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Sensitivity Analysis and Evaluation of Forest Biomass Production Potential Using SWAT Model

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Abstract

Sensitivity analysis of crop parameters and the performance of SWAT (Soil and Water Assessment Tool) model to simulate potential forest biomass production were evaluated for the Upper Pearl River Watershed (UPRW). Local sensitivity analysis of seven crop parameters: radiation use efficiency (kg/ha)/(MJ/m^2) (BIOE), potential maximum leaf area index for the plant (BLAI), fraction of growing season at which senescence becomes the dominant growth process (DLAI), fraction of the maximum plant leaf area index corresponding to the 1st point on the optimal leaf area development curve (LAIMX1), fraction of growing season corresponding to the 1st point on the optimal leaf area development curve (FRGRW1), plants potential maximum canopy height (m) (CHTMX), and maximum rooting depth for plant (mm) (RDMX) reveals that only three parameters: DLAI, BIOE and BLAI are sensitive to forest biomass production. Further, results indicate moderate sensitivity of DLAI and BIOE and low sensitivity of BLAI with relative sensitivity index of 0.44, 0.35 and 0.14, respectively. The performance of SWAT to simulate potential forest biomass was evaluated by comparing simulated data against three years of observed data that were obtained from USDA Forest Service website. The results indicate satisfactory performance of SWAT in predicting potential forest biomass, which is shown by the high value of coefficient of determination (R^2 = 0.83), small root mean square error (RMSE = 11.11 Mg/ha), and small difference between mean. Results also reveal that the UPRW has the potential to produce approximately 49 Mg/ha of average forest biomass annually, which is approximately 6% less than the observed biomass.

Keywords

Sensitivity, Forest Biomass, SWAT, Crop Parameter, Watershed

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1. Introduction

In recent years, there has been growing policy interest about the use of forest biomass not only for generating electricity and producing heat but also for producing biofuel [1]-[3]. For instance, Energy Independence and Security Act of 2007 require 21 billion gallons of renewable fuel to be generated from cellulosic sources by Year 2022 in the US [3]. Further, sustainable use of forest biomass can also have multiple other benefits such as reduction of wildfire, proper functioning of hydrological processes, water quality improvement, and habitat improvement, among others [1]. Given such benefits associated with sustainable forest biomass use, research pertaining to forest biomass assessment is imperative, in particular, to determine the amount of biomass available in the area [4]. Studies in the past have noted that accurate assessment of forest biomass help to understand the productivity and sustainanility of forest [5] [6]. These studies further reported that accurate assessment of forest biomass helps in minimizing negative environmental consequences such as hydrologic imbalance and water quality impairment by controlling possible over harvesting of forest biomass.

The Upper Pearl River Watershed (UPRW) (**Figure 1**) is an important watershed of Mississippi because it drains directly into the Ross Barnett Reservoir (RBR). The RBR is one of the state's largest surface water bodies and serves as the main source of drinking water for the city of Jackson [7]. It is a forest dominated watershed and forest industry which has been identified as the main source of watershed's economy [8]. Given the increasing demand of forest biomass as a feedstock source for bioenergy, excessive forest harvesting for bioenergy production can be expected in the future. Since no studies related to forest biomass assessment have been conducted in the past, assessment of potential forest biomass in the UPRW seems imperative for sustainable extraction of forest products without degrading watershed health.

While comprehensive field based methods are considered to be an established practice to quantify forest biomass, these methods are, on the other hand, laborious, time consuming, and costly [7]. Given such limitations of field methods, computer simulation models have evolved as an effective tool to predict crop yield/biomass [7] [9]. Lately, Soil and Water Assessment Tool (SWAT), which is a computer based hydrologic models, has evolved as an important tool to predict crop yield and biomass production [10]-[12]. For instance, SWAT was applied in the Upper Mississippi River Basin (UMBR) to predict hydrologic budget and crop yield [12]. Likewise, it was applied in the Arkansas Red-White river basins to quantify the availability of switchgrass for producing bioenergy at the regional scale [10]. The model has also been applied in Iran to predict spatial and temporal variability of wheat yield at the sub-basin level with and without irrigation system [11]. These studies, in general, have reported the ability of SWAT to successfully predict crop yields and biomass of agriculture and herbaceous crops that are available in the watershed. However, to the best of our knowledge, a comprehensive study on forest biomass assessment using SWAT is still limited. Therefore, SWAT was used in this study to determine the availability of potential forest biomass in the watershed.

