Use of the SWAT model to evaluate the sustainability of switchgrass production at a national scale

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Abstract

As the US begins to integrate biomass crops and residues into its mix of energy feedstocks, tools are needed to measure the long-term sustainability of these feedstocks. Two aspects of sustainability are long-term potential for profitably producing energy and protection of ecosystems influenced by energy-related activities. The Soil and Water Assessment Tool (SWAT) is an important model used in our efforts to quantify both aspects. To quantify potential feedstock production, we used SWAT to estimate switchgrass yields at a national scale. The results from this analysis produced a map of the potential switchgrass yield along its natural eastern range. To quantify ecological protection, we are using the SWAT model to forecast changes in water quality and fish richness as a result of landscape alterations due to incorporating bioenergy crops. We have implemented the SWAT model in the Arkansas-Red-White region, which drains into the Mississippi River, and we present our methods here. We identified two sub-watersheds for sensitivity analysis and calibration of the water quality results, and then, explored ways to apply the calibration results to the whole region and validate the model setup. We also present an overview of our research in which results from the calibrated regional SWAT model were used to analyze potential changes in fish biodiversity. Only by evaluating the energy and environmental implications of landscape changes can we make informed decisions about bioenergy at the national scale, and the SWAT model will enable us to reach that goal.

Keywords: sustainability, bioenergy, biodiversity, water quality, switchgrass

1. Introduction

Projecting how changes in the agricultural landscape influence water quality is a complex issue that requires an appropriate modeling tool capable of representing important aspects of the system. Our research is focused on quantifying the changes in water quality associated with introducing dedicated energy crops to some parts of the current landscape and harvesting residues of other crops. Our choice of a watershed model was dependent on two factors: 1) its ability to predict both the yields of bioenergy crops and crop residues, and 2) its ability to represent watershed influences on water quality at regional-to-national spatial scales.

Working at regional-to-national scales placed a number of constraints on our choices. First, although bioenergy land covers are the focus of our research, we must include other land covers because they also influence water quality. Therefore, we require a model that can address the influence of natural, agricultural and bioenergy vegetation as well as urban and other non-vegetated land covers on the watershed. Second, the model must be capable of using spatially explicit input data that are generally available throughout the conterminous US. Third, the model must be capable of representing watershed influences on water quality adequately at relatively coarse spatial scales consistent with the resolution of national GIS input datasets. The size of sub-watersheds used in modeling is limited by the ability to process high-resolution digital elevation maps and the inherent resolution of satellite-derived spatial data. We identified the Soil and Water Assessment Tool (SWAT) as an appropriate candidate for our efforts to quantify bioenergy crop yields and water quality effects at regional-to-national scales. Another advantage of the SWAT model is its large user community, which has led to testing in a wide variety of settings (Gassman et al., 2007).

Applications of SWAT to large, regional river basins are much less common (e.g., Arnold et al., 2000, Upper Mississippi River basin) than those for smaller spatial areas (e.g., Vache et al., 2002; Nelson et al., 2006, 45 subbasins spanning 119,400 ha). A number of applications have examined the relationship between sensitivity of SWAT predictions and scale. Scale is likely to have little influence on biomass yield predictions. However, water quality and nitrate, in particular, can be better predicted (up to a point) with higher resolution data (Jha et al., 2004; Chaubey et al., 2005).

In this paper, we present three sections that provide an overview of three studies at regional and larger scales. First, we present the results of a study to estimate Alamo switchgrass yields within its natural range in the eastern US using SWAT. Second, we present calibration results from a companion study to predict water quality from current Midwest landscapes. Finally, we present an overview of our research to predict how bioenergy landscapes will alter fish biodiversity. Only by evaluating energy and environmental implications of landscape changes can we make informed decisions. Therefore, we are looking to the SWAT model as a tool that will enable us to reach that goal at a national scale. We also discuss challenges of working at this scale, including difficulties involved in model validation and scaling-up calibration results.

