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Understanding shifts in agricultural landscapes: context matters when simulating future changes in water quantity and quality

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Environmental Science Division

UNDERSTANDING SHIFTS IN AGRICULTURAL LANDSCAPES: CONTEXT MATTERS WHEN SIMULATING FUTURE CHANGES IN WATER QUANTITY AND QUALITY

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ABSTRACT

Introducing energy crops to the US agricultural landscape will undoubtedly result in changes to water quality and quantity. The magnitude and direction of change will likely depend on how current and future land cover and management practices compare. Focusing on the Arkansas-White-Red river basin (AWR), we describe our method for projecting future shifts in water quantity and quality in rivers based on economic projections for future changes in land use. The main tools used were the POLYSYS economic forecasting model and the Soil Water Assessment Tool (SWAT). This paper documents our methods to setup the agricultural context in SWAT for the AWR river basin and describes sensitivities of our results to model assumptions about management (e.g., fertilizer application). Our sensitivity analysis results show that fertilizer applied by simulating cattle from USDA data was much lower than that simulated using SWAT's autofertilization routine. Sensitivity analysis for switchgrass fertilizer application indicated that higher amounts of fertilizers resulted in higher yield, but at the cost of higher stream nitrate concentrations. Lower amounts of fertilizers were applied by the switchgrass autofertilization routine and resulted in a spatially variable distribution of yield that produced reasonable switchgrass yields and lower stream nitrate concentrations in the eastern part of the study region. This study illustrates the importance of setting the agricultural context for modeling bioenergy based land-use changes and also shows how the model sensitivity to management conditions can help analyze tradeoffs between different intensities of land management and water-quality implications.

1 INTRODUCTION

Agricultural landscapes are constantly shifting in response to economic and social trends. These shifts can have positive or negative effects on freshwater ecosystems. With concern over long-term sustainability, greenhouse gas emissions and energy security, biomass feedstocks provide an attractive option for domestic energy. However, public support has wavered because of environmental concerns. These concerns need to be given forethought and consideration to ensure a sustainable bioenergy future (McLaughlin and Walsh 1998; Robertson et al. 2008; Tolbert and Wright 1998). Large-scale conversions of land for biomass feedstock can result in changes in how the land is managed, such as changes in fertilizer application, tilling practices, and collection of harvested biomass (Perlack et al. 2005). These changes can impact the environmental conditions of the land and the streams into which these lands drain. Agricultural activities in the form of crop production, grazing and animal feeding operations are a leading cause of impairment in assessed rivers and streams (US EPA 2009). Hence it is important to consider and assess the impacts of large-scale conversions of land to grow bioenergy crops including annual crops such as corn and perennial grasses such as switchgrass or short rotation woody crops.

Models simulating future bioenergy-based land-use changes can help understand the environmental impacts of a bioenergy future. Such models must take into account the future crop-management options available and the corresponding sensitivity of the model to such options. The management assumptions for future energy crops and pasture, which are not well documented, have an important influence on predicted water quality outcomes for future scenarios. Specifically, it is important to understand how fertilizer over existing land compares with that of energy crops in order to quantify the water quality benefits of land conversion from the one to the other.

In this report we focus on modeling bioenergy-based land-use futures in the Arkansas-White-Red (AWR) river basin which encompasses parts of 8 states in the central US and drains into the Mississippi river

(Figure 1). The AWR river basin has the highest economic and agronomic potential for growing cellulosic grasses as bioenergy feedstocks in the US. According to the Billion Ton study (USDOE 2011), pasture will be one of the main land-uses replaced by switchgrass (Figure 2), and this is mainly predicted to occur in the middle third in a vertical strip through Arkansas and Kansas. Moving west across the 100th parallel, drier areas become costly to irrigate for traditional agricultural crops. Prairie grasses, whether grown for grazing livestock or for bioenergy, become the economical land use of choice in this transition zone. In this study, we present methods for representing what we view as likely changes in agricultural landscapes over the next three decades in the AWR river basin, with a focus on changes that relate to water quality. We also studied the sensitivity of the model to changes in fertilizer application for pasture and switchgrass with respect to changes in water quality.

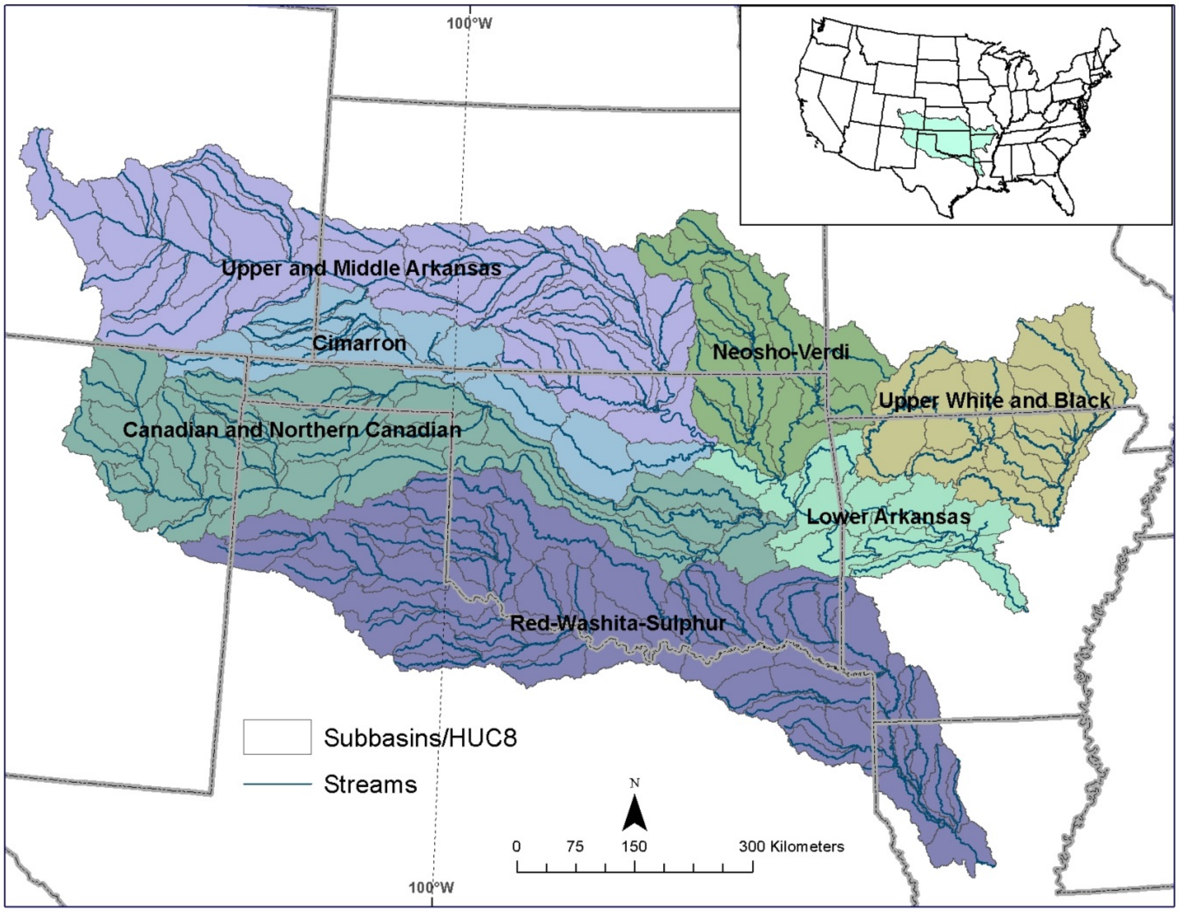

Figure 1. Major river basins in the Arkansas-White-Red river basin.