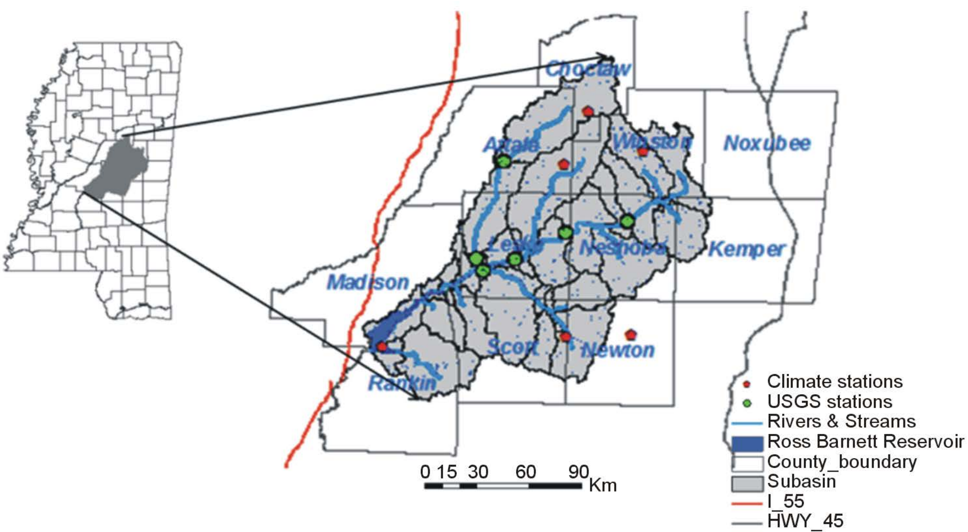

Figure 1. Location map of the Upper Pearl River Watershed showing climate stations, USGS gage stations, highway and reservoir.

The SWAT is a distributed hydrological model, and is characterized with large number of model parameters related to hydrology, water quality, and biomass and crop yields predictions. However, the actual value of many of the model parameters is little known because of the spatial and temporal variability in the processes that are being simulated [13] [14]. As a result, simulated model parameters are often doubted for introducing certain degree of uncertainty in the simulated results. Therefore, adjustment of model parameters within their given range is important to obtain close match between simulated and observed values [14]. This can be done by sensitivity analysis (SA) approach which helps to identify and rank parameters that have significant impact on simulated outputs. Thus, it helps in making appropriate selection of parameter(s) during model calibration [15]-[17].

Sensitivity analysis can be classified as local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis, also known as one-at a-time (OAT) approach, involves changing only one parameter at a time by a certain fraction from its base value for identifying model output responses [14] [15]. During this time, other parameters are kept constant and therefore change in the model output during each model simulation is considered as the contribution from parameter that was modified from base [18] [19]. Global sensitivity analysis, in contrast, allows changing random parameters simultaneously over their entire range. A global technique differs from local technique by accounting for variance of the model output associated with model parameter over their entire range of uncertainty [20]. However, if a model is complex and requires large input data, local sensitivity analysis method is preferred over global analysis due to its ease of operation [21]. Many studies in the past have indicated local sensitivity analysis as a good and simple approach for identifying sensitivity of model parameters on the model output [20] [22] [23]. The amount of avilable literature on sensitivity ananlysis of crop paramters for simulation of yield/biomass production using SWAT is still very limited. A study used the SWAT model to conduct sensitivity analysis of crop parameters that influence biomass and yield prediction of switch grass and cotton. Likewise, similar study was conducted to identify sensitive crop parameters for wheat yield calibration [11]. These studies, few in numbers, were primarily focused on identifying parameters sensitive to crop yield prediction of agricultural crops. However, none of these studies have focused on sensitive crop parameters that have significant impact on forest biomass production. The objectives of this study were to conduct: 1) sensitivity analysis of SWAT crop parameters to predict forest biomass production, and 2) performance analysis of SWAT to simulate potential forest biomass production in the Upper Pearl River Watershed.

