Evaluating the impacts of agricultural land management practices on water resources: a probabilistic hydrologic modeling approach

A. F. Prada^a, M. L. Chu^b, J. A. Guzman^c, D. Moriasi^d

^a Andres F. Prada
Agricultural and Biological Engineering
University of Illinois at Urbana-Champaign
1304 W. Pennsylvania Ave.
Urbana, IL 61801, USA
pradase2@illinois.edu

^b Maria L. Chu
Agricultural and Biological Engineering
University of Illinois at Urbana-Champaign
1304 W. Pennsylvania Ave.
Urbana, IL 61801, USA
mlchu@illinois.edu

^c Jorge A. Guzman
Center for Spatial Analysis
Department of Microbiology and Plant Biology
University of Oklahoma, Norman 73019, USA
Jorge.guzman@okstate.edu

^d Daniel Moriasi, PhD
Research Hydrologist
USDA-ARS Grazinglands Research Laboratory
7207 W. Cheyenne Street
El Reno, OK 73036, USA
daniel.moriasi@ars.usda.gov

Abstract

Evaluating the effectiveness of agricultural land management practices in minimizing environmental impacts using models is challenged by the presence of inherent uncertainties during the model development stage. One issue faced during the model development stage is the uncertainty involved in model parameterization. Using a single optimized set of parameters (one snapshot) to represent baseline conditions of the system limits the applicability and robustness of the model to properly represent future or alternative scenarios. The objective of this study was to develop a framework that facilitates model parameter selection while evaluating uncertainty to assess the impacts of land management practices at the watershed scale. The model framework was applied to the Lake Creek watershed located in southwestern Oklahoma, USA. A two-step probabilistic approach was implemented to parameterize the Agricultural Policy/Environmental eXtender (APEX) model using global uncertainty and sensitivity analysis to estimate the full spectrum of total monthly water yield (WYLD) and total monthly Nitrogen loads (N) in the watershed under different land management practices. Twenty-seven models were found to represent the baseline scenario in which uncertainty of up to 29% and 400% in WYLD and N, respectively, is plausible. Changing the land cover to pasture manifested the highest decrease in N to up to 30% for a full pasture coverage while changing to full winter wheat cover can increase the N up to 11%. The methodology developed in this study was able to quantify the full spectrum of system responses, the uncertainty associated with them, and the most important parameters that drive their variability. Results from this study can be used to develop strategic decisions on the risks and tradeoffs associated with different management alternatives that aim to increase productivity while also minimizing their environmental impacts.

Keywords: APEX model, global uncertainty and sensitivity analysis, model parameterization, best management practices, probabilistic approach, water quality.

Introduction

Land management practices have been implemented in the United States for over 80 years to mitigate land degradation and environmental impacts of traditional agricultural practices (Richardson et al., 2008). The U.S. Department of Agriculture (USDA) has promoted the application of these practices like cover crops, riparian buffers, or no-tillage, and landowners receive financial incentives to implement them (Tomer & Locke, 2011). However, the actual environmental benefits of these practices, especially at watershed scale where the primary public benefit is observed, remain unknown (Richardson et al., 2008; Tomer & Locke, 2011). Some factors such as inaccessibility of privately owned agricultural lands for monitoring, the complexity linked to agro-production, the elevated cost of long-term data collection, and the difficulty to conduct physical experimentation at farm production scales, limit field testing of these land management practices at larger scales (Gassman, et al., 2007). Experimentation at smaller scales, for instance, field or plot scale, and controlled conditions, are more accessible but results may not properly upscale with expected benefits at the watershed scales (Tomer & Locke, 2011).

A better understanding of land management practices impacts on water resources, including water quality, may also be assessed if the physical processes are understood and the possible water quality outcomes to alternative future scenarios can be reasonably predicted. This may be achieved through long-term monitoring and use of environmental models that can represent the responses of the system (Gassman, et al., 2007; Starks, et al., 2014a; Tomer & Locke, 2011). However, the development and use of environmental models (hydrologic and water quality) are accompanied by inherent uncertainties from different sources that can hinder the interpretation and use of the results. Uncertainty can be present in input data (climate data, elevation, land

cover, soil, etc.), data processing (rainfall and runoff data aggregation and interpolation), model parameters, spatio-temporal discretization, and model structure (Guzman, et al., 2015a) that can be propagated non-linearly to the model outputs for example runoff, nutrient concentration, and sediment load.

