when compared to irrigated cotton (Fig. 3a). As shown in Fig. 3a,b, the monthly ET pattern under the perennial grass scenarios shifted two to three months early relative to the baseline cotton scenario. This finding would be helpful in planning appropriate management strategies for growing perennial grasses in the SHP region.

A well-developed root system and better ground cover under the switchgrass scenario enhanced the soil water content significantly ($P < 0.05$) from January to April and from August to October compared to the baseline irrigated cotton scenario. However, the soil water content was reduced significantly from April to July under the dryland *Miscanthus* scenario when compared to the dryland cotton scenario. Several studies from the Midwestern United States have also reported reductions in soil water content under the *Miscanthus* land use when compared to that of maize (McIsaac *et al.*, 2010; VanLoocke *et al.*, 2010; Le *et al.*, 2011). The large leaf area index of *Miscanthus* (*Miscanthus* vs. switchgrass: 11 vs. 6) resulted in a very high ET which depleted the soil water content.

The average annual N loads through surface runoff decreased significantly ($P < 0.05$) by more than 86% under the perennial grasses scenario compared to the baseline cotton scenario (Table 1). Using the SWAT model, Sarkar & Miller (2014) also predicted that the N losses through surface runoff under switchgrass were approximately 73% lower than that under cotton in the Black Creek watershed in South Carolina. In another SWAT modeling study in the Arkansas–White–Red River Basin, Jager *et al.* (2015) predicted an 84% reduction in average annual $\text{NO}_3\text{-N}$ load through surface runoff under the projected future (2022) switchgrass landscape compared to baseline no-cellulosic bioenergy grass scenario. Although the percent reductions in $\text{NO}_3\text{-N}$

N losses in above studies were lower, absolute losses in their study were comparable to our results. The reduction in surface runoff and high N use efficiency were the main reasons for substantial reduction in N loads in surface runoff under the perennial grasses scenario when compared to baseline cotton scenario.

The $\text{NO}_3\text{-N}$ leaching to groundwater was reduced by 99.5% under the perennial grasses scenario relative to the baseline cotton scenario (Table 1). From a four-year field experiment in central Illinois, McIsaac *et al.* (2010) also concluded that the average annual $\text{NO}_3\text{-N}$ leaching under maize–soybean land use was much higher (about 40 kg N ha^{-1}) when compared to switchgrass (1.4 kg N ha^{-1} ; 97% reduction) and *Miscanthus* (3 kg N ha^{-1} ; 93% reduction) land uses. Approximately 95% and 57% of total N inputs (N in fertilizer and rainfall) were taken up by harvested portion of the irrigated switchgrass and dryland *Miscanthus*, respectively, whereas harvested portion of cotton used approximately 27% to 25% of total N inputs (Table 2). Powers *et al.* (2011) also reported that about 87% of the applied N was taken up by the harvested portion of the switchgrass in an APEX modeling study in eastern Iowa. Groundwater contamination by $\text{NO}_3\text{-N}$ is a major concern in the THP region (Chaudhuri & Ale, 2014a,b), where groundwater is the major source of drinking water for >95% of rural population (Texas Water Development Board, 2007). Results from this study indicated that the land use change from cotton to perennial grasses could potentially reduce $\text{NO}_3\text{-N}$ leaching to groundwater and thereby improve groundwater quality in this region in a long run.

It is also interesting to notice that the surface runoff, $\text{NO}_3\text{-N}$ load, and organic-N load through surface runoff decreased significantly ($P < 0.05$) by about 98.9%, 99.9%, and 99.5% under the post-mesquite-harvest scenario compared to the baseline mesquite scenario (Table 4). The fast regrowth of the harvested mesquite showed higher simulated ET than the undisturbed mesquite, especially under the wet years. This was a major reason for the reduction in surface runoff and associated N losses. The harvest of honey mesquite could therefore not only benefit the water quality in the study watershed, but also supply biomass for biofuel production.

Biomass and biofuel production potential of irrigated switchgrass, dryland Miscanthus, and honey mesquite

The land use change from cotton to irrigated switchgrass and dryland *Miscanthus* exhibited superior biomass and ethanol production potential per ha compared to the honey mesquite harvest (Table 3). However, the vast extent of honey mesquite acreage in the Southern Great Plains (21 million ha in Texas alone) has the

potential to supply abundant quantities of honey mesquite biomass for bioenergy purposes (Ansley *et al.*, 2010; Park *et al.*, 2012). For example, based on an estimated average standing biomass of a 10-year-old honey mesquite of 19.4 Mg ha^{-1} (about 1.94 Mg ha^{-1} biomass accumulation per year) reported in Whisenant & Burzlaff (1978), harvest of honey mesquite from the entire rangelands of Texas annually can provide the biomass required for producing 12.6 million m^3 of biofuels, which is approximately equal to 16.6% of the mandated 2022 U.S. biofuel target of 76 million m^3 of second-generation biofuel. In addition, honey mesquite has a high regrowth potential, and it does not require planting, irrigation, and fertilization costs (Park *et al.*, 2012; Wang *et al.*, 2014). These advantages make honey mesquite an appropriate supplementary bioenergy crop in the downstream subwatershed of this study and other similar areas in the TRP region.

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Supporting Information

Additional Supporting Information may be found online in the supporting information tab for this article:

Table S1. Simulated management practices of cotton, winter wheat, Southwestern U.S. range and honey mesquite in APEX and SWAT models.

Table S2. Default and calibrated values of some major hydrology, crop growth and water quality related parameters in APEX and SWAT models.

Table S3. Simulated management practices for irrigated switchgrass and dryland *Miscanthus* in the APEX model.

Figure S1. Location of the study watershed, weather stations and USGS gauging stations.

Figure S2. Illustration of the patterns of sampling for assessing water quality.

Figure S3. Comparison of observed and simulated monthly streamflow at watershed outlet during the model a) calibration (1994–2001) and b) validation (2002–2009) periods.

Figure S4. Comparison of observed and simulated monthly total nitrogen load in streamflow at watershed outlet during the model a) calibration (1995–1997) and b) validation (1998–2000) periods.