2. Materials and Methods

2.1. Study Area

This study was conducted in the UPRW, which is located in east-central part of Mississippi (**Figure 1**) and has an area of approximately 7885 km^2. It covers a total of the 11 counties of Mississippi: Choctaw, Attala, Winston, Leake, Neshoba, Kemper, Madison, Rankin, Scott, Newton and Noxubee and flows down to the Ross Barnett Reservoir [8]. The dominant land use of UPRW is forest, which accounts for about 75% of the total watershed area. Longleaf pine, mixed pine-hardwood, dense cypress-Tupelo swamps and bottomland hardwood are the most common types of forest in the watershed [8]. Other land use types of the watershed include pasture (19%), and urban and others (6%). Fine sandy-loam and silt loam are the dominant soil texture of the UPRW. Based on climate data from the National Climatic Data Center during 1980 to 2010, average annual rainfall was about 145 cm with average annual temperature close to 16.3˚C for the watershed. More information about weather stations is described in Section 2.3.

2.2. SWAT Model

The SWAT version 2005 [24] was used for this study. The SWAT is a physically based, watershed scale hydrological model that uses various sets of spatial (such as digital elevation model (DEM), landuse, soil) and non-spatial datasets (precipitation, minimum and maximum temperature, wind speed, snow and relative humidity) [25].

The SWAT first delineates and divides the watershed into a number of sub-watersheds, which are further subdivided into hydrologic response units (HRUs). The HRUs are the smallest units in the sub-watershed and are considered to be homogenous with respect to their hydrologic properties [24] [26]. The HRU's are created by combining unique landuse, soils and topography within sub-watershed [24].

The SWAT operates on a daily time steps to predict hydrology, water quality and crop growth [27]-[29]. It simulates plant biomass and crop yield by using crop growth component, which is a simplified version of Environmental Policy Integrated Climate (EPIC) model [30]. Accumulation of biomass in SWAT is a function of intercepted energy, leaf area index (LAI) and the conversion of intercepted energy into biomass based upon radiation use efficiency (RUE). In SWAT, the amount of intercepted daily solar radiation by plant leaf is computed using the Beer's law (Equation (1)) [24]

$$H_p = 0.5 \times H_{\text{day}} \times \left(1 - \exp\left(-k_1 \times LAI\right)\right) \tag{1}$$

where, H_p = intercepted photosynthetically active radiation on a given day, H_{day} = incident total solar radiation on a given day, k_1 = light extinction coefficient, LAI = leaf area index.

The maximum increase in biomass (Δbio) on a given day resulting from the intercepted photosynthetically active radiation is estimated by using Equation (2) [24].

$$\Delta bio = RUE \times H_p \tag{2}$$

where, RUE = radiation use efficiency and is determined from the slope of the regression line between dry matter and cumulative intercepted photosynthetically active radiation [31]. Detail description about SWAT can be found in the SWAT documentation [24].

2.3. Model Input

The SWAT model requires input of spatial datasets, such as digital elevation model (DEM), soil data, and land use/land cover data. In addition, it also requires non-spatial time series of weather data, such as precipitation, temperature, wind speed, snow and relative humidity. In this study, we used USGS 30 m × 30 m DEM (USGS) [32] for delineating watershed boundary, defining stream network, creating sub-watershed, and for determining topography related information such as slope and angle. The land cover data layer of Year 2009 was obtained from US Department of Agriculture, National Agricultural Statistics Service [33]. The soil database for the study area was created by using State Soil Geographic Database (STATSGO) available within SWAT 2005 database [34]. The precipitation and temperature data are the weather data used in this study. These data were obtained from National Climatic Data Center (NCDC) for a period from 1980 to 2010 [35]. The observed daily precipitation data were obtained from ten rainfall stations: Ackerman, Canton, Carthage, Forest, Gholson, Kosciusko, Louisville, Newton, Philadelphia and Walnut Grove. Likewise, observed daily temperature data were obtained from seven climate stations: Carthage, Canton, Forest, Kosciusko, Louisville, Newton and Philadelphia [35].