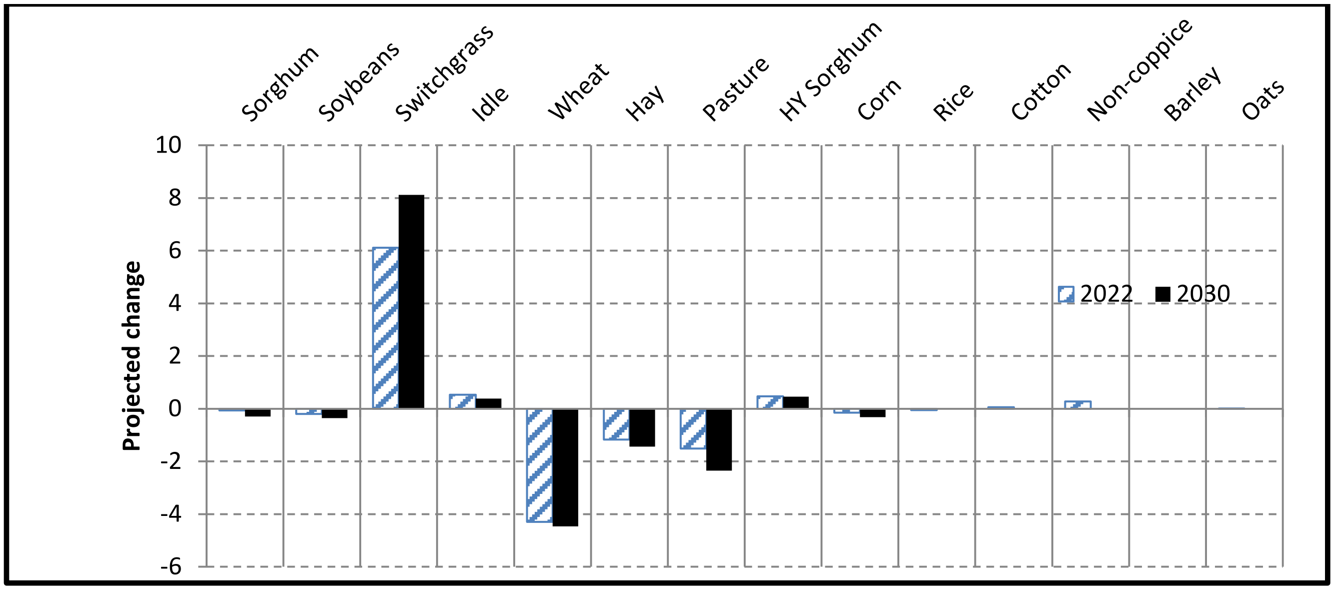

Figure 2. Estimated percentages of land cover converted to switchgrass between the 2008 baseline and a 2022 and 2030-POLYSYS future scenarios with $50/dry ton of switchgrass and 1% annual yield increases.

2 METHODS

We used the Soil and Water Assessment Tool (SWAT) to simulate future bioenergy-based land-use management changes. SWAT is a physically based, semi-distributed hydrologic model to simulate changes in land management and the resulting changes in the hydrologic cycle and water quality. SWAT has been used extensively around the world for different applications ranging from TMDL analysis at the local scale to macro scale analysis of the entire US (Gassman et al 2007). SWAT was developed as an integration of several models – EPIC, CREAMS, GLEAMS and a weather generator model (Krysanova and Arnold 2008). The crop growth component of SWAT simulates all crops with a single crop-growth model with the use of unique parameter values for each crop (Neitsch et al. 2005). Plant growth is represented by an increase in biomass that is based on daily accumulated heat units. The crop-growth model is also used to assess removal of water and nutrients from the root zone, transpiration, and biomass production (Neitsch et al. 2005).

We customized the SWAT setup for the Arkansas-White-Red River basin for baseline and future bioenergy scenarios using information obtained from land-use data, existing crop management operations, expected crop yield in the region, potential future land-use changes and potential energy crop management. In the following sections we describe how we specified the agricultural context for the setup and evaluated the model sensitivity to pasture management and fertilizer application over the bioenergy feedstock, switchgrass.

2.1 SPECIFYING THE AGRICULTURAL CONTEXT

2.1.1 Watersheds

We used the SWAT option of specifying watershed boundaries, rather than delineating them based on elevation and stream data. This permitted us to use a lower resolution, 56-m, digital elevation model. As hydrographic input, SWAT requires one main stream channel per subbasin in the format of the EPA REACH files. We converted watersheds and streams from 2008 USGS National Hydrographic Data

(NHD+) into the format required by SWAT. We aggregated catchments to create new sub-basin boundaries consistent with NHD+ flowlines. Within each of these subbasins, we identified the collection of reaches sharing the largest stream order. To identify the main channel, we selected the reach with the smallest value of "levelpath" as the one farthest downstream. The final set of reaches was dissolved to produce a GIS layer with one stream feature per subbasin.

We used spatial layers describing soils from STATSGO (Soil Survey Staff, 1994), slope from the National Elevation Dataset (Gesch et al. 2002), and land cover from the 2009 cropland data layer (USDA National Agricultural Statistics Service Cropland Data Layer 2009) to partition each subbasin into hydrologic response units (HRUs). HRUs represented unique combinations of three attributes within a subbasin: soil type, slope, and land-use/land-cover. We used climate data from DAYMET (Thornton *et al.*, 1997) estimated for the center of each sub-basin over the period 1980 to 2011. Daily climate variables included were total precipitation (mm), minimum and maximum temperatures (°C), and solar radiation (MJ m^{-2} d^{-1}). Three other variables (wind speed, relative humidity and potential evaporation) were simulated by SWAT's climate generator (Gassman *et al.*, 2007, Srinivasan *et al.*, 2010).

2.1.2 Agricultural management

Management options include planting date, harvest, treatment of tile drainage, fertilizer application, stover removal, and tillage practices. For each of the crop categories we customized the management options through literature reviews and analysis of data from USDA.

2.2 SENSITIVITY OF SWAT-SIMULATED WATER QUALITY TO ASSUMPTIONS RELATED TO PASTURE FERTILIZATION

Energy crops are expected to replace forage crops and pasture in the AWR region. Management of these crops is therefore important when considering the net effect of introducing energy crops. In particular, pasture is one of the main land-use/cover that POLYSYS predicts will be displaced by switchgrass in this region.

To model pasture management, we considered scenarios with grazing by cattle and also a scenario with as-needed fertilizer application (autofertilization). Starting with a baseline number of cattle (and associated manure) reported by the Department of Agriculture (NASS statistics 2010-2011), we compared nutrient concentrations at the outlets of rivers draining major basins for the NASS baseline, a scenario with half the baseline number of cattle, a scenario with a 50% increase in cattle, and a scenario with no cattle. Another scenario included used SWAT's autofertilization routine that applies fertilizer when vegetation becomes nutrient-stressed. Following our management assumptions for hay, we specified an upper limit of 200 lbs/acre of N fertilizer applied in a year. Likewise, when phosphorus stress caused plant growth to fall below 75% of potential growth, the model applied mineral P equal to 1/7th of the mineral nitrogen applied.

Grazing operations in pasture lands were simulated by considering the presence of cattle in the study region. County level cattle data were obtained from the USDA Agricultural Census Data (NASS 2011). The number of cattle per hectare and corresponding manure per hectare within a subbasin were determined using an area-weighted averaging approach for manure application (Demissie et al. 2011), described by Equation 1.

$$F_{sub} = Ex\left(\frac{\sum_{cty} H_{cty}\, A_{cty,sub}}{\sum_{cty} A_{cty,sub}}\right), \qquad (1)$$

Where F_{sub} is the annual amount of manure fertilizer per hectare applied in subbasin, *sub*, *Ex* is the per-capita manure excreted per year, *H* is the head of cattle in a given county, and *A* is the area of pasture in a county that lies within the subbasin of interest.

2.3 SENSITIVITY OF SWAT-SIMULATED WATER QUALITY TO ASSUMPTIONS RELATED TO SWITCHGRASS MANAGEMENT

Modifications to growth and management parameters were required to represent energy crops. Crops added to the landscape in simulations of 2030 were switchgrass, poplar, and high-yield sorghum. Among these crops, switchgrass is the most significant bioenergy crop, with about 5.12% added to the 2030 landscape. Only 0.6% of poplar and 0.2% of high yield sorghum were added to the 2030 landscape. Owing to the prevalence of switchgrass and its importance in the future landscape, we focused our sensitivity analysis on switchgrass-related fertilizer application. The locations of these crops in the BT2 simulations are mapped in Figure 3.

The default management routines in SWAT are generic starting points for modeling a crop, and changes and additions can be made to them. For switchgrass, the default fertilizer application mechanism is through an autofertilization operation for elemental nitrogen fertilizers. When the nutrient stress falls below a specific threshold (the default value is 0.85), nitrogen fertilizers are applied. If phosphorus stress causes plant growth to go below 75% of the potential growth, a small amount of mineral phosphorus fertilizers, equal to about one-seventh the amount nitrogen fertilizers, is also automatically applied (Neitsch et al. 2005). This approach ensures that on the basis of the plant nutrient demand, fertilizers are applied to keep the plant in a reasonable growth range. In large-scale applications and in the absence of region-specific data on fertilizer application, the autofertilization operation may help to simulate switchgrass growth under near-ideal nutrient conditions (Baskaran et al. 2010). However, there are also recommendations for N and P fertilizer application for switchgrass. We used the recommended 44.8 kg/ha/year of P every year starting from the establishment year, and 87.4 kg/ha/year of N from the third year. We compared scenarios with different amounts of fertilizers applied for switchgrass - autofertilization with the recommended amounts of N fertilizers (87 kg/ha/year) as upper limits, half the recommended amount (43 kg/ha), about twice the recommended amount (150 kg/ha) and the maximum allowable amount of N fertilizers (300 kg/ha). We compared the switchgrass yield response to these various scenarios and also compared the nitrate concentrations in the streams in each scenario. We also analyzed the spatial distribution of fertilizers applied in the autofertilization scenario and the resulting switchgrass yield, stream nitrate concentrations from the model. We used yield per nitrate as a variable to help understand the yield and nitrate concentration tradeoffs at different fertilizer application levels. To identify factors contributing to this distribution, we used a regression analysis with fertilizers applied, soil variables, area in tile drainage and precipitation as potential variables affecting yield and nitrate response of the model.