2. Background

2.1 Estimation of Bioenergy Feedstock

Biomass productivity is an important aspect to address when considering the large-scale sustainability of a bioenergy future (Hall, 1997). Unfortunately, there are a limited number of sites where dedicated energy crops have been planted and production potential measured. Better estimates of dedicated energy crop productivity are essential to providing more accurate spatial estimates of resource potential. The purpose of this analysis was to estimate switchgrass yield for major hydrologic regions of the United States using SWAT. We focused our analysis on the natural eastern range of switchgrass (Parrish and Fike, 2005), so the SWAT model was run by each 2-digit hydrologic region spanning this range. Parameters for the lowland variety of Alamo switchgrass were used for the model runs.

2.2 Modeling water quality

Modeling water quality at a regional scale involves a number of steps that consider the scale of the problem for large spatial extents. Some of the issues to consider include data availability, scaling of results and computing capabilities. We assembled data from different sources and modeled water quality for the Arkansas-White-Red River (AWR) basin. We then performed sensitivity analysis and streamflow calibration at two subbasins and afterward scaled up these results to the whole region.

2.3 Modeling aquatic biodiversity

With the nation's increasing interest in the production of switchgrass as a bioenergy crop, it is important to understand and evaluate the potential effects of switchgrass production on water quality and stream aquatic biota. We used SWAT to link land-use changes brought about by biomass production with changes in aquatic habitat for fish. We are developing empirical models for fish richness at the regional scale based on a number of predictors, including SWAT-predicted nutrient concentrations and flows.

3. Methods and Results

3.1 Estimation of Bioenergy Feedstock

As the first step, subbasins were delineated for each region of interest using a 1-km resolution digital elevation model (DEM) based on Shuttle Radar Topography Mission - SRTM data (Farr et al., 2007). We superimposed the network of larger, main-stem streams onto the DEM. The main-stem streams were identified from the National Hydrologic Dataset (NHDPlus) (NHDPlus 2009) as reaches with a "thinnercod" value of 1. The average delineated subbasin size was set to 500,000 hectares (or 100,000 hectares in cases where a drainage area of 500,000 was too large to capture all the area within a region).

SWAT predictions of switchgrass yield were made for each hydrological response unit (HRU) within each subbasin. An HRU is a unique combination of land cover, soil and slope class. For the purpose of obtaining regional estimates of switchgrass yield, we created two land cover classes within each subregion by reclassifying all land cover classes other than water to Alamo switchgrass in the 30-m resolution 2001 National Land Cover Dataset (Homer et al., 2004). The reclassified land cover had two classes — switchgrass and water. Soil characteristics were defined by the STATSGO dataset (Soil Survey Staff, 1994). We defined three slope classes, slopes of 0 to1%, 1 to 5% and greater than 5%, based on the 1-km resolution SRTM data. All HRUs created using the aforementioned land cover, soil and slope data were used in the SWAT runs.

The SWAT default parameters for Alamo switchgrass were used except as noted below. The defaults are nearly all derived from Kiniry et al. (2005). Because switchgrass is a perennial grass, switchgrass was already planted and had an initial leaf area index of 0.5 and biomass of 500 kg/ha when we initialized simulations. Each year, we assumed that switchgrass required 1,100 physiological heat units to reach maturity. This estimate is at the low end of the reported range (Kiniry et al., 2005). To allow for crop drying, we delayed harvesting until reaching the 120% of heat units required to reach maturity and assumed that 80% of the above-ground biomass was harvested each year.

Starting from 1985, SWAT was run for 21 years with simulated climate (using the SWAT weather generator). We treated the first two years of the model run as spin-up years and excluded them from our reported time-averaged switchgrass yield predictions. To produce spatially-explicit predictions, we averaged predicted switchgrass yields for the remaining 19 years (Figure 1). Consequently, our yield predictions should be treated as those of mature stands of switchgrass.

SWAT-projected switchgrass yields varied from zero in the northern latitudes to over 16 Mg/ha in southern Illinois, Arkansas, western Kentucky and Tennessee (Figure 1). In addition to the latitudinal gradient, predicted yields increased while moving east from very low values west of the 100th parallel (Figure 1). Predictions across the southern extremes of the eastern US were typically between 6 and 12 Mg/ha (Figure 1). The low values at higher latitudes reflect the fact that the parameters used are for a lowland ecotype. Future efforts will examine yields for the upland ecotype, which is grown successfully at higher latitudes as well.