2.4. Model Calibration and Validation

The adequacy of SWAT model to accurately simulate forest biomass was first tested by calibrating and validating the model with streamflow data obtained from the six USGS stations: Burnside, Edinburg, Ofahoma, Kosciousko, Carthage, and Lena. With an exception of Lena, calibration period at other stations was from 1980-1995 (16 years) and validation period was from 1996-2008 (13 years). Calibration at Lena station was done from 1998-2002 (5 years) and validation was done from 2003-2008 (6 years). Calibration was done manually by adjusting six streamflow parameters curve number (CN), soil evaporation compensation factor (ESCO), base flow alpha factor (ALPHA_BF), surface runoff lag coefficient (SURLAG), ground water "revap" coefficient (GW_REVAP) and threshold depth of water in the shallow aquifer for baseflow (GWQMIN) (**Table 1**). During parameter adjustment, different land use types were assigned with different CN value ranging between 70 and 92. The CN value of 77 for deciduous forest, 70 for evergreen forest, 73 for mixed forest, 77 for wetland forest, 79 for pasture, 89 for corn, and 92 for residential medium density showed the maximum model efficiency. In the case of the remaining parameters, same value of respective parameter was assigned for all land use type. For example, the ESCO factor of 0.40, the base flow alpha factor of 0.9, the ground water "revap" coefficient of 0.2, the threshold depth of water in the shallow aquifer of 1000, and the SURLAG coefficient of 1 were assigned for all land use types. These parameters and their values were selected based on the earlier studies conducted in the same watershed [7] and in other similar watersheds [30] [36] [37]. The final value of each model parameter that showed optimal model efficiency during model calibration was used for model validation without their further modification. The streamflow parameters that were selected for model calibration, their range, default value and final value are presented in **Table 1**.

Table 1. Adjusted parameters' range, default values, and final values used for streamflow calibration.

No.	Parameters	Range	Default Value	Final Value
1	Curve Number (CN)			
I	Deciduous Forest (FRSD)	70 - 77	83	77
II	Evergreen Forest (FRSE)	70 - 77	77	70
III	Mixed Forest (FRST)	70 - 77	79	73
IV	Wetland Forest (WETF)	70 - 77	83	77
V	Pasture (PAST)	74 - 86	84	79
VI	Corn (CORN)	85 - 90	83	89
VII	Residential Medium Density (URMD)	77 - 94	79	92
2	Soil Evaporation Compensation Factor (ESCO)	0 - 1	1	0.4
3	Base Flow Alpha Factor (ALPHA-BF)	0 - 1	0.048	0.9
4	Ground Water "Revap" Coefficient (GW-REVAP)	0 - 1	0.02	0.2
5	Threshold Depth of Water in the Shallow Aquifer (GWQMIN)	0 - 5000	0	1000
6	Surface Runoff Lag Coefficient (SURLAG)	1 - 12	4	1

2.5. Sensitivity Analysis

Local sensitivity analysis was done for assessing sensitivity of seven crop parameters of SWAT to predict forest biomass production. This was done by changing value of each crop parameter one at a time from its base value, while keeping other parameters constant at their base value. **Table 2** shows studied model parameters, their definition, base value and their range. The selection of these parameters was based on SWAT manual [24] and earlier literatures that have either reported about sensitivity of these parameters for crop yield calibration [11] [38] [39] or have performed sensitivity analysis for crop yield prediction [40] [41]. However, it is important to mention that all these past studies were primarily focused on either agricultural crops (cotton, wheat) or bioenergy crops (switchgrass, miscanthus).

The sensitivity of the model to each crop parameter was computed by using relative sensitivity index (Equation (3)) [42]-[46].

$$S_r = \frac{p_b}{R_b} \times \left(\frac{R - R_b}{P - P_b} \right) \tag{3}$$

where, S_r is the relative sensitivity index, R is the result or output, P is the model input parameter and b represents the base value. Higher the value of relative sensitivity index, the more sensitive is the SWAT simulated biomass to that parameter value. Once the relative sensitivity index of seven crop parameters was obtained, maximum relative sensitivity index of all parameters were compared to determine the most sensitive parameter that affects forest biomass production. Further, all the highest parameters were ranked as highly sensitive, low sensitive, moderately sensitive and no sensitive to forest biomass prediction based on the sensitivity class outlined by earlier study [28]. The range of sensitivity class used in this study is given in **Table 3**.

