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Title: Improved hydrological modeling with APEX and EPIC: Model description, testing, and assessment of bioenergy producing landscape scenarios

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Abstract

A Richards-based soil water model was implemented in the APEX and EPIC terrestrial ecosystem models to improve their hydrologic modeling capabilities. The Richards model together with two existing soil water models were calibrated and evaluated to assess their performance for simulating watershed-level hydrology under scenarios of landscape conversion to bioenergy crop production. The Richards model was shown to better reflect observed soil-water dynamics in grain (corn) and cellulosic (switchgrass) bioenergy agroecosystems, whereas all three models simulated historic streamflows comparably. Application of the models to understand the impacts of widespread landscape conversion from traditional agriculture to bioenergy producing landscapes indicated disparate conclusions, with the Richards-based simulations indicating a modest 1.0% reduction in streamflow whereas the existing models simulated sizable reductions of 10.6-16.1%. This study clearly demonstrates the impact of model methodology on system understanding and contextualizes the wide range of simulated streamflow impacts from bioenergy conversions reported in the literature.

Keywords: Richards equation; soil water modeling; bioenergy landscape conversion; watershed; maize; switchgrass

1. Introduction

Cellulosic feedstocks are capable of providing substantial low-carbon energy and spurring local bio-economies (Dale et al., 2014; Jones et al., 2017; Kim et al., 2018; Robertson et al., 2017). Among the more promising avenues for providing cellulosic feedstocks is the harvesting of crop residues, such as corn (a.k.a. maize, *Zea mays*) stover, and the cultivation of dedicated perennial energy crops such as switchgrass (*Panicum virgatum*), particularly on marginal lands (Gelfand et al., 2013) so as to avoid displacement of food crop production and produce bioenergy feedstocks on presently underutilized lands. These two feedstock production pathways have divergent environmental impacts, with residue harvest incurring risks including soil carbon loss and elevated susceptibility for erosion compared to cultivation of perennials, which tend to provide ecosystem services including soil carbon sequestration and reduced erosion. However, outcomes are not simplistic as options exist to improve the environmental impacts of residue harvest (Jones et al., 2018).

Among the primary concerns regarding the expansion of dedicated bioenergy cropping systems is the potential for increased crop water use, with resultant decreases in groundwater recharge and stream flow (Berndes, 2002; Le et al., 2011). Perennial energy crops are generally expected to have greater evapotranspiration (ET) than traditional annual crops due to factors including extended seasonal canopy coverage and root activity. However, comparative studies have shown disparate water use patterns, with perennials showing both elevated ET as well as comparable ET relative to annuals (Daigh et al., 2014; Hamilton et al., 2015; Le et al., 2011), suggesting that relative ET responses may depend on context and specifically soil-plant-climate interactions. Incorporation of cover crops into rotations can similarly result in increased water use by extending the period of active vegetative growth (Gabriel et al., 2012; Zhang and Schilling, 2006). Yet alterations to the water balance can be more complex as vegetative cover, root biomass, and long-term impacts on organic matter can have impacts such as reduced overland runoff, reduced evaporation, and increased soil-water storage (Basche et al., 2016; Blanco-Canqui et al., 2015, p.; Drury et al., 2014), which could offset or even reverse water use increases from expected increases in crop transpiration. Conversely, harvesting of residues such as corn stover is expected to have the opposite effect, inducing reduction in soil cover and depletion of soil organic matter, resulting in increased runoff, increased evaporation, and reduced soil-water retention (Demissie et al., 2012; Johnson et al., 2016; N. L. Klocke et al., 2009).

Due to these complex soil-plant-climate-management interactions, models are needed to assess system-level responses to bioenergy production scenarios in a manner that capably considers site-specific characteristics and drivers to characterize system behavior. Existing modeling studies have investigated the impacts of bioenergy production on system behaviors and outcomes (Chen et al., 2017; Cibin et al., 2016, 2012; Demissie et al., 2012; Ha et al., 2020; Wu and Liu, 2012). However, the capacity of such models to skillfully simulate soil-water dynamics under novel bioenergy cropping systems has not been assessed.

Here we present improvements to the methodology of soil-water modeling and calibration of bioenergy crop production systems, judging model performance against soil water data from field experiments and applying the models at the landscape scale. As a representative bioenergy cropping system landscape, we chose the North Raccoon River Basin, a HUC-8 subbasin of the Des Moines River watershed in Iowa (USA). This sub-basin was chosen as it is an intensive agricultural area that shows promise for cellulosic feedstock production (Jones et al., 2017) and feeds into the Des Moines River, the predominant source of water for the City of Des Moines. The specific objectives of this work are to 1) describe a Richards-based soil-water flow model that we have incorporated into APEX and EPIC, two widely used field- and watershed-scale terrestrial ecosystem models, 2) assess the efficacy of the existing and Richards-based soil-water flow models at site and watershed scales, and 3) utilize the models to assess the implications of conversion to perennial bioenergy feedstock production for watershed-level water balances.

2. Methods

To quantitatively compare system behavior and responses under current and potential future bioenergy producing scenarios at management and policy relevant scales, we utilized the Agricultural Policy Environmental eXtender (APEX) model (Gassman et al., 2009). The APEX model, which is designed for large farm to small watershed scale applications, and the Environmental Policy Integrated Climate (EPIC) model (Williams, 1995), which represents the field-scale version of APEX, have been widely used for simulating biophysical and biogeochemical processes in managed terrestrial ecosystems including bioenergy production systems and watershed-level environmental assessments (Francesconi et al., 2014; Gassman et al., 2004; Jones et al., 2018; Wang et al., 2012). These models are continually being updated to improve model performance or expand applicability as dictated by the needs and interests of the model development and user community. Here we describe improvements made to the soil water modeling methods to allow more skillful assessment of the watershed-level water use implications of potential bioenergy crop production scenarios.

2.1 Improved hydrologic modeling

The default Saturation Hydraulic Conductivity soil-water flow model in APEX and EPIC utilizes a tipping bucket approach, herein referred to as the “original” soil-water flow model, which has been shown to overestimate the rate of soil water drainage (Doro et al., 2017). An improved Variable Saturation Hydraulic Conductivity model was implemented, referred to here as the “slug” soil-water flow model, that utilized an empirical approach with inputs and complexity harmonized with the standard soil inputs required for APEX and EPIC simulations (Doro et al., 2017). However, despite achieving improvement, limitations in skill remained. To improve simulation of soil-water dynamics, we incorporated a Richards-based (Richards, 1931) soil-water flow model into APEX and EPIC, which will be referred to as the "Richards" soil-water flow model. Richards-based approaches are considered state-of-the-art for simulating soil water flow (Twarakavi et al., 2008; Vereecken et al., 2016). The main drawbacks of the Richards approach are the computational time required, as the equation can only be solved analytically under limiting assumptions, and parameterization, which requires measurements at a level of detail exceeding what is commonly available at large-scales (e.g., traditional soil surveys).

Since the APEX and EPIC models are traditionally applied at coarser spatial resolution and larger time and space scales than typical Richards-based model applications, we sought to implement a solution to the Richards Equation that would minimize the added computational burden. An approach developed by Ross (Crevoisier et al., 2009; Ross, 2003), which has demonstrated computational efficiency, accuracy, robustness, and reliable convergence, solves the mixed form of Richards equation, making it suitable for variably-saturated soils.