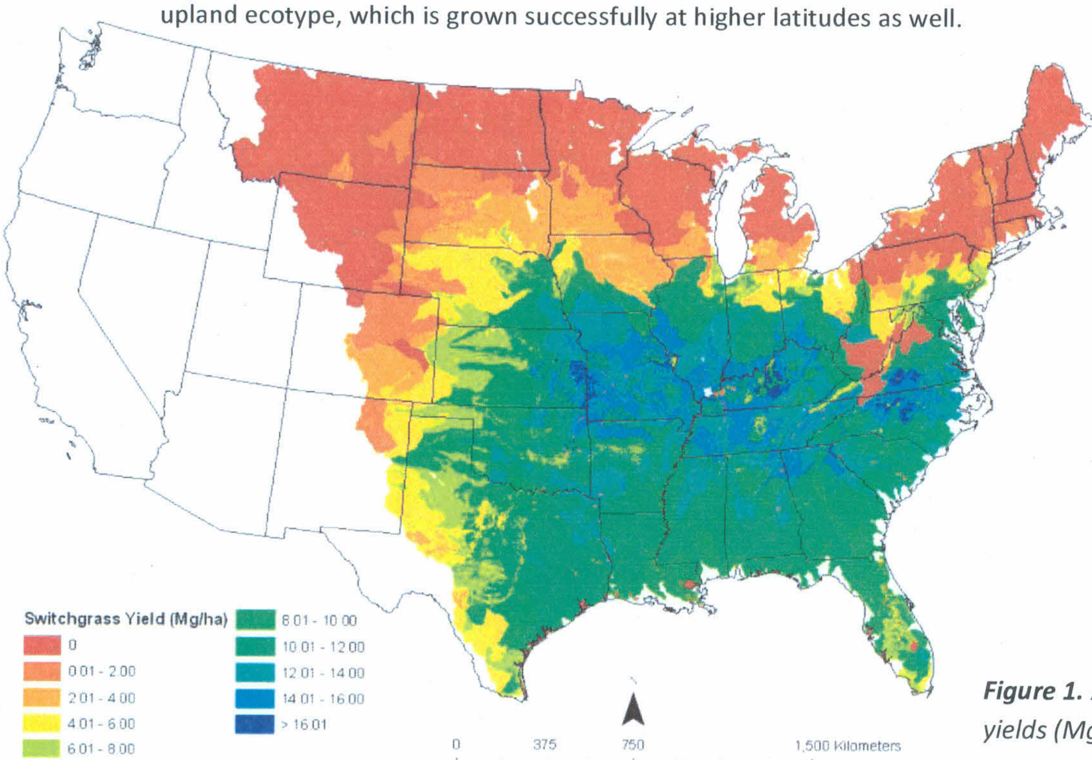

Figure 1. *Average Alamo switchgrass yields (Mg/ha) projected by SWAT*

3.2 Modeling water quality

To quantify water quality and biodiversity implications of biofuel production at the regional scale, we used USGS-defined, 8-digit hydrologic units (HUC) obtained from NHDPlus as subbasins instead of SWAT-delineated subbasins. Because SWAT requires one major stream reach per subbasin, we used the following procedure to derive main reaches from NHDPlus data. Within each subbasin, 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 "levelpathi" as the one farthest downstream (levelpathi is a code assigned to all channels from the stream's mouth to the stream's headwater and can be defined as a unique identifier for the mouth of a stream network). The final set of reaches was merged to produce a GIS layer with one stream feature per subbasin.

HRUs within each subbasin were defined as unique combinations of dominant soil type, land cover and slope as described earlier with a few modifications. We used the 2008 Crop Data Layer (CDL-08) to define land cover, substituting 2001 NLCD for one state (NM) lacking CDL-08 data. We assigned CDL land cover categories to SWAT land cover categories with the help of expert advice (personal communication with Anthony Turhollow). Each unique STATSGO map unit and land cover category that comprised more than 10% of a subbasin was used to define HRUs.