2.6. Forest Biomass Simulation

Forest biomass simulation was performed by adjusting crop parameters within their given range. Provided that the studies related to forest biomass prediction using SWAT is still limited, crop parameters for forest biomass simulation were selected based on the earlier studies related to crop yield prediction for agricultural crops [11] [47] and crop parameters listed in the SWAT manual [24]. According to these studies, BIOE and BLAI are the two important parameters for crop yield prediction, among others. Therefore, during model simulation, these two parameters were modified in the forested HRUs.

The annual average simulated forest biomass of three forest types (deciduous, evergreen and mixed) was compared against the observed forest biomass data obtained from USDA website [46]. The obtained observed data were available at the county level; therefore, to make them consistent with the format of SWAT output,

Table 2. Parameters selected for local sensitivity analysis along with their definition, base value and range.

Parameter	Definition	Base Value	Range
LAIMX1	Fraction of the maximum plant leaf area index corresponding to the 1st point on the optimal leaf area development curve	0.05	0 - 1
CHTMX	Plant's potential maximum canopy height (m)	6	0.1 - 20
FRGRW1	Fraction of growing season corresponding to the 1st point on the optimal leaf area development curve	0.05	0 - 1
RDMX	Maximum rooting depth for plant (mm)	3.5	0 - 3
BLAI	Potential maximum leaf area index for the plant	5	0.5 - 10
BIOE	Radiation use efficiency in ambient CO_2 ((kg/ha)/(MJ/m^2))	15	10 - 90
DLAI	Fraction of growing season at which senescence becomes the dominant growth process	0.99	0.15 - 1

Table 3. Sensitivity class [28].

SN	Value Range (S_r)	Sensitivity Class
1	0.00 - 0.05	No sensitivity
2	0.05 - 0.20	Low sensitivity
3	0.20 - 1.00	Moderate sensitivity
4	>1.00	High sensitivity

data were adjusted at the sub-basin level by calculating their weighted biomass yield. The biomass data for the UPRW were available for only three different years: 1994, 2006 and 2010. Therefore, based on the range of data available, model was run from 1990-2010 considering first three years as the model warm up period. Simulated forest biomass was then verified against the observed data.

3. Results and Discussion

3.1. Streamflow

The performance of SWAT to predict streamflow was analyzed statistically by using four widely used model efficiency statistics: Coefficient of determination (R^2), Nash-Sutcliffe model efficiency index (NSE), root mean square error (RMSE), and percent bias (PBIAS) [7] [47]-[49]. The classification of model performance was done based on the performance rating outlined by earlier studies [49] [50]. The results of model calibration and validation are shown in **Table 4**. The results indicate fair [47] to very good performance of SWAT for the UPRW, which is indicated by the values of R^2 and NSE, ranging from 0.58 to 0.82 and 0.43 to 0.83, respectively (**Table 4**). Reasonably good performance was also obtained for validation period with values of R^2 and NSE ranging from 0.36 to 0.68 and 0.25 to 0.64, respectively (**Table 4**). These values indicate fair to good correlation between the simulated and observed streamflow during calibration and validation periods.

Furthermore, the values of RMSE that ranged from 13.27 to 39.60 m^3/s and 12.31 to 52.44 m^3/s during calibration and validation period, respectively, also reveal better match between simulated and observed streamflow (**Table 4**). Even though RMSE is slightly poor at the Carthage and Lena station, other statistics indicate good model performance at these two stations (**Table 4**). Likewise, values of PBIAS that ranged from −2.70% to −22.91% and −4.89% to −36.98% during calibration and validation periods, respectively, also illustrate good fit between simulated and observed streamflow. These values, however, suggest that the model has overestimated bias at all the six stations during calibration period and at the three stations (Kosciousko, Lena and Ofahoma) during validation period, respectively. Possible explanations for such discrepancies between different stations for streamflow prediction may be due to the variation of precipitation input at these stations.