Parameterization that involves calibration can introduce another layer of uncertainty in model outputs while trying to improve model performance metrics. Multiple acceptable parameter combinations for a set of model inputs may exist that can represent the observed watershed systemic behavior, that is, equifinality. Equifinality makes it difficult to determine whether or not the selected set of parameters is the most appropriate to represent the system response. However, Beven (2006) argued that evaluation of equifinality should be given serious consideration not because of the difficulty of identifying parameter values but as an indication of multiple functional hypotheses about how the system is working. In most cases, no a priori knowledge of the number of acceptable model outputs is available and thus outputs generated from a single optimized set of parameters are considered the “true” solution. Using an optimized model to represent baseline conditions of the system, limits the applicability and robustness of the model to properly represent future or alternative scenarios. This is especially critical when model results are used to evaluate the impacts of environmental decisions or to formulate new policies. It is crucial that the results are interpreted in light of the risk associated with model output uncertainty (Cariboni et al., 2007; Guzman et al., 2015a) in which long-term systemic responses are better understood if the full spectrum of system behavior is considered.

The objective of this study was to develop a framework that facilitates model parameterization, that is, the selection of parameters and their values, while evaluating uncertainty to assess the impacts of land management practices at the watershed scale. The

model framework was applied to the Lake Creek watershed located in southwestern Oklahoma, USA. A two-step probabilistic approach was implemented to parameterize the Agricultural Policy/Environmental eXtender (APEX) model using global uncertainty and sensitivity analysis (GUSA). A baseline model, consisting of a family of APEX models, was derived and used to estimate the full spectrum of water yield (WYLD) and Nitrogen loads (N) in the watershed under different land management practices.

Materials and Methods

Study area

The Lake Creek watershed is one of the three main sub-watersheds that composed the Fort-Cobb Reservoir Experimental Watershed (FCREW) located in southwestern Oklahoma. It drains an approximate area of 154 km² towards the Fort-Cobb reservoir located near the main FCREW outlet (Figure 1) (Guzman et al., 2015b). The FCREW region is mostly agricultural land composed of croplands and pastures. Soils are mostly fine silty loams of different erodibility (Steiner, et al., 2008). The climate in southwestern Oklahoma is sub-humid with long and hot summers, and short and temperate winters. The mean daily temperature during summer is about 28°C while in winter is 3°C. The annual precipitation is approximately 800 mm with the largest monthly average at the end of spring (May-June) and beginning of fall (September-October) (Steiner, et al., 2008).

The Fort-Cobb reservoir is an important source of public and domestic water supply. However, it has been added to the list of water bodies that do not meet the water quality standards as given in the Clean Water Act (Steiner, et al., 2008). The agricultural practices in this watershed release nutrients, especially Nitrogen (N) and Phosphorus (P), to the surface streams

that feed the Fort-Cobb reservoir resulting in eutrophication (Steiner, et al., 2008). As a result, several agencies such the Oklahoma Water Resources Board, Oklahoma Department of Environmental Quality, and Oklahoma Conservation Commission recognized the FCREW as an experimental land to improve water quality through land conservation practices. In fact, several agronomic management practices have been adopted in the watershed such as no-tillage management, conversion of cropland to grassland, installation of fencing to exclude cattle from streams, and various structural and water management practices (Storm et al., 2006).

Figure 1. The Lake Creek watershed is one of the three sub-watersheds of the Fort-Cobb Reservoir Experimental Watershed (FCREW) located in southwestern Oklahoma.

Model set-up

The Agricultural Policy/Environmental eXtender (APEX) model (Williams et al., 1995) is a conceptual and distributed hydrologic and environmental model. It simulates the different hydrologic processes at a watershed scale while evaluating the impacts of conservation and best management practices (Wang et al., 2012) on water quality. The primary inputs to the model are elevation, soil, land use, and time series of climate variables. The outputs of the model are time series of computed hydrologic variables, nutrients, and crop yields at different temporal resolutions (annual, monthly, and daily) and different spatial scales (subareas or watershed).

The main outputs of APEX used to evaluate the impacts of the land management practices were the WYLD and N. The WYLD (in mm) was computed in APEX model using the Soil Conservation Service (SCS) curve number (CN) equation (USDA-Soil Conservation Service, 1972) given as follows (Williams et al., 2012):

$$WYLD = \frac{(P - 0.2S)^2}{P + 0.8S} \quad (1)$$

where P is the daily rainfall (mm), and S is a retention parameter (mm). The parameter S implicitly depends on the curve number (CN) expressed as $S = 254(100/CN - 1)$.