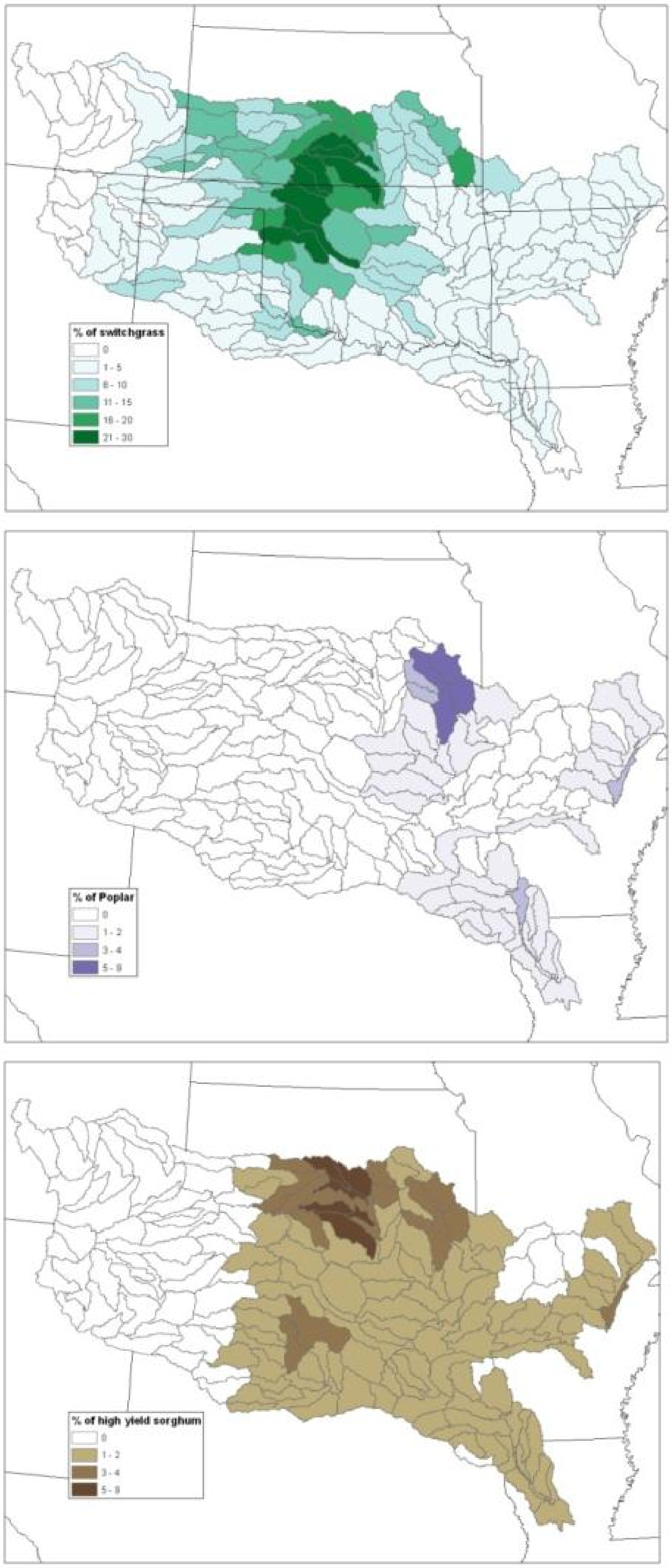

Figure 3. Geographic distribution of three cellulosic feedstocks, switchgrass, poplar, and high-yield sorghum.

3 RESULTS

3.1 SPECIFYING THE AGRICULTURAL CONTEXT

3.1.1 Watersheds

We implemented SWAT for 173 subbasins (USGS 8-digit-HUCs) within the AWR drainage with a single stream reach within each subbasin (Figure 1). HRUs with soil classes that comprised more than 10% of a subbasin and land-use classes that comprised more than 5% of the subbasin were retained. We discretized slope into three categories, <2%, 2 to 5%, and >5% and retained all slope classes. The major SWAT agricultural land-use classes in the baseline scenario were corn, cotton, hay, oats, pasture/grassland, rangeland, rice, sorghum, soybeans, and winter wheat. The future scenario included switchgrass, poplar and high-yield sorghum along with the base agricultural classes.

3.1.2 Agricultural Management

3.1.2.1 Planting

We simulated plant growth and assigned planting dates using the heat units scheduling approach. Using monthly maximum and minimum temperature from Daymet (Thornton *et al.*, 1997) for locations along latitudes 38N and 33N (to represent the northern and southern boundaries of AWR basin), we estimated the average daily temperature and then calculated the total heat units accumulated in each year and also the proportion of heat units accumulated on each day. We averaged the results for 20 years of data and derived the average proportion of heat units accumulated on a given day (Figure 4). Using the usual planting dates of major crops in Texas and Kansas (representing the southern- and northern-most states of AWR region) (USDA 1997), we derived the corresponding proportion of heat units reached during planting (Table 1). The average of the proportion of heat units accumulated at planting in Texas and Kansas was used as the proportion of heat units at which a crop will be planted in the AWR river basin. For the energy crops, we assumed the heat units of planting as 0.15.

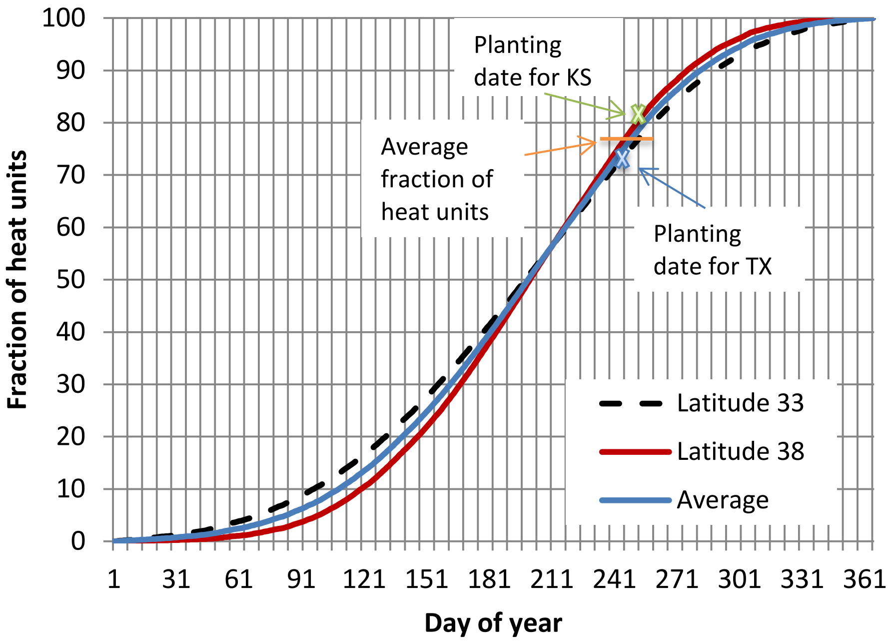

Figure 4. Average proportion of heat units accumulated on a given day for locations along latitude 33N and 38N. The planting dates for winter wheat in Texas and Kansas are marked along the 33N and 38N curves respectively.

Table 1. Usual planting/harvest dates for major crops and the calculation of average heat units accumulated at planting for AWR based on heat units accumulated at 33N (shaded in gray) and 38N

Crop	State	Planting/Harvest date	Julian date	Proportion of accumulated heat units (HU)	Average HU
Winter wheat	Texas	31-Aug	243	0.724	0.765
	Kansas	10-Sep	253	0.806	
	Texas	25-May (harvest)	145	0.252	0.273
	Kansas	15-Jun (harvest)	166	0.294	
Soybeans	Texas	16-Apr	106	0.123	0.128
	Kansas	10-May	130	0.134	
Sorghum	Texas	3-Mar	62	0.040	0.087
	Kansas	10-May	130	0.134	
Corn	Texas	28-Feb	59	0.037	0.044
	Kansas	10-Apr	100	0.051	
Cotton	Texas	10-Mar	69	0.049	0.084
	Oklahoma	6-May	126	0.120	
Rice	Arkansas	7-Apr	97	0.101	0.073
		7-Apr	97	0.046	

3.1.2.2 Harvest

The annual crops in the region were to set to harvest at 1.2 heat units to maturity. This allowed the plants to dry down after they reach maturity. Winter wheat was modeled as a winter crop with planting in fall and harvest the next summer/spring. We calculated potential heat units accumulated for planting and harvest using the usual planting and harvest dates for winter wheat (Table 1). After planting in fall, the wheat crop is not cut the same year. The following year, we assumed an initial leaf area index of 0.3 and initial biomass of 300 kg/ha. We assigned the potential heat units to maturity (PHU) as 1551.95.