The model efficiency statistics computed in this study for the monthly streamflow prediction are found to be in general agreement with those reported by earlier studies using the SWAT model [7] [29] [36] [50]-[52]. A study conducted in southeast Indiana reported calibrated monthly streamflow NSE values between 0.59 and 0.80 for three different watersheds [52]. Likewise, a study determined R^2 = 0.81, NSE = 0.56, and PBIAS = −95.06% for calibrated monthly streamflow for Red Rock Creek watershed in south-central Kansas [50]. Moreover,

Table 4. Model performance during streamflow calibration and validation.

Station	Calibration Period				Validation Period			
	R^2	NSE	RMSE (m^3/s)	PBIAS (%)	R^2	NSE	RMSE (m^3/s)	PBIAS (%)
Burnside	0.78	0.75	13.60	−9.90	0.36	0.25	18.48	9.85
Carthage	0.81	0.80	32.63	−2.70	0.64	0.56	34.97	11.06
Edinburg	0.82	0.80	20.90	−4.50	0.58	0.55	24.74	−9.47
Kosciousko	0.58	0.43	13.27	−22.91	0.49	0.25	12.31	−15.29
Lena	0.75	0.73	39.60	−8.43	0.63	0.54	52.44	4.89
Ofahoma	0.72	0.65	14.96	−20.67	0.68	0.33	14.93	−36.98

SWAT model performance in this study is also consistent with the performance statistics reported by a study conducted in the same watershed [7]. The values of R^2, NSE and RMSE estimated at the five USGS gauge stations were reported between 0.69 m^3/s and 0.79 m^3/s, 0.68 m^3/s and 0.79 m^3/s, and 14.14 m^3/s and 37.03 m^3/s, respectively. Thus because of the good performance shown by the model in this study, the calibration SWAT model was further used to perform sensitivity analysis of crop parameters as well as to evaluate SWAT's performance to predict potential forest biomass production in the UPRW.

Figure 2 illustrates the relative sensitivity of studies crop parameters. The Y-axis represents the relative sensitivity index and the X-axis represents parameter values that were varied over their entire range. Visual analysis of **Figure 2** indicates that DLAI, BIOE, BLAI and RDMX showed positive relative sensitivity and FRGRW1, LAIMX1 and CHTMX showed negative relative sensitivity. Furthermore, it also indicates that relative sensitivity of parameters such as DLAI, BIOE, BLAI, RDMX, CHTMX increases with decrease in value from their base value. On the contrary, relative sensitivity of parameter FRGRW1 seems to be increasing when its value was increased from 0.25 to 0.45. However, further increase in its value causes decrease in the relative sensitivity. Similarly, relative sensitivity of LAIMX1 increases with increase its value from 0.25 to 0.65, but further increase in value from its base value decreases the relative sensitivity.

3.2. Model Sensitivity to Crop Parameters

Figure 3 demonstrates all the highest relative sensitivity index of each crop parameter. Results indicate that the relative sensitivity of studied parameters varied between no sensitivity ($S_r = -0.0080$) to moderately sensitivity ($S_r = 0.44$). **Figure 3** shows that only three parameters: DLAI, BIOE and BLAI are sensitive (with relative sensitivity greater than 0.1). Further classification of relative sensitivity index using sensitivity class outlined by earlier study [28], DLAI and BIOE were only moderately sensitive and BLAI shows low sensitivity with relative sensitivity index of 0.44, 0.35 and 0.14, respectively (**Table 2**). Other parameters: RDMX, FRGRW1, CHTMX and LAIMX1, though they directly impact the amount of light intercepted by leaves, were not found to be sensitive in predicting forest biomass production.

Our results on the value of relative sensitivity for all studied parameters appear to be lower than the values reported by past study for switch grass and miscanthus [41]. In contrast to our finding, BIOE and BLAI were reported as the most sensitive parameter followed by the DLAI [41]. On the other hand, with an exception of BLAI, our finding appears to be consistent with earlier study [41] if the relative sensitivity shown by each parameter is classified in accordance with sensitivity class outlined by another study [28]. It is worth mentioning that due to the limited availability of studies related to sensitivity analysis of SWAT crop parameter for forest biomass prediction, comprehensive comparison of relative sensitivity showed by each studied parameters for forest biomass production is limited in this study.