The Nitrogen load (in kg/ha) was computed by accounting for the Nitrate lost when water flows through a layer. It was estimated as the change in Nitrogen concentration and was computed separately for surface runoff, lateral flow, quick return flow, and horizontal pipe flow (for drains) using the equation (Williams et al., 2012):

$$N = W \left(1 - e^{-\frac{Q_i}{kV}} \right) \quad (2)$$

where N is the amount of Nitrogen lost from a soil layer at the end of the day (kg/ha), W is the Nitrogen load contained in a layer at the beginning of the day (kg/ha), Q_i is the volume of water

percolating through the layer, V is the storage volume occupied by percolating water, and k is the porosity. The Nitrogen load in the stream is the sum of the four components (surface runoff, lateral flow, quick return flow, and horizontal pipe flow).

In this study, the GIS interface for APEX (ArcAPEX) was used to build the model for the Lake Creek. This interface requires three different data layers: the Digital Elevation Model (DEM), soils, and land use. In addition, weather data (precipitation and temperatures) and information on land management operations were also needed. The DEM and land cover maps were obtained from USGS (USGS, 2016) while the soil map from the Web Soil Survey (USDA, 2016).

Measurement of hydrologic variables and water quality in the FCREW began in the late 2004 as part of the Conservation Effects Assessment Project (CEAP). This project was designed to estimate the environmental benefits of conservation practices implemented on agricultural lands (Mausbach & Dedrick, 2004). Fifteen climate stations, known as the Micronet stations, were installed in the FCREW to measure weather (rainfall, solar radiation, and air temperature) and soil data (soil profile moisture content). The daily precipitation and temperature (minimum and maximum) time series for Lake Creek were obtained from these stations (Guzman et al., 2014). Land management data were collected from literature in the form of reports of conservation and management schemes implemented in the watershed from 2005 onward (Storm et al., 2006). Daily streamflow and Nitrogen concentration at the outlet of Lake Creek were used to evaluate the performance of APEX in simulating WYLD and N. Nitrogen concentration collected at USGS streamflow sites was part of a water quality monitoring program in the FCREW for dissolved O₂, pH, total N, total P, and suspended sediment concentration (Starks et al., 2014b; Moriasi et al., 2014).

WYLD and N were simulated at a daily time step for nine years (2005-2013) and evaluated with observations. However, the first two years of the simulations were used to obtain the initial conditions of the model and were not considered in the analysis.

Global uncertainty and sensitivity analysis

Sensitivity analyses are commonly used to optimize the process of model development (Saltelli et al., 2008). They facilitate the adjustment of model parameters by establishing their impact on model outputs. The most common type of sensitivity analysis, the local one-at-a-time approach, is based on derivatives and evaluates the impact of changing one parameter on the output while considering a constant value for other parameters. This approach is, however, problematic if the inputs are uncertain (measured value differs from true value) or the linearity (the rate of change between inputs and outputs) of the model is unknown since this approach provides information only at the point where they were taken and do not explore the entire input sampling space (Saltelli et al., 2008). If used in environmental models that are nonlinear or the linearity changes with model assumptions, the derivative equation may no longer apply. In contrast, the global approach explores the entire input sampling space and evaluates the impact of each parameter by simultaneously varying the other parameters over a defined range (Saltelli et al., 2008). This approach does not require a priori information of the linearity of the model and it also allows evaluation of the interactions among the different parameters.

In this study, a two-step probabilistic approach using GUSA was implemented to parameterize the APEX model for Lake Creek watershed. The global uncertainty analysis quantified the output uncertainties propagated from uncertain APEX parameters. A variance-based sensitivity analysis was then performed to divide the output uncertainty according to the

contribution of each of the model parameters (Figure 2). The general process of performing GUSA was described in Figure 2. The first step was to assign probability distribution functions (*pdf*) to the uncertain model inputs/parameters. Each *pdf* was then sampled using a particular method, for instance, the Sobol method. These sample points were used to run the model from which a spectrum of model outputs, like discharge and crop yield, can be obtained. Using the variance of the output of interest, sensitivity analysis determines the sensitivity indices of each contributing input/parameter.