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(h)\left(\frac{\partial h}{\partial z} - 1\right)\right] \quad (1)$$

where θ is the soil water content (cm cm^{-1}), t is time (hr), z is depth (cm), K is the unsaturated hydraulic conductivity (cm hr^{-1}), and h is the soil matric pressure (cm H_2O). The soil profile is discretized into n_soil layers, and the model is applied to simulate vertical water flows through soil layers. The Richards equation is solved non-iteratively utilizing temporal linearization of fluxes as

$$q_i^\sigma = q_i^0 + \sigma\left(\left.\frac{\partial q_i}{\partial S_i}\right|^0 \Delta S_i + \left.\frac{\partial q_i}{\partial S_{i+1}}\right|^0 \Delta S_{i+1}\right), \text{ for i = 1 to n\_soil - 1} \quad (2)$$

$$a_i \Delta S_{i-1} + b_i \Delta S_i + c_i \Delta S_{i+1} = d_i, \text{ for i = 1 to n\_soil}$$

$$\text{where } a_i = \left.\frac{\partial q_{i-1}}{\partial S_{i-1}}\right|^0$$

$$b_i = \left.\frac{\partial q_{i-1}}{\partial S_i}\right|^0 - \left.\frac{\partial q_i}{\partial S_i}\right|^0 - \frac{\Delta z_i(\theta_{Si} - \theta_{ri})}{\sigma \Delta t}$$

$$c_i = \left.\frac{\partial q_i}{\partial S_{i+1}}\right|^0$$

$$d_i = -\frac{(q_{i-1}^0 - q_i^0)}{\sigma}$$

$$S_i = \frac{\theta_i - \theta_{r,i}}{\theta_{s,i} - \theta_{r,i}}$$

where q is the water flux (cm hr^{-1}), i is the soil layer number, σ is the fraction of the timestep, S is the degree of saturation, a-d are equation coefficients, Δz is the layer thickness (cm), θ is the soil water content (cm cm^{-1}), θ_r is the residual soil water content (cm cm^{-1}), and θ_s is the saturated soil water content (cm cm^{-1}). Note that $\sigma = 1$ in the presence of saturated conditions and $\sigma = 0.5$ under unsaturated conditions. Also, a_1 and c_n equal zero as S_0 and $S_{n\_soil + 1}$ do not exist. The flow of water into a layer can then be calculated as

$$\frac{\Delta Q_i}{\Delta t} = q_{i-1}^{\sigma} - q_i^{\sigma} \tag{3}$$

where Q is the flow of water (cm), and t is the timestep (hr). The equations are solved on a sub-daily time step, with the time step varying to limit the maximum allowable change in degree of saturation.

$$\Delta t = \frac{\Delta S_{max}}{\left|\left(\frac{q_{i-1} - q_i}{(\theta_{s,i} - \theta_{r,i})\Delta z}\right)(t)\right|_{max}} \tag{4}$$

where S_{max} is the largest allowable change in degree of saturation. Iteration is incurred as necessary to ensure the change in S in all soil layers falls below the S_{max} threshold. If this change threshold is exceeded, a smaller timestep is implemented as

$$\Delta t_{it} = \Delta t \frac{\Delta S_{max}}{\Delta S} \tag{5}$$

where Δt_{it} is the updated time step (hr). Percolation from the lowest soil layer is assumed to occur as either free gravitational drainage, seepage, or a constant head boundary condition, allowing flexibility as well as incorporation of elevated groundwater tables or subirrigation practices. Infiltration and evaporation from the surface soil layer as well as root water extraction from root-penetrated soil layers are simulated daily following standard APEX and EPIC methodologies (Gassman et al., 2009). Subsurface horizontal water flows, similarly to Warrick et al. (2008), were simulated assuming zero pressure gradients across horizontal boundaries such that gravity-driven Darcian flow occurs in the horizontal direction as a function of slope and soil hydraulic characteristics.

$$J_x = K(h)\, m\_land \tag{6}$$

where J_x is the horizontal subsurface flow (cm hr^{-1}), and m_land is the slope gradient (cm cm^{-1}). In order to parameterize the model, soil-water-retention and unsaturated hydraulic conductivity functions were characterized using a modification similar to van Genuchten-Mualem (VGM) soil hydraulic models (Schaap and van Genuchten, 2006) but instead retaining the occurrence of saturation at zero matric pressure and allowing macropore flow in the unsaturated zone (Ross, 2006). Hence the soil-water retention model is characterized as

$$S(h) = \left(1 + \left(\frac{h}{h_g}\right)^n\right)^{-m} \text{ for h} \geq \text{h}_{thresh} \quad (7)$$

$$S(h) = 1 + \frac{2(S_{thresh}-1)h_{thresh}}{a_1+\sqrt{a_1^2+4a_2h_{thresh}}} \text{ for h} < \text{h}_{thresh}$$

$$m = 1 - \frac{1}{n}$$

$$a_1 = 2h_{thresh} - (S_{thresh} - 1)\left.\frac{dh}{dS}\right|_{S_{thresh}}$$

$$a_2 = h_{thresh} - a_1$$

where h_g (cm water) is a scaling parameter, m and n are shape parameters, S_{thresh} is the degree of saturation threshold for saturated conditions, h_{thresh} (cm water) is the soil matric pressure when S = S_{thresh} , and a_1 and a_2 are equation coefficients. Here it is assumed that S_{thresh} equals 0.99. The hydraulic conductivity model is defined as

$$K(h) = \left(\frac{K_s}{K_v(h)}\right)^{R(h)} K_v(h) \quad (8)$$

$$R(h) = 1 - \frac{(1-R_{mac1})h}{h_{mac1}} \text{ for } 0 \geq \text{h} \geq \text{h}_{mac1}$$

$$R(h) = \frac{R_{mac1}(h-h_{mac2})}{h_{mac1}-h_{mac2}} \text{ for h}_{mac1} > \text{h} > \text{h}_{mac2}$$

$$R(h) = 0 \text{ for h} < \text{h}_{mac2}$$

$$K_v(h) = K_s x^{mp}((1-(1-x)^m)^2 \text{ , for h} < \text{h}_s$$

$$K_v(h) = K_s \text{ , for h} \geq \text{h}_s$$

$$x = \frac{1}{1+h^n}$$

where K_s is the saturated hydraulic conductivity (cm hr^{-1}), K_v is the macropore adjusted hydraulic conductivity (cm hr^{-1}), R is an equation coefficient, h_{mac1} (cm water) and h_{mac2} (cm water) are soil matric pressure thresholds distinguishing between exponential macropore flow, non-exponential macropore flow, and soil matrix flow, R_{mac1} is the R at a soil matric pressure of h_{mac1}, x is an equation coefficient, and p is a pore connectivity parameter. Here it is assumed that h_{mac1} equals -4 cm water, h_{mac2} equals -40 cm water, R_{mac1} equals 0.25, and p equals 0.5.

These models avoid highly non-linear hydraulic property changes near soil water saturation, improving the efficiency and stability of numerical solutions. Since the VGM models require parameters not included in the standard APEX and EPIC soil inputs, the capacity to specify these parameters by soil layer was added. However, most APEX and EPIC model applications utilize cardinal soil water thresholds or texture-based pedotransfer functions (PTFs) to characterize the soil hydraulic characteristics. To align parameterization with the needs of the model user base, PTFs were included to estimate the VGM parameters based on soil texture and cardinal water content thresholds. Hence existing PTFs developed by Jones et al. (2014), Weynants et al. (2009), and Wösten et al. (1999) were incorporated as well as the option to enter the VGM parameters directly.

2.2 Improved parameterization of bioenergy cropping systems

To evaluate and improve the performance of the updated model for simulating soil water dynamics under bioenergy cropping systems, a field experiment in southwestern Michigan including various candidate bioenergy cropping systems (Hamilton et al., 2015) was utilized for model calibration and independent assessment of model skill utilizing similar methodologies to Jones et al. (2018). The experiment was selected due to its detailed monitoring of soil water content at seven depths using time-domain reflectometry (TDR) probes under continuous corn and switchgrass treatments. We used soil water content measurements from 2010-2013, with data from the even years used for calibration purposes and the data from the odd years was reserved for independent model evaluation.

The watershed is the relevant scale for assessing the net impact of landscape changes in crop water use on streamflow. As a representative agricultural watershed in the Midwest U.S., we chose the North Raccoon River Basin, which is a HUC-8 subbasin of the Des Moines River watershed (Figure 1). This watershed was chosen as it is a highly agricultural area, lies in a promising area for cellulosic feedstock production (Jones et al., 2017), and feeds into the Des Moines River, which is the predominant source of water for the City of Des Moines, where the Des Moines Water Works have dealt with a long history of water quality issues at least partially linked to agricultural practices (Hatfield et al., 2009). Daily streamflow data were available from the United States Geological Survey stream gage (Station 05482500) dating back to 1940. Here we simulated the 1980-2016 period, with data from even years utilized for calibration and data from odd years used for independent model evaluation.