3.3. Forest Biomass Production Potential

Forest biomass simulated with the default value of selected crop parameters resulted in poor model performance due to their much lower prediction. Therefore, increasing the value of simulated forest biomass was the main focus of this study during forest biomass simulation. For this purpose, selected parameters were modified gradually from their base following the sequence of sensitivity shown by these parameters during sensitivity analysis.

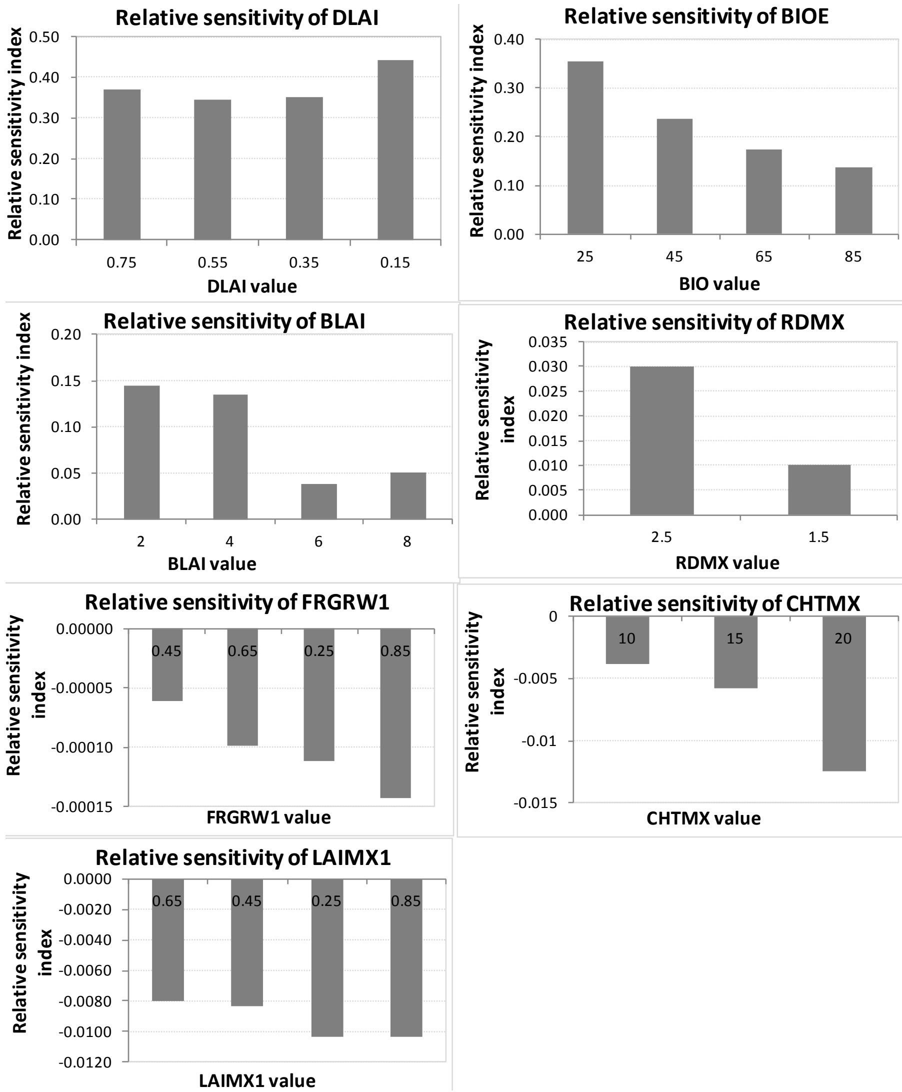

Figure 2. Relative sensitivity of selected crop parameters within their tested range.

It was observed that increasing the value of BIOE and BLAI resulted in increase forest biomass, whereas increasing the value of DLAI shows opposite result. Forest biomass remained unchanged when other parameters were modified, which was expected, because these parameters were not sensitive at the time of sensitivity analysis. Hence, these parameters including DLAI were set to their default value at the time of final simulation process.

The BIOE value in this study was increased gradually and was finally set to 75. On the contrary, other studies related with yield prediction of agricultural crops were found to have reduced the value of BIOE because, in their study, the default value resulted in higher yield [45] [53]. Additionally, the value of BLAI was also gradually increased and was set to 8 as it resulted in good agreement between observed and simulated data. The final value of BLAI for forested area was selected following the earlier literature [54].