We treat both grassland hay and pasture hay as perennial crops with "harvest only" operations simulated for 9 years followed by harvest and kill during the end of the 10th year and planting after the 10th year. Harvest of hay was simulated three times per year and 90% of the above ground biomass is removed during each harvest. Conventional tillage was simulated for the first nine years. In the 10th year we simulated a no till operation, 2 harvest-only operations and a final harvest and kill operation.

We simulated a ten-year rotation for switchgrass (US Department of Energy, 2011) with "harvest only" operations simulated for 9 years followed by harvest and kill during the end of the 10th year and planting after the 10th year. Each year, switchgrass required 1,854 physiological heat units to reach maturity. Literature values vary from 1,100 at higher latitudes to 2,300 in Texas (Kiniry, 2005). We simulated harvest after reaching 1.2 heat units to allow for crop drying. We assumed that 80% of the above-ground biomass was harvested each year. To be consistent with this, we also decreased the minimum harvest index under water stress from the default value to 0.8. We assumed a maximum rooting depth of 2.2 m (Kiniry, 2005), although values as high as 3 m have been reported (Bransby *et al.*, 1998).

3.1.2.3 Tile Drainage

Tile drainage is common in the Midwest and can have significant effects on water quality in rivers adjacent to croplands because nutrient uptake and removal processes are short-circuited. We therefore simulated tile drainage in cropland areas with slopes less than 2% in areas with soils characterized by poor drainage. We assumed the depth of tiles as 1.1 m and the drainage time as 36 h. We modified the depth to impermeable layer for regions with tiles to ensure that the depth to the impermeable layer was greater than to the depth to the tiles. The distance to bedrock data set from STATSGO provided the depth to impervious layer up to a maximum of 1.52 m (Miller & White, 1998). Because depths to bedrock exceeded 1.52 m for the majority of the region with tiles, we set this as the depth to impermeable layer for HRUs with tile drainage.

3.1.2.4 Denitrification

Our water quality validation suggested that simulated nitrate levels were too high. This was also found by Hu et al. (Hu *et al.*, 2007) using a denitrification rate of 0.3. To improve simulation of nitrate, we adjusted parameters that control denitrification, including threshold water content (SDNCO) defined as the fraction of field capacity water content above with denitrification takes place, and the denitrification exponential rate coefficient (CDN). The values for these parameters were derived by comparing parameter values listed in the literature and by comparing the resulting denitrification values with those reported in field studies, and through our validation efforts. Annual N_2O fluxes (precursor to N_2) based on average dynamics (2 and 4 kg N/ha) were considered low by Tonitto et al. (Tonitto *et al.*, 2009), whereas values between 10 and 40 kg N/ha were described as typical for high-flux years. Hofstra and Bouwman (Hofstra & Bouwman, 2005) measured rates that varied from 9 to 49 kg/ha, with the highest values in areas growing rice, followed by grass. We found that a CDN value of 0.3 and and SDNCO value of 0.95 provided denitrification rates close to values reported in the literature.

3.1.2.5 Tillage

Tillage practices have been shifting from conventional to no-till over the past decades, and this trend is likely to continue (Horowitz *et al.*, 2010, Uri, 2000). Statistics on tillage practices reported by farmers may reflect differences in understanding what constitutes no-till, particularly for corn (Uri, 2000). We used a time-for-space substitution to simulate spatial variation in tillage. Based on the acreage of major US crops by tillage practices and by state continue (Horowitz *et al.*, 2010), we obtained the proportion of tillage practice within our study region. Knowing the proportions of land in each of three tillage categories (no till, reduced till, and conventional till), we evaluated rotations between 3 and 10 years long. For each, we apportioned years among tillage practices according to the known proportions. The rotation period selected for each crop was the one that minimized truncation error (Table 2).

Table 2. Reported proportion of land in three tillage classes, no till, reduced till, and conventional till simulated using temporal rotations for 2009 and 2030

Crop	Spatial proportions - 2009	Rotation period (y)	2009 schedule (y)	Spatial proportions - 2030	Rotation period (y)	2030 schedule (y)
Corn	32.4, 31.3, 36.3	3	1,1,1	44.3, 25.3, 30.4	4	2 ,1,1
Cotton	9.9, 10.9, 79.2	10	1,1,8	13.6, 9.1, 77.3	9	1,1,7
Rice	7.4, 16.8, 75.9	4	0,1,3	10.0, 15.5, 74.5	8	1,1,6
Sorghum	24.3, 36.3, 39.3	8	2,3,3	33.3, 31.9, 34.8	3	1,1,1
Soybean	37.4, 25.0, 37.6	8	3,2,3	51.1, 18.1, 30.7	6	3,1,2
Wheat	22.1, 49.0, 29.0	4	1,2,1	30.2, 44.9, 24.9	4	1,2,1
Hay		10			10	
Switchgrass					10	9,0,1
Poplar					8	7,0,1
High Yield Sorghum					1	

In the future bioenergy scenario for 2030, we assumed higher proportions of no-till land by altering the rotations (Horowitz *et al.*, 2010). We assumed an 1.5% increase in land allocated to no-till each year and estimated the proportion of land in no-till for the year 2030 (Table 2). Half of area of land in no-till was removed from land in conventional till and the other half from land in reduced till.

3.1.2.6 Irrigation

Irrigation of corn was simulated when water stress reduced growth by 7.5%. Water was drawn from a shallow aquifer within the same sub-basin. Based on the 2007 Census of Agriculture, irrigated corn is predominantly grown in the western half of the AWR region. The Ogallala aquifer is a major aquifer in the region and is a significant source of groundwater for irrigation (Colaizzi *et al.*, 2009). Irrigation was not simulated for other crops.

3.1.2.7 Fertilizer application

We calibrated upper limits on nitrogen fertilizer amounts for major crops in the region (wheat, hay, soybeans, corn, sorghum) by comparing applications simulated using auto-fertilization with fertilizer use reported by USDA (USDA, 2009). Nitrogen fertilization of all crops occurred when nutrient stress reduced growth by 25%. Initially, we simulated addition of mineral P if phosphorus stress caused plant growth to fall below 75% of potential growth, where the amount added was 1/7th of the mineral N applied (Neitsch SL *et al.*, 2005). However, this approach simulated lower rates of P fertilizer addition than indicated by USDA. Based on the reported fertilizer use by USDA, both N and P were applied for most crops. We therefore modified our approach by creating hypothetical fertilizers in SWAT corresponding to the USDA-reported ratios of N and P for each crop. Auto-fertilization of a crop was simulated using its crop-specific fertilizer with a limit set on the amount of nitrogen applied annually. For example, for corn, the average annual application rate was 143.7 kg/ha N. We simulated autofertilization of corn using a fertilizer with 75.75% of N and 24.25% of P, with a specified annual maximum of 143.7 kg. This resulted in an average of 143.7 kg of N and 46 kg of P applied to corn, matching USDA-reported quantities.

We compared the resulting yields of the major crops with the yields reported by National Agricultural Statistics Service (USDA, 2011) (Table 3). The crop yields reported by state were averaged for the states in the AWR basin to obtain the average observed yield for a crop. The values reported in bushels/acre were converted to units of tons/ha using conversion values reported by Murphy (Murphy, 1993). The average yield of corn from the simulation was 12.39 t/ha which is close to the observed average yield for the region 12.33 t/ha (assuming that 1 bushel represents 70 lbs of corn).

Table 3. Literature-based fertilizer amounts for conventional and cellulosic bioenergy crops. Values are used as maximum annual application rates

Crop	N Fertilizer (kg/ha/year)	P Fertilizer (kg/ha/year)	N:P Ratio	Observed Yield (t/ha)	Model Yield (t/ha)
Corn	143.7	46	75.75 / 25.25	12.33	12.35
Sorghum	66.1	25.8	71.93 / 28.07	3.92	2.65
Soybean	0.0	0.0	-	2.08	1.88
Winter wheat	64.6	34.5	65.19 / 34.81	2.78	2.78
Hay	67.2				
Switchgrass	87.4 (years 3 to 10)	44.8	66.11/33.89		
Poplar	100.9 (years 3 & 6)	16.8 (year 3)	85.73/14.27		
High-yield sorghum	168.1	67.2	71.44/28.56		

Simulating autofertilization of hay resulted in high estimates, which we reduced by limiting the annual amount to 224 kg N/ha (Redfearn *et al.,* 2010). In practice, fertilizer amounts depend on whether alfalfa (a nitrogen fixer) is included in the mix of forage grasses. According to the 2009 National Land Cover Data, grass hay is more common than alfalfa in this region (Homer *et al.*, 2004).