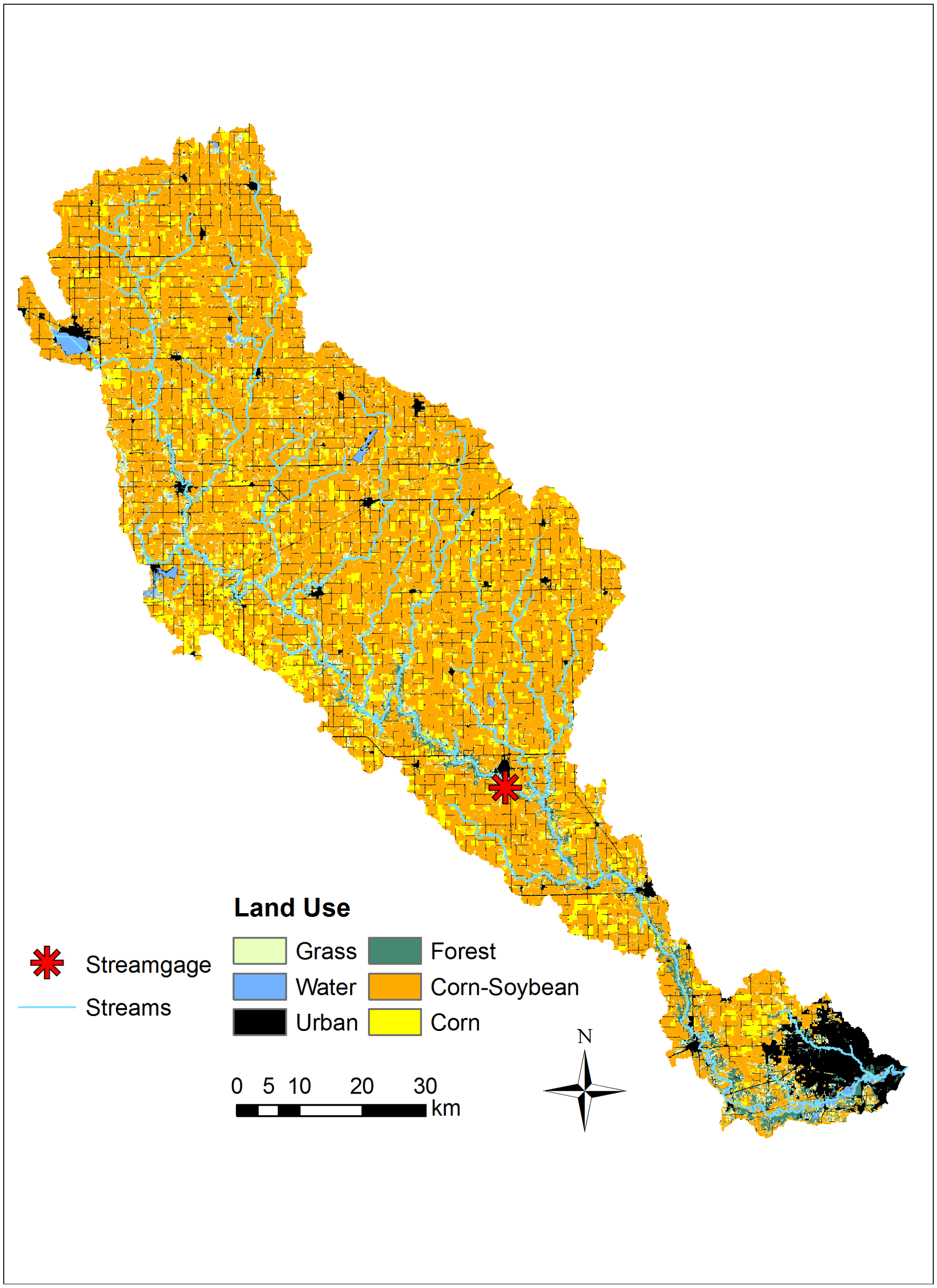

Figure 1. Major land use classes in the North Racoon River watershed (Iowa, USA). The streamflow gauge station maintained by the US Geological Survey is also marked.

The APEX model was set up to represent the land characteristics and management in the watershed. The ArcAPEX tool (Tuppad et al., 2009) was utilized to delineate 99 individual subareas within the watershed according to land use, soil type, and topography. Soils were characterized using the United States Department of Agriculture (USDA) State Soil Geographic (STATSGO) database, selecting the most dominant soil type within a subarea. The dominant land use in each subarea was characterized using a crop rotation product derived from the USDA Cropland Data Layer (CDL) from 2012-2014 according to (Sahajpal et al., 2014). Planting and harvesting dates for row crop production were derived from USDA estimates of typical dates (USDA NASS, 2010). Daily meteorological data including maximum and minimum temperature, precipitation, solar radiation, relative humidity, and wind speed were obtained from the North American Land Data Assimilation System project phase 2 (NLDAS-2; Xia et al.). This is a gridded reanalysis product that resulted in 21 unique grids within or adjacent to the watershed. Weather data within subareas were defined by the nearest grid according to the centroid of the subarea and the NLDAS-2 grid.

Parameters were selected for calibration based on expert knowledge of APEX and the most influential parameters for soil water content and subsurface and surface water flow. A parameter screening step was conducted to eliminate the least influential parameters through implementation of the Method of Morris (Campolongo et al., 2007), considering the influence (μ^*) of a parameter on model skill for simulating soil water content according to the Nash-Sutcliffe coefficient of efficiency (NSE), with the average of the NSEs calculated from the soil water content and streamflow simulations utilized for a balanced assessment. Each soil water model was executed for 570 iterations at the site and watershed levels for the sensitivity analysis. The reduced set of parameters were calibrated utilizing the Differential Evolution Adaptive Metropolis (Vrugt and Braak, 2011) algorithm (DREAM), utilizing minimization of the root mean squared error (RMSE) as the objective function. To balance unit magnitude differences, soil water content and streamflow were normalized according to their respective observed means and standard deviations. The model was executed for 3,000 iterations at both the site and watershed scales to implement the calibration for each soil water model. Both the DREAM and Method of Morris methods were implemented using the R software (R Core Team, 2015). Together, these steps were implemented to better characterize parameter sensitivities and estimate effective parameter values for accurate simulation of soil water dynamics. To contextualize the performance of the Richards model relative to APEX and EPIC, this model evaluation process was conducted for each of the three soil-water flow models.

Subsequently, we utilized the parameterized APEX model to assess the impact of conversion to bioenergy producing landscapes within the watershed on water fluxes and streamflow. The baseline scenario was represented by the unmodified setup utilized for the calibration and evaluation procedures, while bioenergy producing landscapes were created to convert varying proportions of the row crop subareas from corn or corn-soybean rotation to switchgrass. To simulate the impacts of varying intensities of landscape conversion, row cropped subareas were selected for conversion to switchgrass in increments of three, comprising 3.8% of the 78 subareas under row crop agriculture per iteration. Switchgrass biomass was assumed to be harvested each fall while grain crops were assumed to be under no-till management to ensure the baseline scenarios reflected aspirational management practices. Scenarios were assessed in terms of impacts on streamflow as well as water fluxes and biophysical drivers. It should be noted that while model improvements were made to both the APEX and EPIC models, APEX was selected for parameterization, evaluation, and application purposes because while both models are comparable at the plot to field level, only APEX is capable of simulating watershed level processes.

3. Results and discussion

3.1 Improved parameterization of bioenergy cropping systems

The Method of Morris screening procedure resulted in similar parameter importance metrics across soil water models (Figure A1), resulting in retention of similar parameters for the calibration procedure (Table A1). Layer-level lower limit of soil water content and field capacity were calibrated for all soil water models to ensure inaccurate soil characterization data did not incur biases and force parameters towards extremes to compensate. In addition to these soil water holding limits, an additional 11, 15, and 10 parameters were retained for the original, Richards, and slug methods, respectively.