The results demonstrate good correlation ($R^2 = 0.83$) between simulated and observed biomass. Visual analysis of **Figure 4** demonstrates that except in Year 1994, simulated forest biomass is lower than observed biomass. Similarly, minimum degree of average error (RMSE = 11.11 Mg/ha) between simulated and observed forest biomass data. The finding of this study also shows that the UPRW has the potential to produce approximately 49 Mg/ha of average forest biomass annually (**Figure 4**). This value is less by 3 Mg/ha (approximately 6%) than the average observed forest biomass in the study area. It is important to note that 85% of total available biomass can be sustainably obtained for bioenergy using an integrated system [55].

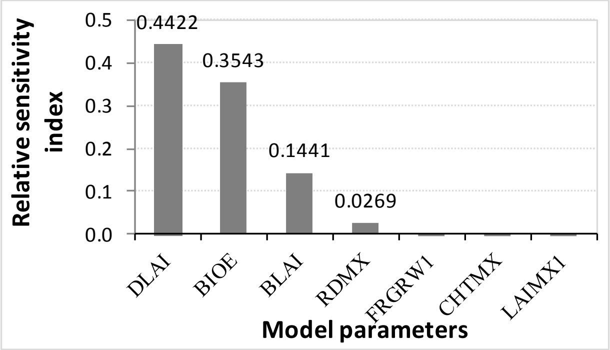

Figure 3. Overall relative sensitivity index of studied crop parameters.

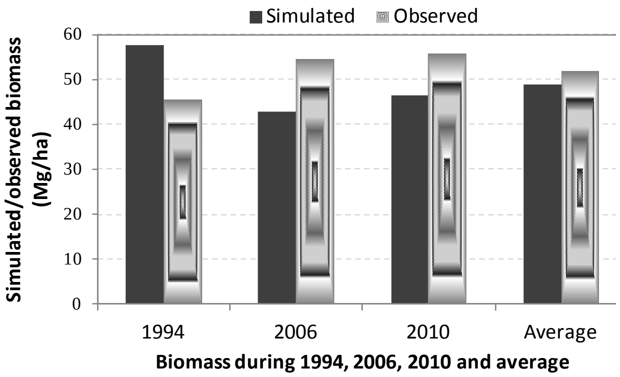

Figure 4. Comparison of observed versus simulated forest biomass during 1994, 2006, 2010 and average.

Following this logic, approximately 42 Mg/ha of forest biomass can be sustainably recovered for bioenergy production from the UPRW. However, given the incipient bioenergy market and conventional use of biomass in forest product industries, actual biomass available for bioenergy use cannot be predicted as such.

4. Conclusions

Results on SWAT performance to predict streamflow revealed satisfactory performance (R^2 and NSE > 0.6) and low value of PBIAS and RMSE. Furthermore, results on local sensitivity analysis of seven crop parameters to predict forest biomass production determine three parameters: DLAI, BIOE and BLAI as sensitive to predict forest biomass production. DLAI and BIOE are moderately sensitive and BLAI shows low sensitivity. In contrast to the sensitivity analysis conducted in switchgrass and miscanthus, relative sensitivity of all studied parameters in this study has shown lower value of relative sensitivity index. Thus, sensitivity analysis conducted in this study provides baseline information about the sensitivity of seven crop parameters of SWAT to influence forest biomass production and, therefore, may serve as a basis for similar future research.

Likewise, SWAT adequately predicted potential forest biomass for the UPRW with high value of R^2 (0.83), small difference (<6%) between predicted and observed mean and low RMSE value (11.11 Mg/ha). Results further indicate that the UPRW has the potential to produce approximately 49 Mg/ha of average annual forest biomass, which is slightly less (3 Mg/ha or 6%) than the average observed forest biomass in the study area. Overall, this study demonstrated that SWAT can be a useful tool for modeling the availability of forest biomass as a potential bioenergy feedstock. However, further studies using additional data were recommended to better analyze the performance of SWAT in simulating the availability of potential forest biomass.

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