For switchgrass we used autofertilization routines and applied up to 44.8 kg/ha P for all ten years and 87.4 kg/ha N after the first two years. The first two years do not receive nitrogen to discourage the growth of weeds from the applied nitrogen. Switchgrass removes about 4.55 kg of P per metric ton (Flueck et al., 2011). We modified default parameters for switchgrass by reducing the fraction of nitrogen in crop yield to 0.007 (Bransby et al., 1998). The default value of 0.0022 for phosphorus is well supported (Sanderson et al., 2001) (Clark et al., 2005). Runoff curve numbers used were 31, 59, 72, and 79 (Kiniry, 2005).

We simulated an eight-year poplar rotation based on BT2 assumptions (US Department of Energy, 2011). 100.9 kg/ha N were applied in the 3rd and 6th years and 16.8 kg/ha P was applied in the 3rd year. High-yield sorghum is an annual cellulosic feedstock (Venuto & Kindiger, 2008). We applied 168.1 kg/ha N and 67.2 kg/ha P each year. Our growth parameters for energy sorghum were derived from USDA values (White, 2006).

We found fertilization assumptions for pasture to be uncertain because data are not collected and reported by USDA as part of the agricultural census. We fertilized pasture with manure by simulating cattle using data obtained from the USDA agricultural Census Data, as explained in the next section.

3.1.2.8 Stover removal

Stover removal was simulated only for corn in future bioenergy scenarios. We removed 80% of aboveground biomass upon harvest.

3.2 SENSITIVITY ANALYSIS OF PASTURE FERTILIZATION

The spatial distribution of the pasture in the AWR indicated most pasture land in the western part of the river basin (Figure 5). NASS data was downloaded for all the counties within the AWR and based on an area weighted proportioning approach in ArcGIS, the county level data were distributed to the subbasins, and the number of cattle per hectare within a subbasin was determined. The average density in 2010-2011 was 0.267 (range 0.018 to 1.284) head of cattle per hectare.

The baseline scenario of simulating manure application required us to estimate manure characteristics. We assumed that cattle in a feedlot initially weigh 338 kg, gain 1.42 kg/d, consume 8.84 kg dry matter/d, and require 153 days of feeding to reach market weight, estimated at 554 kg (Erickson *et al.*, 2003). A beef cow excretes an average of 6.6 kg of dry matter/d (ASAE, 2005). The biomass trampled is assumed to be equal to the biomass eaten (Chaubey *et al.*, 2010). We estimated daily biomass eaten (BIO_EAT), manure excreted (MANURE_KG) and biomass trampled (BIO_TRMP) for each subbasin from the number of cattle, each in units of kg/ha/day.

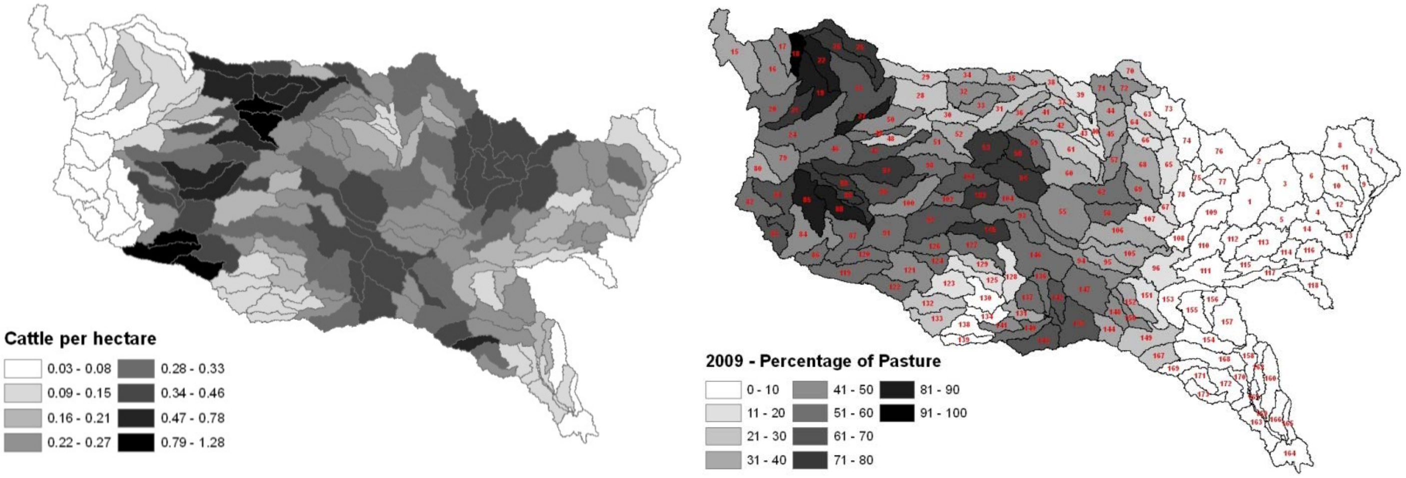

Figure 5. Spatial distribution of cattle (left) and pasture (right) in the Arkansas-White-Red region based on 2011-2011 NASS statistics.

SWAT-simulated nitrate exports varied spatially in the baseline simulation using NASS statistics (Figure 6). Nitrate concentrations were high in the Neosha-Verdigris basin and generally lower in the west than in the east, and in headwater subbasins (Figure 6). Both nitrate and total phosphorus showed a pattern of higher concentrations in subbasins along the Lower Arkansas River mainstem (see Figure 1 for reference). Total phosphorus (TP) concentrations were low in more remote, headwater watersheds in non-agricultural areas, particularly in the Upper White and Black River basin (Figure 6). TP concentrations were higher in agricultural areas of the Upper and Middle Arkansas and Neosho-Verdigris

River basins and the headwaters of the Red and Sulphur basin (Figure 6). Those in the upper Red and Sulphur basin correspond with high cattle densities (Figure 5).

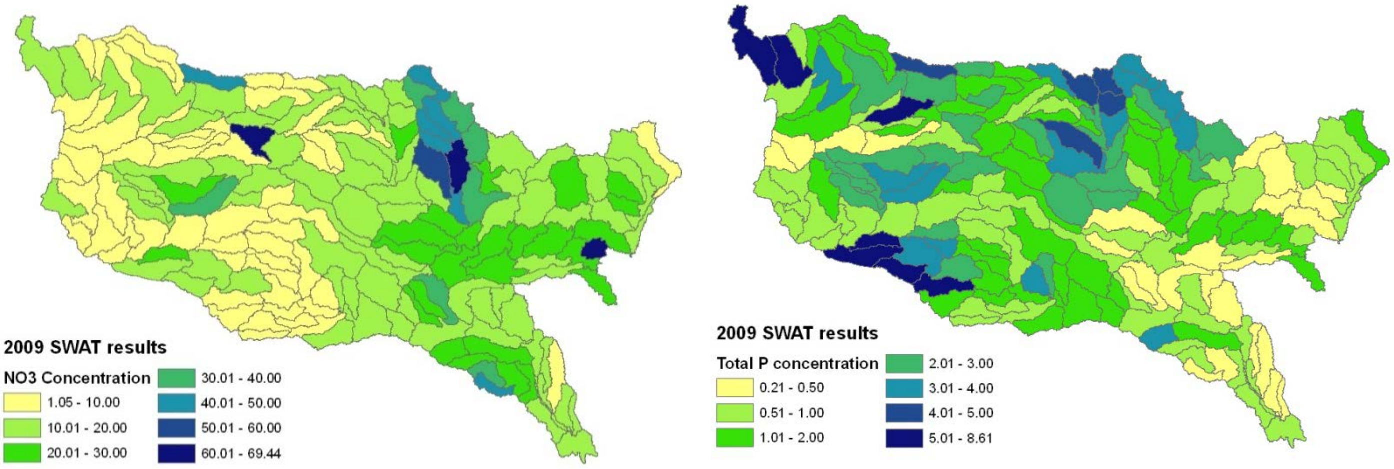

Figure 6. Spatial distribution of SWAT-simulated water quality using baseline NASS cattle statistics as the basis for manure application on pasture lands.

Among the other scenarios considered, in general, the pasture management scenario using autofertilization resulted in higher nitrogen fertilizer application and nitrate in streams than scenarios managed based on recent cattle statistics (NASS 2011; Figure 7). However, differences in phosphorus were small.