The calibration procedure resulted in reasonable fits ($R^2 \geq 0.49$) for soil water content simulations across soil water models and cropping systems (*Figure 2*; Table 1). Simulations were notably more skillful under corn (R^2 0.63–0.81) than under switchgrass (R^2 0.49–0.63), and the Richards soil water model produced the best fits of the three models for both corn and switchgrass cropping systems. Notable residual trends can be observed in *Figure 2*, particularly for the original and slug submodels, whereas the Richards submodel demonstrated more balanced distribution of residuals across the range of VWC. Investigating the model fits by soil layer, Figure 3 indicates an inability of the original model to capture soil water dynamics near the soil surface. This known model inadequacy in part motivated implementation of the slug method into EPIC (Doro et al., 2017), which here is shown to improve this shortcoming under corn cropping whereas the insufficiency remains under switchgrass. Additional patterns of model bias are observed for many of the soil layers for the original and slug submodels under both crops but to a greater severity under switchgrass. The Richards model demonstrated some consistent bias at certain layers, particularly under switchgrass, but proved consistently more aligned with the observed soil water dynamics.

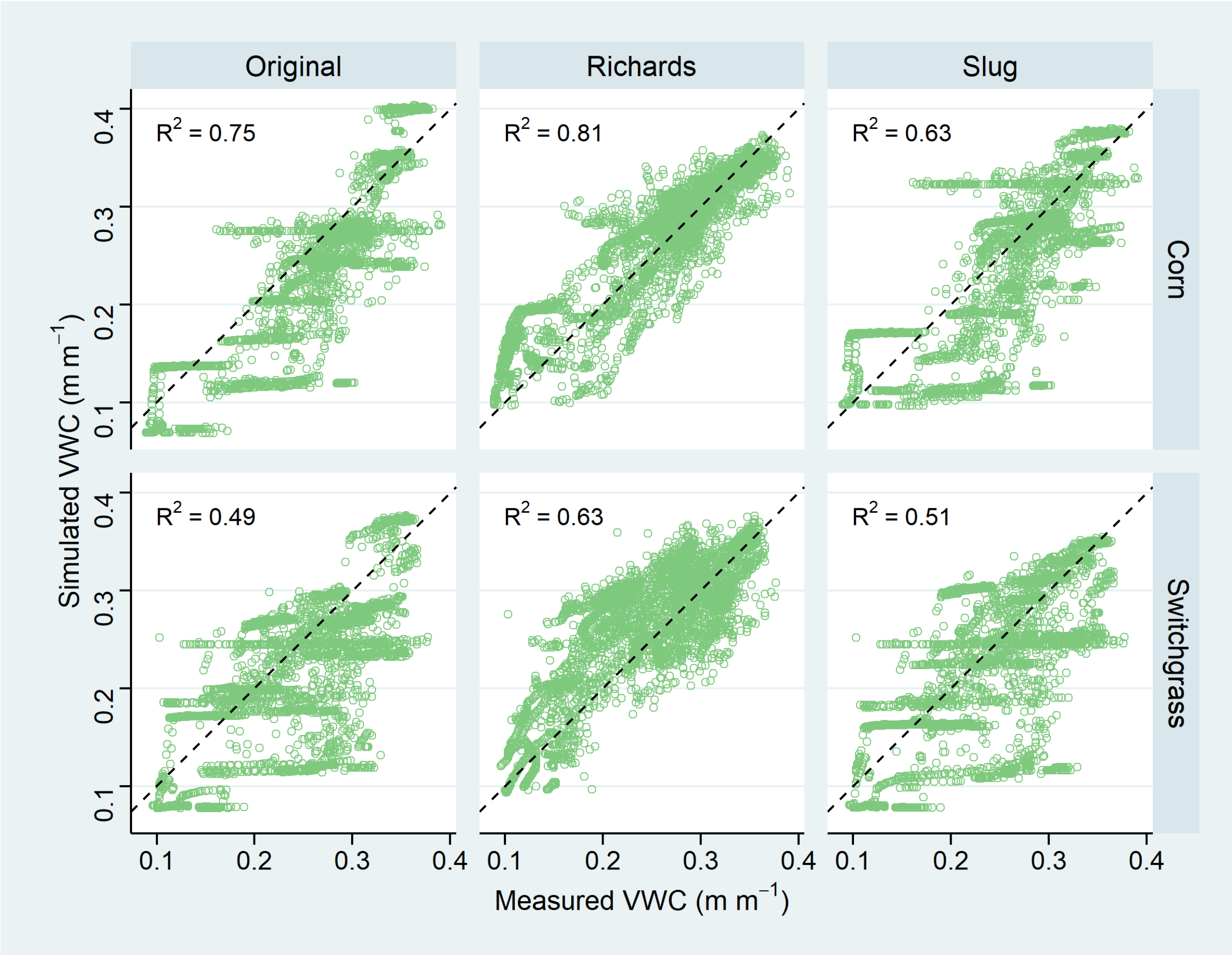

Figure 2. Evaluation of the APEX model utilizing the original, Richards, and slug soil water models for simulating volumetric soil water content (VWC) compared against field measurements under corn and switchgrass. Soil water content measurements were taken annually from March through November.

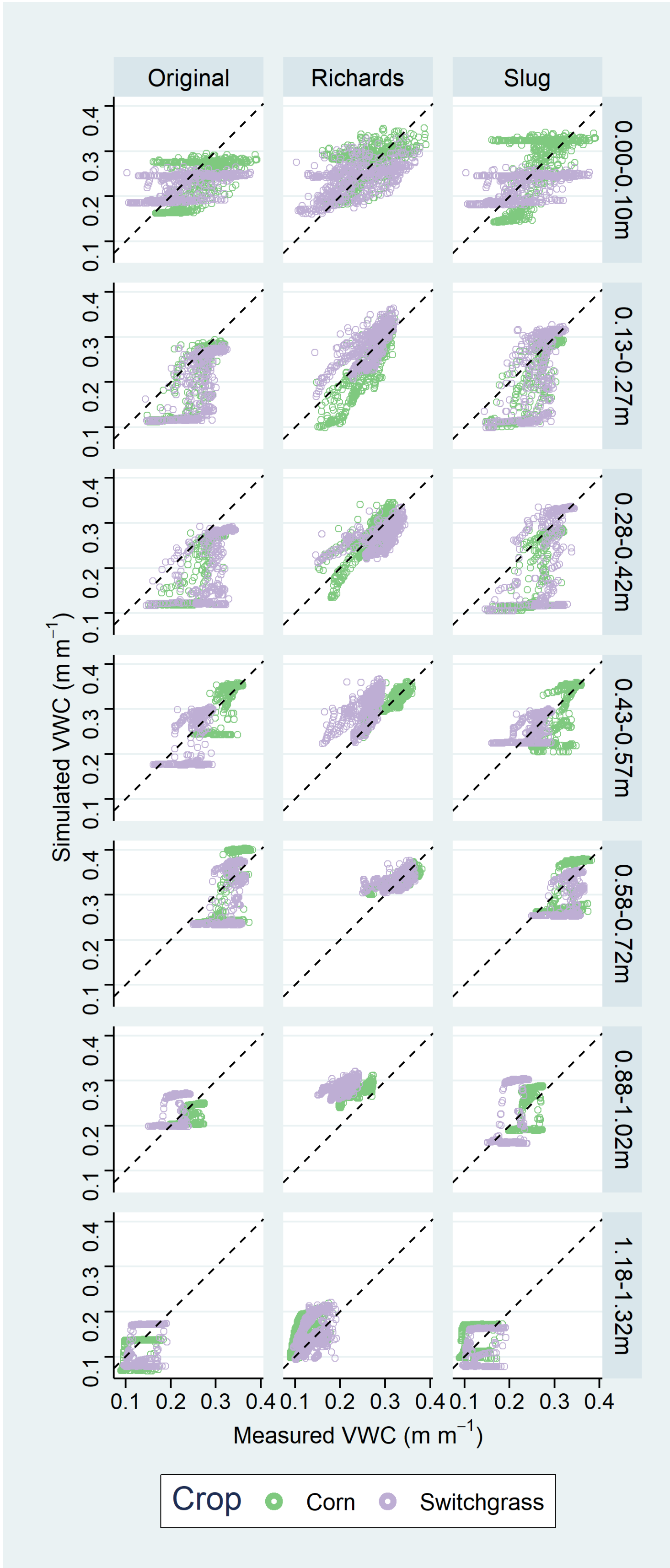
Original
Richards
Slug
0.00-0.10m
0.13-0.27m
0.28-0.42m
0.43-0.57m
0.58-0.72m
0.88-1.02m
1.18-1.32m
Simulated VWC (m m^{-1})
Measured VWC (m m^{-1})
0.1
0.2
0.3
0.4
Crop
Corn
Switchgrass

Figure 3. Evaluation of the APEX model for simulating volumetric soil water content under corn and switchgrass against field measurements at seven soil horizon depths. Soil water content measurements were taken annually from March through November.