We reclassified a 30-m digital elevation model (DEM) of the AWR basin to 56 m and used it as the elevation input. This reduced resolution was necessary due to the large size of the study area and limitations on processing a 30-m DEM. We were able to process the AWR basin using the 56-m DEM, which also matched the resolution of the CDL land cover data. Using the 56-m DEM, we categorized slope into three categories, <2%, 2-5% and >5%, and we required all categories to be included in the definition of HRUs regardless of area.

We simulated tile drainage because it is common in the AWR basin and because simulating tile drainage has been shown to improve flow predictions (Green et al., 2006). We assumed that tile drainage was present in cropland areas with poorly drained soils with less than 2% slope. We assumed a tile depth of 1.1 m and a 36 h drain time.

We used climate data from DAYMET (Thornton et al., 1997) estimated for the center of each subbasin over the period 1980 to 2003. Daily climate input variables we included were total precipitation (mm), minimum and maximum temperatures (°C) and solar radiation (MJ/m2/day). Wind speed, relative humidity and potential evaporation were simulated by SWAT.

We performed a sensitivity analysis to identify parameters with the largest influence on streamflow (van Griensven et al., 2006). The analysis was conducted for each of two subbasins — one heavily forested and the other with grassland, shrubland and agricultural land (referred to as "agricultural") (Figure 2). Monthly flows were most sensitive to the baseflow alpha factor (Alpha_Bf) in the forested subbasin and to the curve number (CN2) in the grassland-agriculture subbasin. In both subbasins, the parameter ranked second was soil evaporation compensation factor (Esco in Table 1). The results of the sensitivity analysis helped to identify a subset of parameters that could be used to calibrate the model effectively.

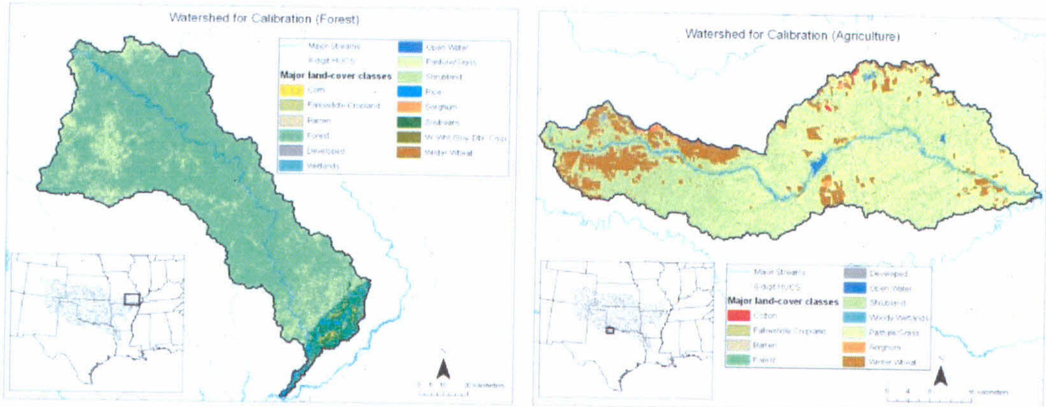

Figure 2. *Land cover in two subbasins used to calibrate parameters against monthly flow data*

We calibrated monthly flows against monthly streamflow records from USGS gauging stations near the outlets of the two subbasins of interest. We selected parameters that had the most influence on streamflow and entered them into the auto-calibration routine. SWAT-predicted monthly flows were automatically calibrated against monthly flows between 1985 and 1996. The quality of calibration results is typically measured using the Nash-Sutcliffe efficiency (NSE), which ranges from zero to one. Values greater than 0.75 are considered very good, and those above 0.65 are considered good (Moriasi et al., 2007). The NSE for the calibrated forested subbasin was 0.74, and the NSE for the calibrated agricultural basin was 0.78. For each subbasin with its individually calibrated parameters, we validated SWAT-predicted monthly streamflow using data from 1997-2003. The validation data NSE for the forested subbasin was 0.75, and 0.65 for the agricultural basin.