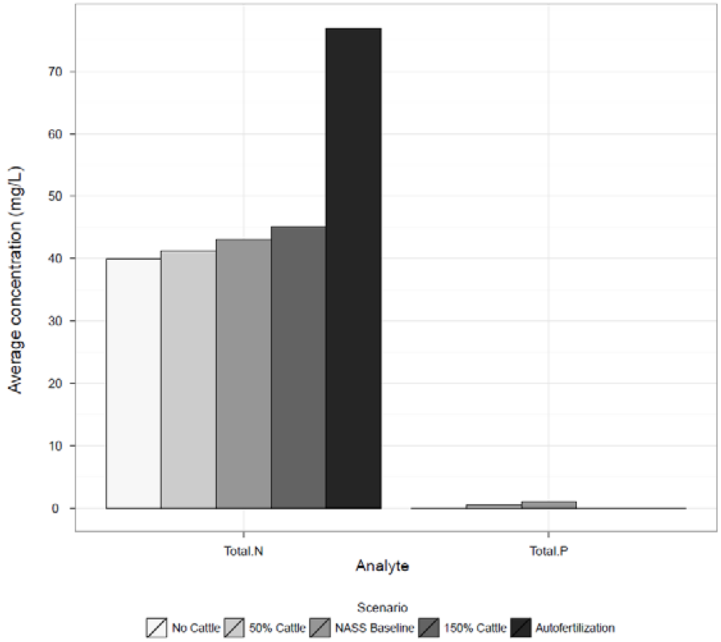

Figure 7. SWAT-reported summary of N and P concentrations across different scenarios of pasture management.

The majority of pasture occurs in the middle and western half of the region (Figure 5). In general, nitrate concentrations in areas with more pasture showed higher sensitivity to the number of cattle (Figure 8).

There was virtually no difference in nitrate among scenarios in the Upper White and Black river basin, where pasture is absent (Figure 8). Sensitivity appears greatest in the Upper and Middle Arkansas, Cimarron, Canadian and Red and Sulphur river basins (Figure 8), where pasture is an important land cover. The Lower Arkansas basin is an interesting case because it contains little pasture, but receives nutrient inputs from western river basins that do contain pasture.

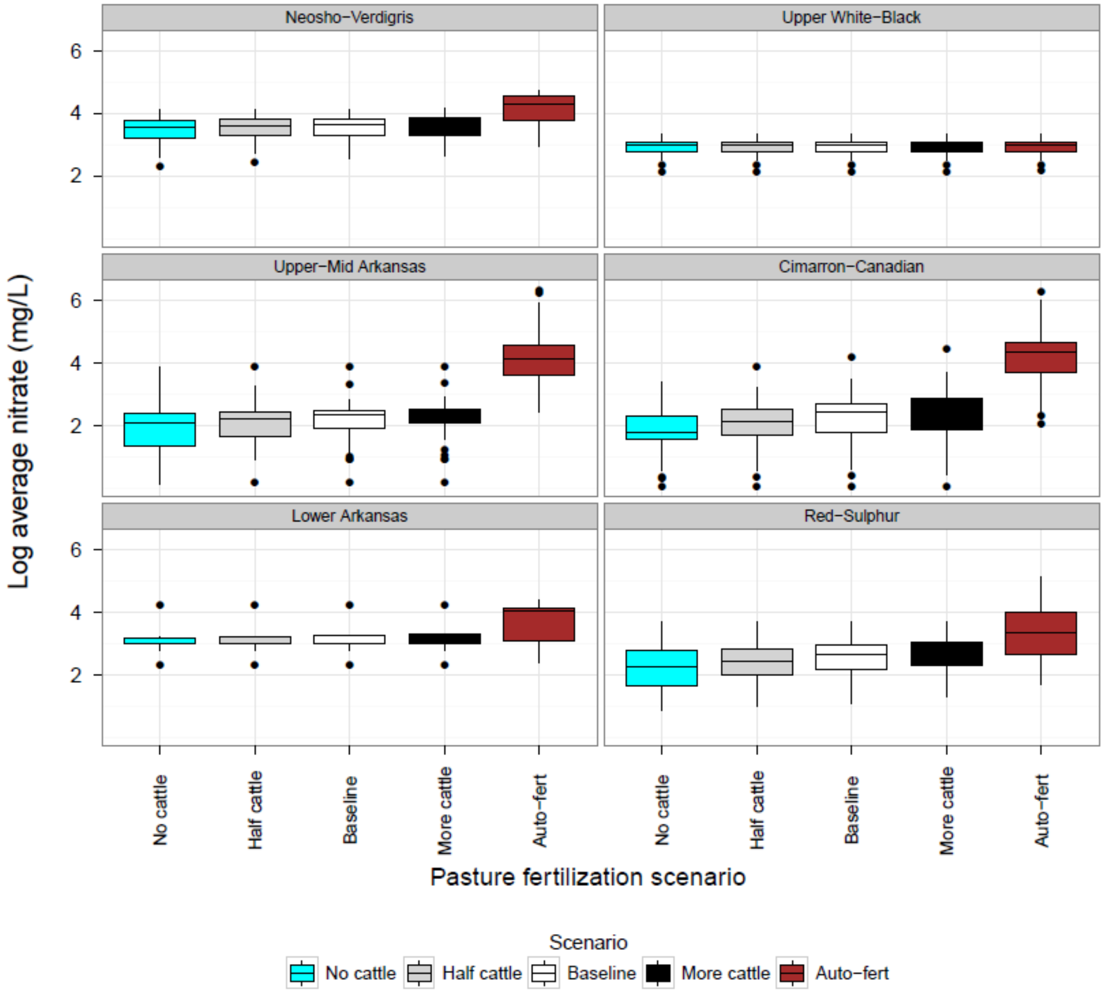

Figure 8. Comparison of log-transformed average nitrate concentrations at the outlets of major rivers basins in the Arkansas-White-Red river basin. River basins are shown in Figure 1.

Total phosphorus showed patterns among the SWAT management scenarios than nitrate did. In particular, whereas SWAT-simulated nitrate was much higher under the autofertilization scenario than the cattle-based scenarios for pasture management, this was not true for phosphorus. Generally speaking, the choice of pasture management option did not have a large influence on the distribution of simulated TP concentration (Figure 9).

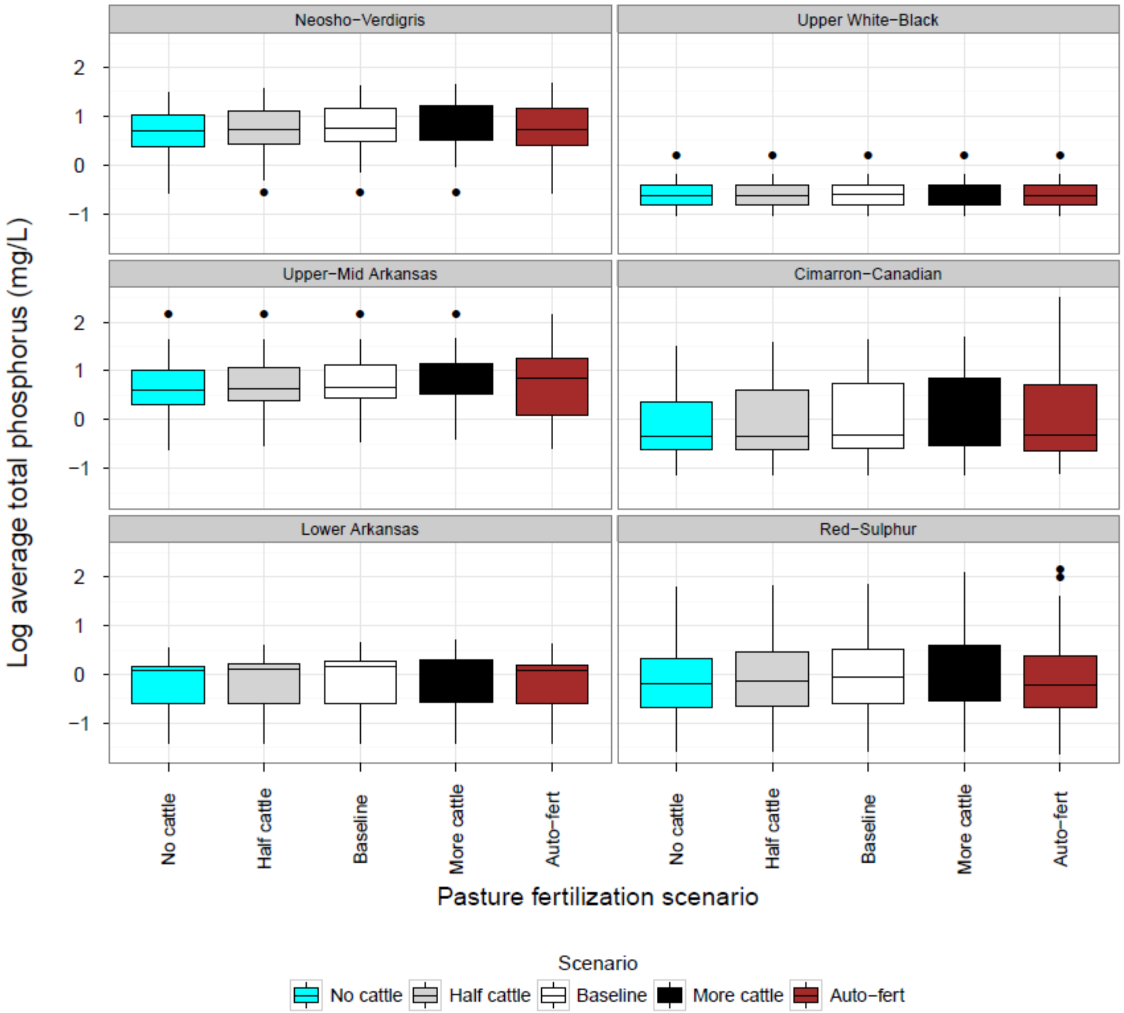

Figure 9. Comparison of log-transformed average total phosphorus concentrations at the outlets of major rivers basins in the Arkansas-White-Red river basin. River basins are shown in Figure 1.