Model	Crop	R^2	NSE	RMSE ($m\ m^{-1}$)	PBIAS (%)
Original	Corn	0.75	0.57	0.047	-7.5
Original	Switchgrass	0.49	0.23	0.060	-8.9
Richards	Corn	0.81	0.79	0.033	3.6
Richards	Switchgrass	0.63	0.53	0.047	8.1
Slug	Corn	0.63	0.52	0.050	-3.0
Slug	Switchgrass	0.51	0.27	0.058	-5.5

Table 1. Evaluation metrics of the APEX model for simulating volumetric soil water content under corn and switchgrass utilizing the original, Richards, and slug soil water models across all measured depths.

In the streamflow simulations, the three soil water models performed quite similarly (Figure 4; Table 2), with R^2 ranging only between 0.64 and 0.65. The slug model compared most favorably with observed streamflows (RMSE = 31.4 $m^3\ s^{-1}$) while the Richards model differed the most (RMSE = 32.3 $m^3\ s^{-1}$), albeit with the lowest percent bias (PBIAS). Overall, the evaluation of the soil water models indicated each was quite comparable in terms of streamflow simulation, whereas the Richards submodel was notably more skilled for simulating soil-water dynamics under both corn and switchgrass cropping. This similarity among the submodels in simulating historic streamflows, for which the dominant land use was grain cropping with no adoption of switchgrass cultivation, and the divergence among the submodels for simulating root-zone soil-water under switchgrass cultivation, indicate the watershed-level hydrology simulated by the submodels will be more divergent under switchgrass cultivation than under traditional grain production systems.

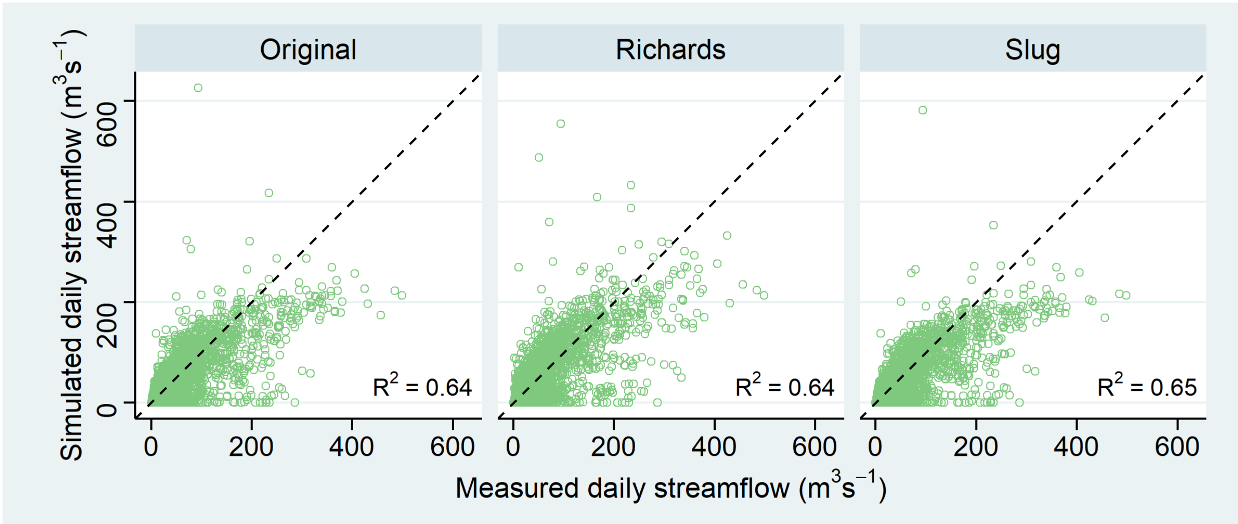

Figure 4. Evaluation of the APEX model for simulating streamflow utilizing the original, Richards, and slug soil water models against measurements made at the US Geological Survey gauge on the North Racoon River.

Model	R^2	NSE	RMSE (m^3 s^{-1})	PBIAS (%)
Original	0.64	0.62	31.6	-24.4
Richards	0.64	0.60	32.3	-19.3
Slug	0.65	0.62	31.4	-24.7

Table 2. Evaluation metrics of the APEX model for simulating streamflow utilizing the original, Richards, and slug soil water models.

3.2. Watershed-level assessment of bioenergy crop production scenarios

The crop rotations product derived from the CDL characterized the watershed area as comprised of 65% corn-soybean rotation, 13% continuous corn, 9% urban/developed land, 7% grassland/pasture, and the remaining 6% as water (Figure 1). Hence 78% of the area was under row crop agriculture, and 85% under managed agriculture. Mean simulated dry matter corn yields from the 1980-2016 period were 11.9, 12.7, and 10.2 Mg ha^{-1} based on the original, slug, and Richards methods, respectively, compared to a mean reported USDA NASS yield from 2007-2016 in Hardin County, Iowa of 9.4 Mg ha^{-1}. While the periods of comparison differ, they were selected as the simulated cultivars and management technologies are better aligned with modern production practices, which evolve over time (Sacks and Kucharik, 2011) and would be expected to influence harvestable yield more than water consumption or streamflow,

which in rain-fed cropping systems can be quite temporally stable in the face of changing agricultural practices because different rainfed cropping systems as well as fallow fields may use all available soil water during the growing season (Hamilton et al., 2018). Mean simulated dry matter soybean yields were 3.5, 3.7, and 2.8 Mg ha^{-1} for the original, slug, and Richards methods, respectively, compared to a mean reported USDA NASS yield from 2007-2016 in Hardin County, Iowa of 3.0 Mg ha^{-1}. Mean simulated dry matter switchgrass yields were 11.5, 11.9, and 10.2 Mg ha^{-1} for the original, slug, and Richards methods, respectively, whereas switchgrass yields in similar regions in north central Iowa have been reported in the 12.0 to 12.3 Mg ha^{-1} range (Gassman et al., 2017; Trybula et al., 2015). Hence, simulated yields in the watershed were comparable to expected yields in the region. Simulated yields for all crops were consistently highest with the slug method and lowest with the Richards method, the latter difference largely driven by lower available soil water in the root zone due to increased simulated percolation utilizing the Richards method compared to the other methods.
Simulation of the grain crop to switchgrass conversion scenarios revealed that while the three soil water models performed comparably for the historical streamflow evaluation, marked differences between the submodels manifested under land use conversion (*Figure 5*). The simulated reductions in streamflow as a result of cropping system conversion to switchgrass was consistently highest with the original model, and simulated reductions with both the original and slug models were much higher than with the Richards model. Under the most extreme scenario of complete conversion of agricultural croplands to switchgrass, APEX simulations utilizing the Richards submodel produced a modest 1.0% reduction in streamflow compared to 10.6% and 16.1% reductions simulated utilizing the slug and original submodels, respectively. Streamflow reduction increased monotonically with increasing cropland conversion for the original and slug submodels, whereas reductions demonstrated site-specific directionality dependence as conversion of some groups of subareas resulted in less streamflow reduction.