We compared parameter changes suggested by the calibration runs for the two basins (Table 1). To apply the calibration results for the whole region, we selected parameters from the two calibrated subbasins with similar final calibrated values. The parameters selected were baseflow alpha factor, maximum canopy storage, channel effective hydraulic conductivity, soil evaporation compensation factor and surface runoff lag time (Table 1). Of these parameters, the 'best' values from the forested and agricultural subbasins were selected and averaged. The average parameter values were then applied over the whole region. For other parameters, such as the curve number, calibrated results were different in the two subbasins. There was a need to reduce the curve number for the agricultural basin and increase it in the forested basin. Consequently, we retained default values for these parameters in the regional run.

Table 1. *Results from sensitivity analysis and auto-calibration of streamflow parameters for the forested and agricultural subbasins (* - parameters chosen for calibration across the whole region; ** - Parameter variation methods: 1 – replacement of initial parameter by value, 2 – adding value to initial parameter and 3 – multiplying initial parameter by value (in %)).*

Parameter code	Parameter description	Sensitivity analysis ranking		Parameter variation method**	Parameter changes for		
		Forested basin	Agricultural basin		Agricultural basin	Forested basin	Average
Alpha_Bf*	Baseflow alpha factor (days)	1	4	1	0.06	0.06	0.06
Blai	Maximum potential leaf area index	6	8	1	1.00	1.00	
Canmx*	Maximum canopy storage (mm)	4	10	1	0.14	0.00	0.07
Ch_K2*	Channel effective hydraulic conductivity (mm/hr)	7	7	1	6.86	8.06	7.46
Cn2	Initial SCS CN II value	8	1	3	-0.34	4.73	
Epco	Plant uptake compensation factor		11	1	0.44	NA	
Gw_Delay	Groundwater delay (days)	12		2	NA	9.84	
Esco*	Soil evaporation compensation factor	2	2	1	0.80	0.01	0.41
Gwqmn	Threshold water depth in the shallow aquifer for flow (mm)	5	9	2	503.76	-868.14	
Revapmn	Threshold water depth in the shallow aquifer for "revap"(mm)	3	12	2	-95.58	99.81	
Sol_Awc	Available water capacity (mm H2O/mm soil)	11	3	3	2.03	-21.03	
Sol_Z	Soil depth (mm)	10	6	3	-3.18	24.95	
Surlag*	Surface runoff lag time (days)	9	5	1	1.79	1.00	1.40

The performance of the five-parameter calibrated run in the forested basin provided good results with an NSE of 0.63. The performance of the five-parameter calibrated run on the agricultural basin was fair with an NSE of 0.45.

The five parameters selected in the calibration were applied over the whole study region, and the model was run from 1980 to 2003. The results from the first two years (1980 and 1981) were skipped in the output. This model setup needed to be validated with data that spanned the whole study region. For this purpose, we obtained streamflow data for each subbasin from NHDPlus data. These streamflow estimates were originally calculated by the unit runoff method in NHDPlus and represent mean annual flow in cubic feet per second (cfs) estimated at the bottom of a flowline (NHDPlus, 2009). The NHDPlus streamflow values were converted to units of cubic meters per second (cms) and then subtracted from SWAT average daily streamflow predictions (in cms), averaged over the 22-year period to obtain the amount by which SWAT over or under predicts streamflow when compared with NHDPlus streamflow estimates.

The results indicate that SWAT overpredicts streamflow in the downstream basins along the eastern regions of the study area and under predicts streamflow in some of the upstream basins (Figure 3). These results suggest that flows predicted by SWAT are higher than expected based on watershed area (unit-runoff method) farther downstream and lower than expected based on watershed area upstream. These results are not surprising because the unit-runoff method does not account for variations in precipitation, and precipitation follows a strong east-west gradient (wetter in the east).