3.3 SENSITIVITY ANALYSIS OF SWITCHGRASS FERTILIZATION

The cumulative distribution of the subbasin wide switchgrass yield and stream nitrate response to fertilizer application scenarios is presented in Figure 10. The plots indicate a yield advantage when increasing from 43 to 87 kg/ha, but not so much beyond that. The corresponding nitrate penalty when increasing from 43 to 87 kg/ha is also low. However, higher amounts of N fertilizers does result in yield improvement, but the corresponding nitrate penalty is higher. The response of the autofertilization are similar to the response of 43 kg/ha of N scenario.

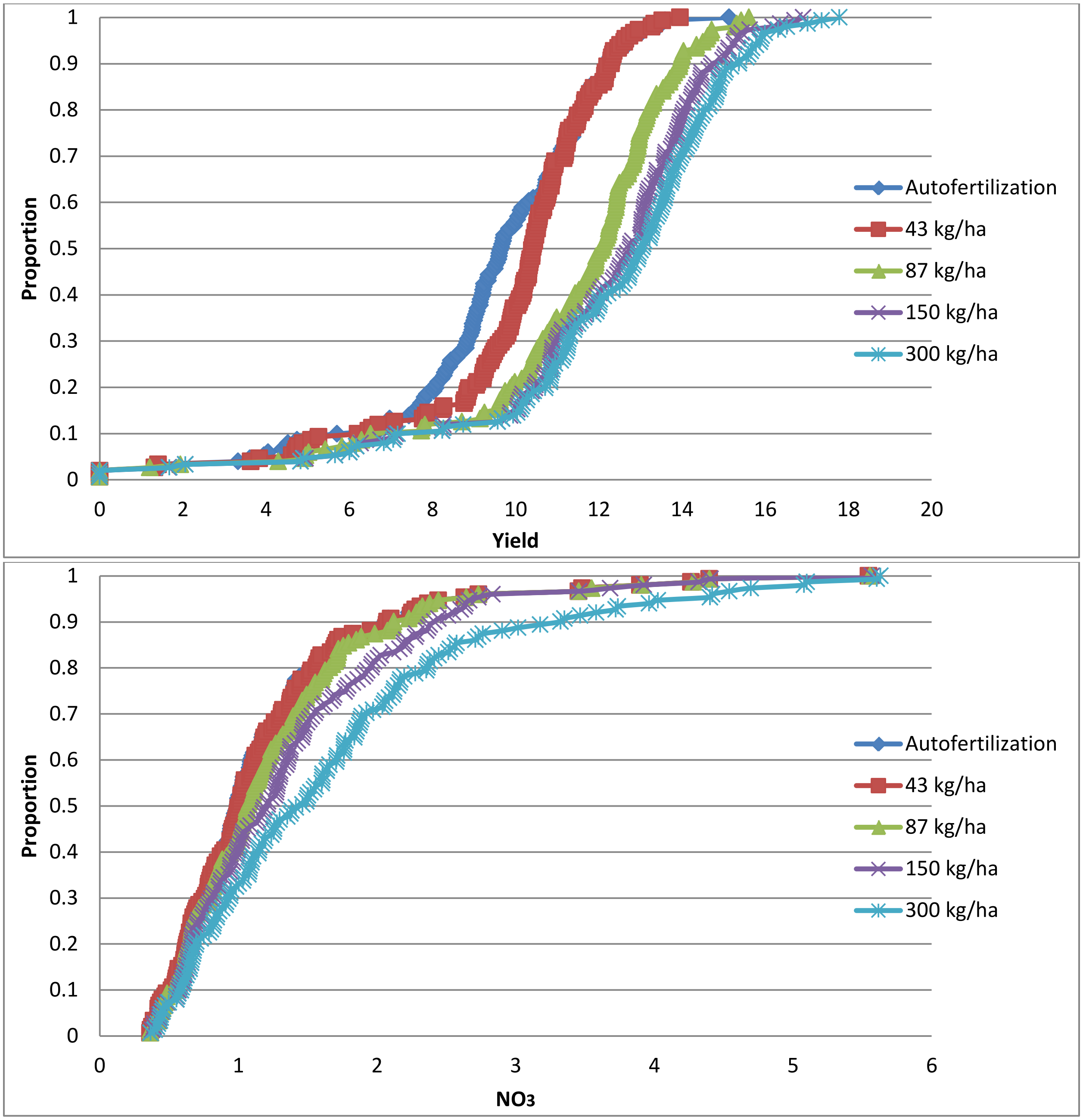

Figure 10. Plots showing the subbasin-wide yield and nitrate response to various fertilizer application scenarios for switchgrass.

The spatial distribution of the amount of fertilizers applied in the autofertilization routine (Figure 11) indicates that the maximum N fertilizers applied were 47 kg/ha, even though an upper limit of 87 kg/ha was set. The higher amounts of fertilizers were applied in the eastern parts of the AWR and also along the Beaver River in the Northern Canadian river basin. We also analyzed the corresponding yield per nitrate variable across the study region (Figure 12). When comparing the yield per nitrate with the fertilizers applied (Figure 12), it can be seen that some of the higher yield/nitrate values in the east correspond to higher amounts of fertilizers (overlay of black and red hatched sections in the east in figure 12). It can be assumed that in these regions the higher amounts of fertilizers were effective in producing higher switchgrass yields, but also with lower nitrate concentrations. However, areas in the west along the

Beaver River in the northern Canadian river basin show low yield/nitrate response in spite of higher amounts of fertilizers applied. Alternatively, medium and low amounts of fertilizers (yellow dotted and green hatched areas) applied close to the Canadian river showed high yield/nitrate values.

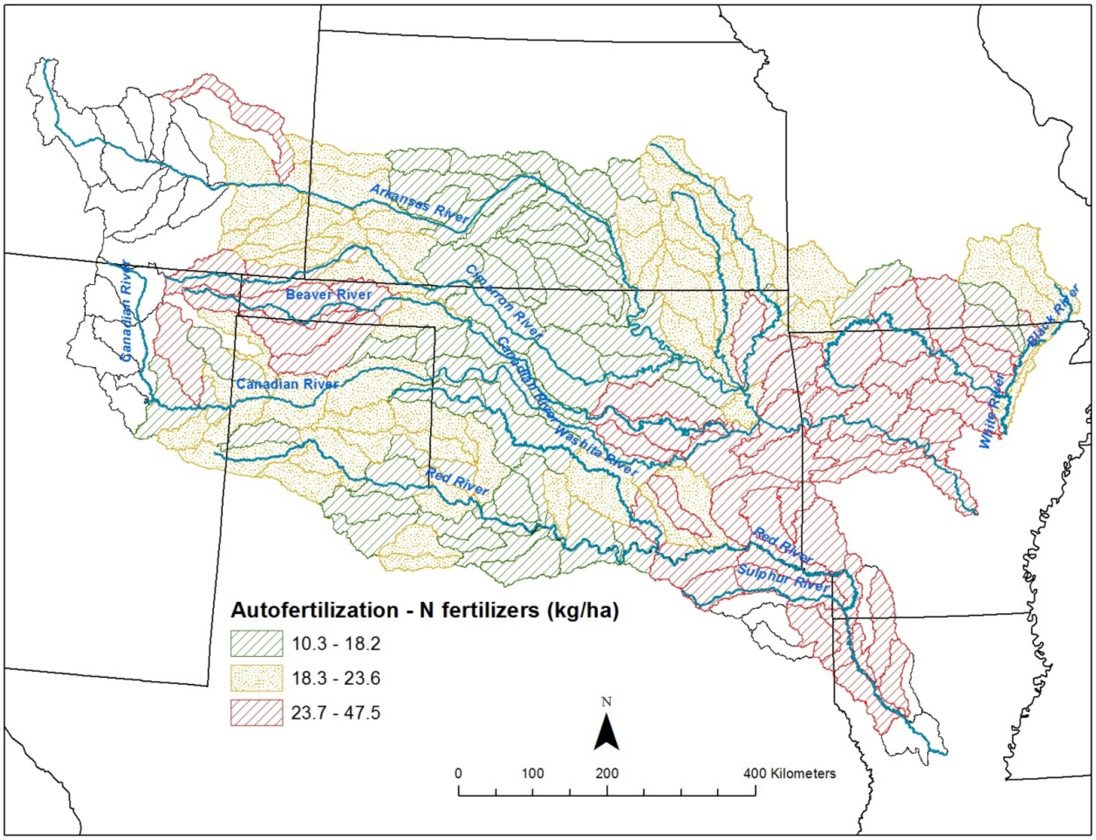

Figure 11. N fertilizers applied across subbasins in the autofertilization scenario.