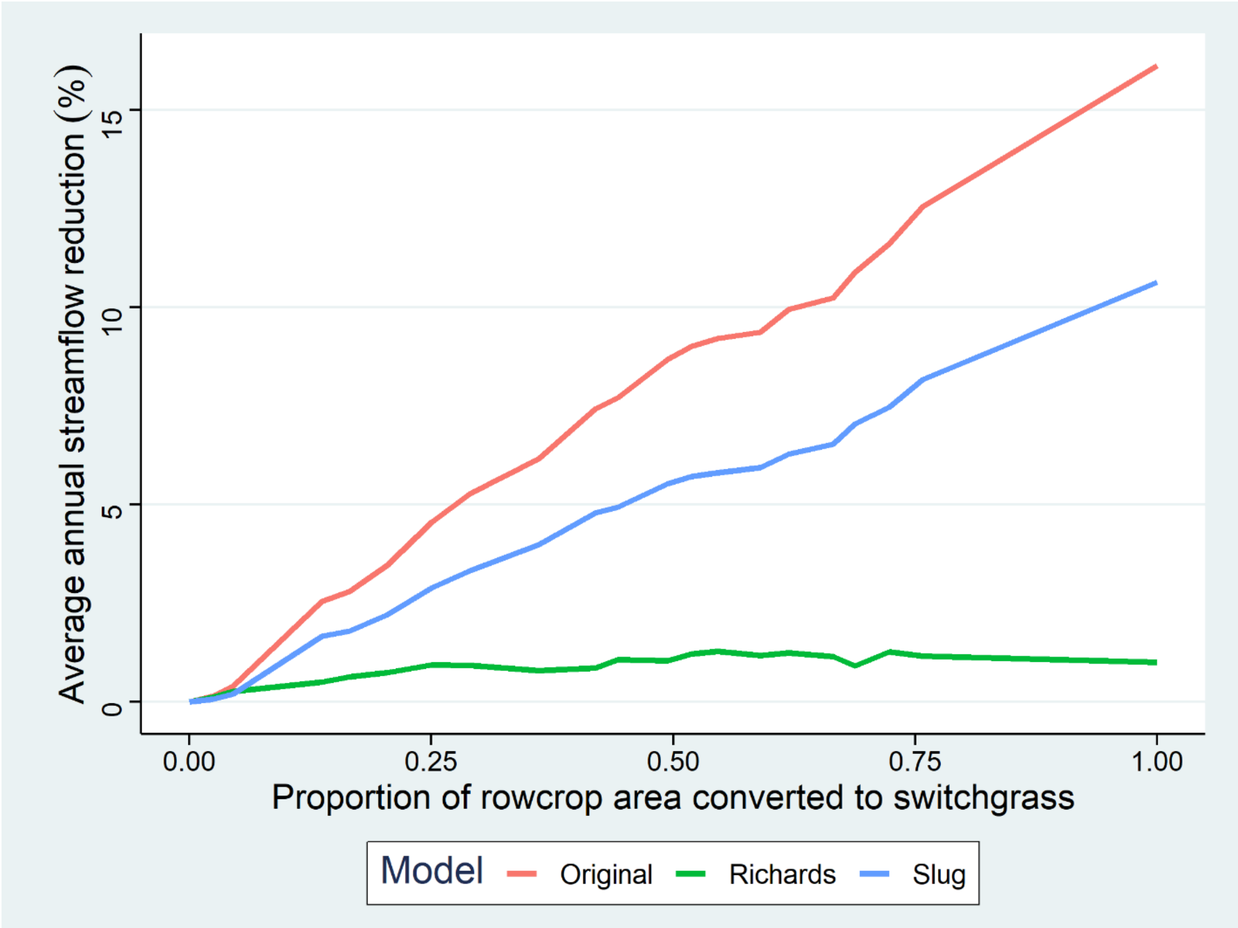

Figure 5. Simulated reduction in average annual streamflow in response to conversion of grain agriculture to switchgrass utilizing the original, Richards, and slug soil water models.

The disparity in simulated streamflow reductions utilizing the Richards submodel compared to the original or slug submodels is driven by inverse simulation of the impacts of the land use conversion on percolation and ET (*Figure 6*; *Table 3*). While all three submodels simulate reduced runoff under greater area in the perennial switchgrass crop, the original and slug submodels simulate increased ET and reduced percolation whereas the Richards submodel simulates reduced ET and increased percolation. This is partly explained by the underestimation of near-surface soil water content by the original model and to a lesser degree by the slug model. Perennial switchgrass cropping systems result in greater surface vegetative and residue cover than annual cropping systems, reducing evaporative losses from the near-soil surface. Hence the underestimation of near-surface soil-water content in the original and slug models mitigates the impact of the increased surface cover under switchgrass towards reduced ET relative to grain cropping. This contributed to water consumption in the two cropping systems being more similar throughout the year with Richards-based simulations than with original- or slug-based simulations (*Figure 7*). The longer growing season of perennials compared to annuals does result in elevated water consumption when perennials are active prior to annual crop establishment and following harvest. However, while the original and slug submodels simulated elevated water consumption and hence lowered streamflow under perennial conversion across the calendar year, the Richards submodel predicted that perennial conversion would increase water consumption outside of peak annual growing season but result in reduced water consumption during peak annual growth months in June and July, when ET rates of corn considerably exceed that of perennials. These intra-annual water consumption patterns with the Richards submodel align more closely with experimental observations than with the original or slug submodels (Abraha et al., 2020; Eichelmann et al., 2016). The increased percolation under perennial cropping systems simulated utilizing the Richards submodel is also supported in the literature (Parish et al., 2019; Stenjem et al., 2019) as increased soil organic carbon and a deeper and denser rooting structure enable greater soil water infiltration and percolation (Zaibon et al., 2017).

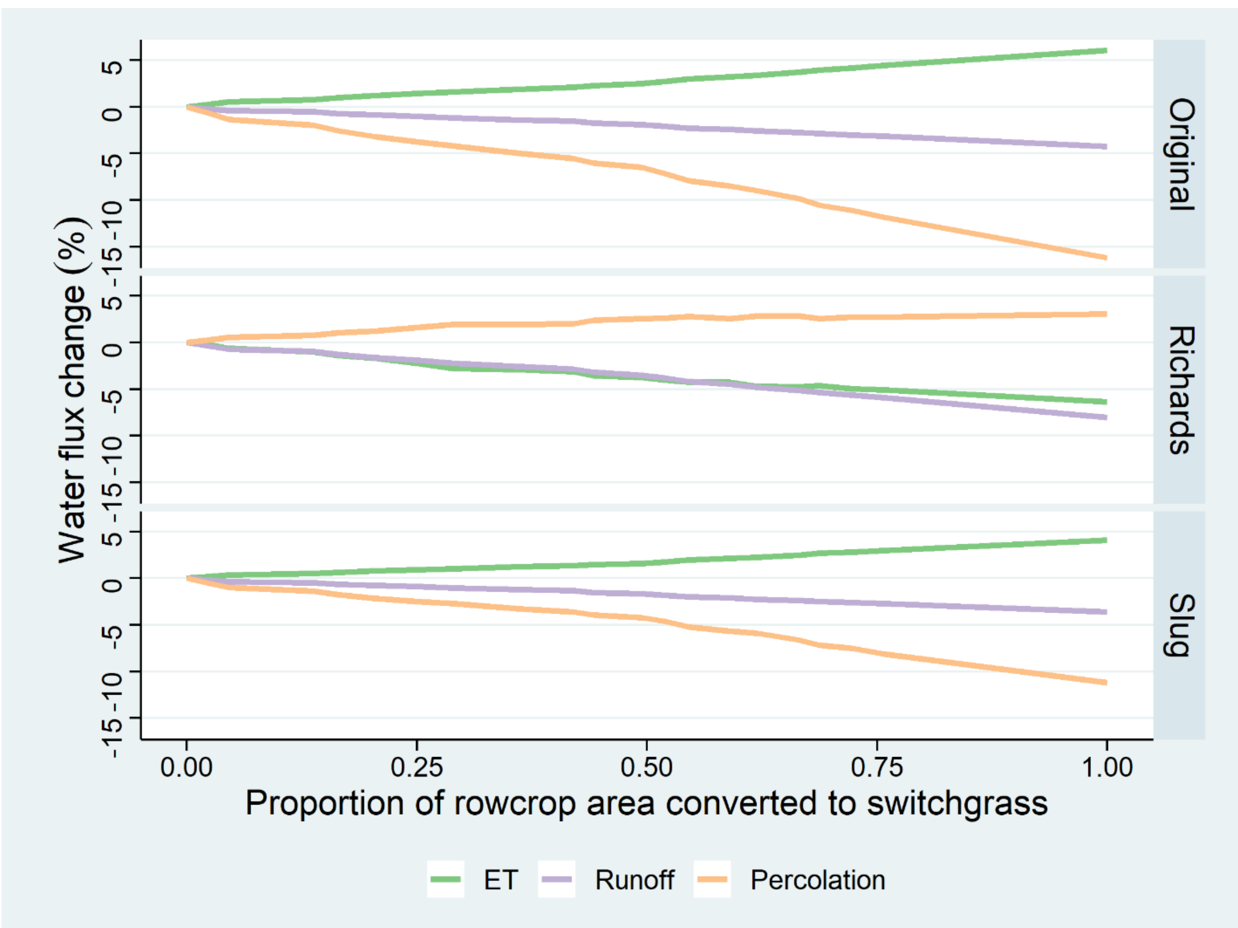

Figure 6. Simulated changes in ET, runoff, and percolation in response to conversion of rowcrop agriculture to switchgrass utilizing the original, Richards, and slug soil water models.