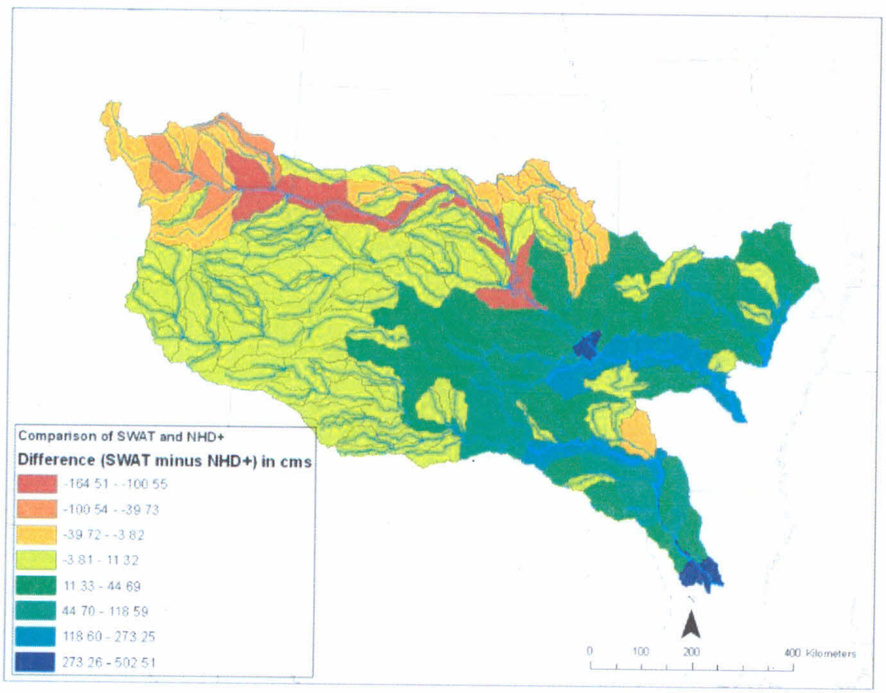

Figure 3. *Long-term flow comparison between SWAT and NHDPlus model predictions*

Our next step will be to evaluate changes in water quality using the validated model to compare current and future land use scenarios based on output from the Policy Analysis System (POLYSYS) (Ugarte and Ray 2000).

3.3 Aquatic biodiversity

We are developing empirical models for fish richness at the regional scale based on a number of predictors, including SWAT-predicted nutrient concentrations and flows. We used SWAT model output for stream discharge, nutrient concentration and sediment loadings to describe watershed water quality (8-digit USGS hydrologic units, HUC). We worked under the premise that streams and rivers with a high biodiversity of fish species need to be protected from declining water quality that can affect aquatic biota (Hails, 2008). Our hypothesis is that the cultivation of switchgrass on agricultural lands can reduce sediment and nutrient loadings to streams and hence improve future water quality and habitat for fish (Berkman and Rabeni 1987; Berka et al., 2001).

Our study focused on the Arkansas-White-Red River (AWR) basin. In building empirical models for biodiversity, we included several SWAT water quality and quantity outputs as predictors (average annual discharge and concentrations of nitrate, total phosphorus and sediment). These were averaged over a 22 year period. Additional predictor variables included mean annual precipitation, upstream drainage area, elevation at watershed outlets, percent land cover and the relative position of each HUC watershed along a downstream longitudinal gradient.

For watersheds in the AWR river basin, measures of streamflow and other predictors correlated with streamflow (e.g., % forest cover) had the largest influence on the species richness of native fish. Among headwater basins, watershed effects on biodiversity were dominated by the percent of forest, which was correlated with percent agriculture.

Our next step will be to predict aquatic species diversity in future agriculture land use scenarios. SWAT-derived water quality and discharge data will play a large role in our future efforts to model patterns in aquatic biodiversity.

4. Conclusion

The methods and results outlined here have shown how SWAT can be useful for exploring the productivity and environmental sustainability of switchgrass as a bioenergy crop at regional to larger scales. As our work with modeling switchgrass production and watershed modeling of bioenergy landscapes continues, we can improve our understanding of which areas provide the highest economic and environmental potential for biomass feedstock production. With the need for better understanding at a national scale, the approach we have outlined can be applied to other regions to produce guidance at this scale.

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