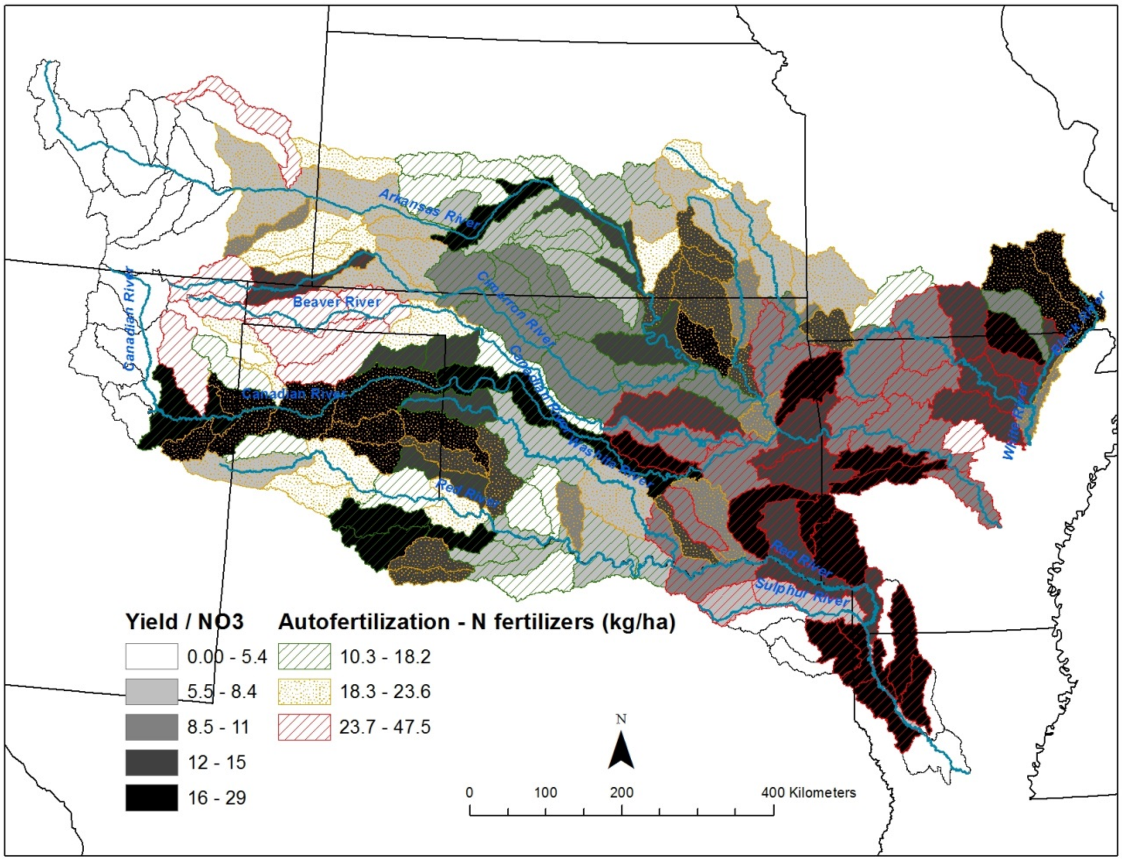

Figure 12. Yield/nitrate response overlaid on the amount of fertilizers applied in the autofertilization scenario.

To further understand the distribution of the switchgrass yield with respect to fertilizers applied and other variables, we performed a regression analysis of the yield with fertilizers applied, soil parameters, area in tile drainage and average precipitation. The soil parameters were summarized by subbasin from STATSGO data and included moist bulk density, available water capacity, saturated hydraulic conductivity, organic C content, sand, silt and clay content and rock fragment content. We log transformed some variables that were skewed (area in tile drainage, saturated hydraulic conductivity, moist bulk density and rock fragment content). The results indicated that the yield response was a function of the area in tiles, precipitation and moist bulk density with an R^2 of 0.54 (table 4).

Table 4. Results of regression analysis of yield (tons/ha) with precipitation, soil variables, area in tile drainage and fertilizers applied as independent variables

Independent Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Precipitation (mm)	.005	.000	.609	10.787	.000
Log of area in tiles (ha)	1.125	.209	.301	5.380	.000
Log of moist bulk density	5.040	2.212	.127	2.279	.024

(Mg/m3)

4 DISCUSSION

In this report we presented the agricultural context for setting up the SWAT model while simulating bioenergy futures. To effectively study the impact of bioenergy futures, it is important to setup the baseline with appropriate information from the study region. In this study we found that crop management is spatially variable and there are different ways to summarize the available information to use in a large study region, such as the AWR river basin. For identifying planting dates, fertilizer application and tillage rotations, we used state wide data and averaged them for the study region. For pasture management, we obtained county-level cattle data and performed an area-based weighting to identify number of cattle per subbasin.

Pasture makes up a significant land-use class in the study region, comprising over 90% of some western sub-basins in the region. The presence of pasture in drier climates will facilitate the introduction of switchgrass as a cellulosic feedstock with low water and nutrient requirements (Figure 3, top). In the NASS baseline, the highest average nitrate concentrations occurred in the Neosho-Verdigris river basin. This is a basin that the Billion-Ton scenario forecasts suggest will grow poplar in future (Figure 3, middle).

The pasture sensitivity analysis demonstrated that nitrate exports in the agricultural mid-section of the region were not greatly influenced by grazing-based pasture management for either nitrate of TP. The distributions of nitrate exports (Figure 7) among the four scenarios using cattle statistics showed considerable overlap. Pasture management as simulated in SWAT had little influence on phosphorus at the densities of cattle simulated here. However, we did observe a large difference between autofertilized pasture management and livestock-based scenarios for nitrate. Autofertilization resulted in higher rates of fertilizer application and higher levels of nitrate export. This result suggests that either cattle statistics underrepresent or autofertilization over represents nitrogen additions. Water quality results for nitrate were clearly sensitive to how pasture fertilization is represented in SWAT.

One secondary purpose of this analysis was to help define realistic assumptions for pasture intensifications for use in future simulations. Billion Ton forecasts of land-use change assumed that pasture intensification would occur, resulting in more livestock per acre of pasture in areas where switchgrass replaces pasture. The idea is that livestock would still be fed, despite loss of pasture. The simulations reported here indicate that sensitivity of water quality (specifically nitrate) to changes in the number of cattle is low when the number decreased. This suggests that intensification of pasture may not have much effect, but it is also possible that there will be a threshold density of livestock that exceeds the capacity of pastureland to remove nitrate and other nutrients. Avoiding this threshold during the transition of land conversion and possible intensification of pasture will provide direct, measurable guidance to ensure sustainable transition to a bioenergy future in this region.

The sensitivity analysis of the SWAT model to fertilizer assumptions for switchgrass led us to conclude that higher fertilizer amounts, though may provide higher yields, it may do so at the cost of higher nutrient concentrations in the stream. The autofertilization method of applying fertilizers had moderate levels of fertilizers applied over the study region (lower than the usual recommended amount) and resulted in reasonable switchgrass yields with lower stream nitrate concentrations in the eastern parts of the study region. However in the west, the results were not very favorable where higher amounts of fertilizers resulted in lower yields/higher nitrate concentrations. This result led us to study the mechanisms that guide the autofertilization and resulting switchgrass yield. Precipitation, which also represents the east-west gradient of the study region, was important in describing the yield levels. Further, the presence of tile drains influenced the switchgrass yield, which leads us to believe that water availability and water drainage may be an important factor.

The results here will help us to quantify trade-offs between switchgrass yield and nutrient exports for different fertilization regimes. Better understanding fertilization requirements for pasture and switchgrass will help to assess geographic areas where water quality will be improved by the transition. In future scenarios, switchgrass is predicted to displace both pasture and wheat in the mid-section of this region. Field studies have not reached a consensus on fertilizer requirements for switchgrass (Parrish and Fike 2005), in part because growing grasses for forage requires more input than those grown for bioenergy. Depending on soil properties and rainfall, annual amounts of nitrogen required range from 40 to 120 kg N/ha (McLaughlin and Kszos 2005). Potentially, nitrogen can be applied every two or three years (McLaughlin and Kszos 2005). Switchgrass performed well when provided with 24 to 40 kg P/ha (Parrish and Fike 2005). In our final SWAT simulations, we applied 44.8 kg P/ha for all ten years and 87.4 kg N/ha after the establishment years. In future, we hope to define levels that attain high yields but that prevent excess leaching of nutrients into streams.

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