Model	ET (%)	Runoff (%)	Percolation (%)	Lateral subsurface flow (%)
Original	6.0	-4.2	-16.2	-6.5
Richards	-6.4	-8.0	3.1	0.0
Slug	4.1	-3.6	-11.2	-3.0

Table 3. Percent change in average annual soil water fluxes from complete conversion of grain cropping to bioenergy cropping as simulated by the three soil water submodels.

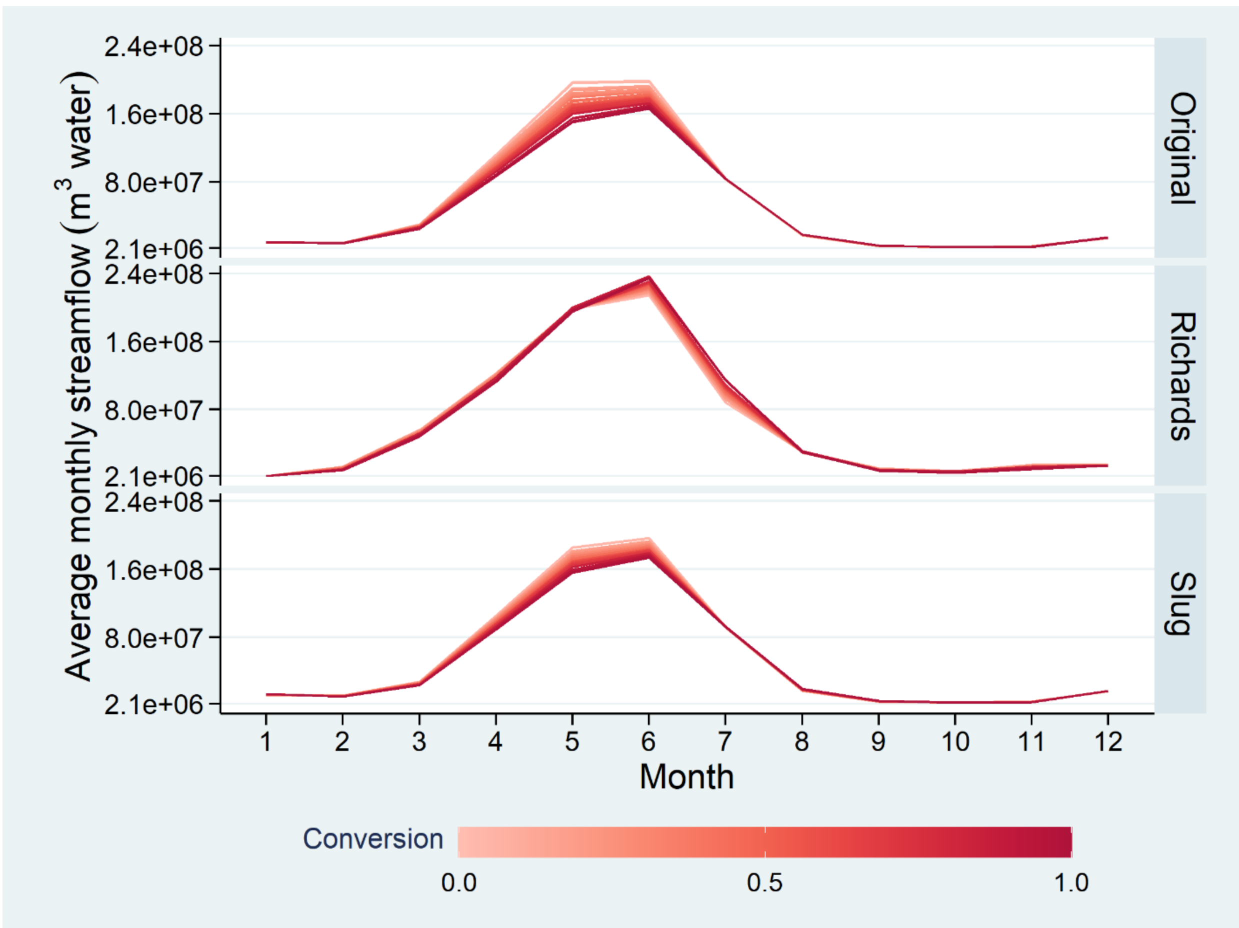

Figure 7. Simulated average monthly streamflow in response to conversion of rowcrop agriculture to switchgrass utilizing the original, Richards, and slug soil water models.

The large disparity in simulated outcomes among the soil water models highlights the importance of soil hydraulic modeling methodology for understanding system behavior and informing management or policy. Here, Richards-based simulations indicate modest water quantity impacts from widespread perennial conversion whereas the impacts simulated utilizing the original or slug submodels would be quite consequential. This methodological disparity aligns with uncertainty in the literature surrounding the water quantity impacts of conversion to bioenergy production landscapes, where the magnitude and directionality of impacts varies widely (Robertson et al., 2017).

The focus here on the implementation of a Richards-based soil water model in the APEX and EPIC models is particularly relevant as these models comprise a family of related models that also includes the Soil and Water Assessment Tool (SWAT), a model that has been widely used for assessing the hydrologic impacts of landscape conversions - including to bioenergy crop production - and can actually ingest APEX simulations for integrating smaller agricultural watersheds into larger-scale mixed land cover studies. The Richards-based methodology is planned for implementation into the SWAT model, replacing the default soil water model that has heretofore been used in SWAT. Past studies using the default soil water model may have reached different conclusions with the Richards-based methodology. For instance, a SWAT modeling study in the Skunk Creek watershed of South Dakota reported streamflow reductions of 19% following conversion of agricultural lands, which comprised 64% of the land area, to perennial grassland (Ahiablame et al., 2019). Similarly, another SWAT modeling study in the Skeleton Creek watershed of Oklahoma reported a 27.7% reduction in streamflow following conversion of grasslands, which comprised 35% of the land area, to switchgrass (Yimam et al., 2017). While these impacts on streamflow would be quite concerning, those studies implemented the default SWAT soil water model analogous to the original soil water model in APEX and EPIC, which may prove similarly incapable of reflecting the differential soil water dynamics under annual and perennial cropping. Nevertheless, it is important to note that those studies were conducted in regions of drier climate, and hence greater potential soil water limitation, than the present study.

The findings presented here indicating minimal impact on annual streamflow from grain crop to switchgrass conversion when utilizing the Richards soil water model align well with other observational studies in humid climates of the Upper Midwest. For instance, eddy covariance and soil moisture monitoring studies in southwestern Michigan have indicated comparable annual ET rates under annual corn and perennial switchgrass or mixed species grassland cropping systems (Abraha et al., 2020; Hamilton et al., 2015). Similarly, a study in southwestern Ontario reported eddy covariance estimates of annual ET that were lower under switchgrass than under corn (Eichelmann et al., 2016). In a more comprehensive assessment of surface, subsurface, and lateral fluxes, an assessment of streamflows in the Augusta Creek watershed in southwest Michigan reported stable streamflows across a 50 year period despite abandonment of 27% of the land area from row cropping to perennial vegetation and 20% of the land area from row cropping to deciduous forest (Hamilton et al., 2018).

Not surprisingly, however, context matters and observational studies in the literature also indicate the reverse. For instance, a soil water monitoring study in east-central Illinois at a location with a high water table reported ET increases of 104 mm and drainage water reduction of 32% following conversion of corn-soybean rotation to switchgrass (McIsaac et al., 2010; Zeri et al., 2013). Biophysical phenomena can be highly spatially variable, as a lysimeter study in southern Wisconsin reported between a 38% reduction and 78% increase in water drainage relative to a corn treatment under various perennial bioenergy treatments, which the authors attributed to the interaction of root development with macropore flow (Parish et al., 2019).

More broadly, it should be noted that while widespread landscape conversion to perennial bioenergy production may have modest impacts on annual water consumption in some ecosystems, the scenarios presented here are intended to demonstrate methodological improvements rather than to influence policy for bioenergy production. A plethora of environmental and socioeconomic factors needs to be considered to inform viable strategies for perennial cellulosic biomass production (Robertson et al., 2017). Tactical approaches such as cultivation on marginal lands or in vegetative buffer strips are generally seen as more viable options to realize meaningful environmental benefits while avoiding displacement of food production on croplands.

While further research is needed to better understand the hydrological effects of different cropping systems and implications of potential landscape conversion to perennial bioenergy crop production, implementation and utilization of more refined hydrologic models with capabilities to account for macropore flow, such as the model implemented here, will be beneficial for clearer scientific understanding and better informing policies and decision makers. Improved modeling techniques might alter response dimensions from indicating more extreme changes towards more modest alterations. For instance, a SWAT based simulation study in the Little Vermilion River watershed in east central Illinois utilized DRAINMOD-based tile drainage parameterization and reported only small reductions in streamflow upon conversion of row crops to switchgrass and other perennials, with the most severe scenario resulting in only a 0.76% streamflow reduction (Guo et al., 2018). Similarly, a simulation study in the Mississippi-Atchafalaya River Basin utilizing the Agro-IBIS dynamic global vegetation model and Terrestrial Hydrology Model with Biogeochemistry indicated stream discharge reductions of less than 1.5%

under the most extreme conversion scenario of row crops to switchgrass or miscanthus (VanLoocke et al., 2017). Hence care must be taken to ensure models are capable of reflecting the scenarios they are being used to assess. Otherwise, such simulation exercises may obfuscate understanding in the literature when the state of knowledge derived from empirical observations is clearer.

4. Conclusions

The updated Richards-based soil water model was implemented into the APEX and EPIC terrestrial ecosystem models. Evaluation of the Richards model compared with two existing soil water models indicated that while all could suitably simulate streamflow under traditional land use, the Richards model was better able to reflect observed soil water dynamics, particularly under switchgrass cropping systems. Independent application of the APEX model utilizing the three soil water submodels to understand the implications of potential conversion of traditional agriculture towards bioenergy production revealed widely different implications for streamflow. The Richards-based estimate indicated only slight (~1%) reductions in streamflow under widespread cropland conversion whereas the original- and slug-based simulations estimated considerable (10-16%) streamflow reductions. Experimental and observational studies in similar climates tend to support more modest estimates of hydrological impacts of land conversion from grain crops to cellulosic bioenergy crops, although contradictory findings have been observed. These findings highlight the importance of modeling methodologies for enabling meaningful understanding of complex systems.

Software availability

Name of software: APEX and EPIC.

Developers: Curtis Jones (cujo@umd.edu), Jimmy Williams (retired), Jaehak Jeong (jjeong@brc.tamus.edu).

Hardware required: PC.

Software required: Windows or Linux.

Availability: Available under GNU license upon request from https://epicapex.tamu.edu/.

Cost: free.

Program language: FORTRAN.

First available: 1980.

Acknowledgements

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Appendices

Parameter	Definition	Original	Richards	Slug
RFT0	Groundwater residence time	X	X	X
RFP0	Return flow/ deep percolation	X	X	X
IWTB	Duration of antecedent period for rainfall and PET to drive water table			
QG	Channel capacity flow rate			
QCF	Exponent in watershed area flow rate equation		X	
CHS0	Average upland slope			
BWD	Channel botom width/depth		X	
FCW	Floodplain width/channel width		X	
FPS0	Floodplain saturated hydraulic conductivity			
GWS0	Maximum groundwater residence time	X	X	X
PARM1	Canopy PET factor		X	
PARM2	Root growth-soil strength			
PARM5	Soil water lower limit	X		X
PARM12	Soil evaporation coefficient	X		
PARM16	CN retention parameter			
PARM17	Soil evaporation - plant cover factor	X	X	X
PARM20	Runoff CN initial abstraction	X	X	X
PARM38	Water stress weighting coefficient			
PARM40	Groundwater storage threshold	X	X	X
PARM42	SCS CN index coefficient			
PARM49	Maximum rainfall interception by plant canopy (mm)	X	X	X
PARM50	Rainfall interception coefficient	X	X	X
PARM51	Water stored in litter residue	X	X	
PARM82	Permeability parameter		X	X
PARM87	Water table recession coefficient			
PARM88	Daily water table movement limit		X	
PARM89	Water table recession exponent			

PARM90	Subsurface flow factor			
U G1	Soil lower limit for corn plot	X	X	X
FC G1	Soil field capacity for corn plot	X	X	X
U G5	Soil lower limit for switchgrass plot	X	X	X
FC G5	Soil field capacity for switchgrass plot	X	X	X

Table A1. Parameters selected for calibration of the APEX model.

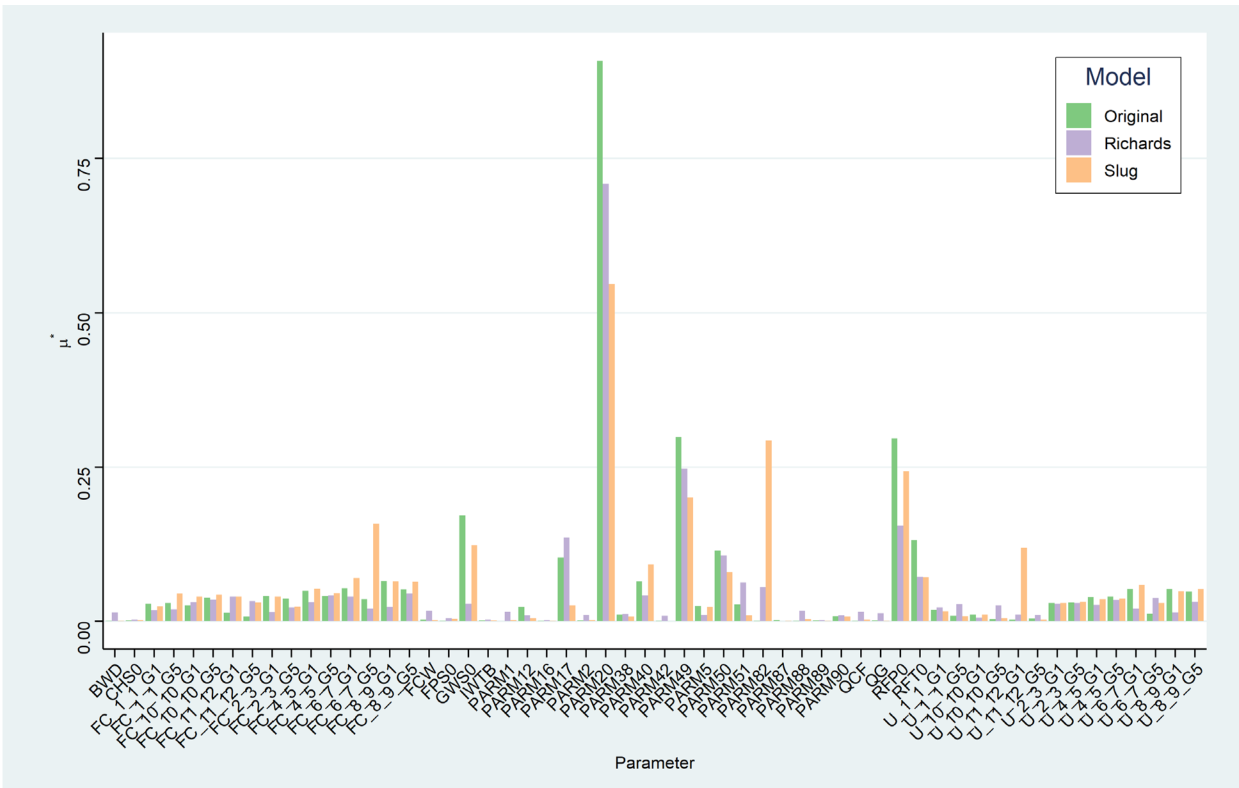

Figure A1. Method of Morris parameter importance for the three soil water models.

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