The Sobol method (Sobol, 1993) is a variance-based sensitivity analysis method that evaluates the sensitivity of each parameter based on the principle of variance decomposition. The sensitivity of the parameters is expressed in terms of the first sensitivity index (S_i) that represents the direct contribution of each parameter to the variance of the output. It is expressed as:

$$S_i = \frac{v_i}{V} \quad (3)$$

where v_i is the part of the variance due to the input parameter x_i , and V is the total variance of the model output. The variance-based analysis is also capable of quantifying the influence of the full range of variation of each parameter and their interaction effects (Saltelli, et al., 2008). The difference, $1 - \sum S_i$, can be used as an indicator of the linearity of the model. A difference equal to 0 indicates that the model is linear, otherwise it is nonlinear. The total effect index (S_{Ti}) accounts for the total contribution of each input parameter, x_i , to the output's variability, that is, its first-order effect (S_i) plus all the higher-order effects due to interactions (Saltelli, et al., 2008).

Figure 2. Schematic diagram of the Global Uncertainty and Sensitivity Analysis. Global uncertainty analysis determines the spectrum of model output due to uncertainty in model inputs/ parameters while global sensitivity analysis quantifies the contribution of each model parameter to output uncertainty.

For example, for three input parameters x_1 , x_2 , and x_3 , the S_{Ti} of parameter x_1 can be expressed as:

$$S_{T1} = S_1 + S_{12} + S_{13} + S_{123} \quad (4)$$

where S_{T1} is the total sensitivity index of x_1 , S_1 is the first-order effect of x_1 , S_{12} is the interaction effect between x_1 and x_2 , S_{13} is the interaction effect between x_1 and x_3 , and S_{123} is the interaction effect between x_1 , x_2 , and x_3 . Using equation (4), $S_{T1} - S_1$ provides a measure of how much x_1 is interacting with the other parameters (Saltelli, et al., 2008). The number of sample points, N , required for Sobol method is given as:

$$N = M(2k + 2) \quad (5)$$

where M is the sample size of each index, typically taken between 500 and 1000 (Chu-Agor et al., 2011; Chu-Agor et al., 2012), and k is the number of parameters.

Upon evaluation of the different parameters in APEX, 44 parameters were found to be uncertain

and independent of each other and were used to estimate WYLD (Table 1) and 15 to estimate N (Table 2) (Steglich & Williams, 2013; Williams et al., 2012). The Nash-Sutcliffe Efficiency Coefficient (NSEC) (Nash and Sutcliffe, 1970) was used as a metric to quantify the performance of the APEX model for Lake Creek. It was used to filter the simulations that were considered acceptable. The GUSA was performed using SimLab (version 2.2), a software designed for Monte-Carlo based uncertainty analysis (Saltelli et al., 2004).

Table 1. APEX parameters for water yield (WYLD) simulation

No.	Parameter	Description	Distribution ^a
1	acsf	Adjusts climatic stress factor	U(40-100)
2	BWD	Channel bottom width/depth (m/m)	U(0-40)
3	CHSO	Average upland slope in watershed (m/m)	U(0.0001-1)
4	cmeq	Coefficient in MUST equation	U(1-4)
5	cnrp	Expands CN Retention Parameter	U(0-3)
6	dlhc	Estimates drainage system lateral hydraulic conductivity	U(0.00001-20)
7	DTHY	Time interval for flood routing (hours)	U(0.1-24)
8	ecri	Exponential coefficient used to account for rainfall intensity on CN	U(0-3)
9	FCW	Floodplain width/channel width (m/m)	U(1-100)
10	fevl	Flood evaporation limit	U(0.001-2)
11	FPSC	Floodplain saturated hydraulic conductivity (mm/hr)	U(0.0001-20)
12	GWSO	Maximum groundwater storage (mm)	U(0-200)
13	gwst	Groundwater storage threshold	U(0.001-1)
14	hdvp	Hydrograph development parameter	U(0.01-2)
15	hpec	Hargreaves PET equation coefficient	U(0.0023-0.0032)
16	hpee	Hargreaves PET equation exponent	U(0.4-0.8)
17	lwtm	Limits daily water table movement	U(0.001-1)
18	QCF	Exponent in watershed area flow rate equation	U(0.1-1)
19	QG	Channel capacity flow rate (mm/hr)	U(0.1-200)
20	QTH	Routing threshold (mm)	U(0-500000)
21	rcfc	RUSL C-factor coefficient	U(0.1-2)
22	rcfx	RUSL C-factor coefficient 2	U(0.1-2)
23	rcia	Runoff CN Initial Abstraction	U(0.01-1)
24	rfic	Rainfall interception coefficient	U(0.01-0.5)
25	RFPO	Return flow/(return flow + deep percolation)	U(0-1)
26	RFTO	Groundwater residence time (days)	U(0-365)
27	rgss	Root Growth Soil Strength	U(0-3)
28	ripc	Maximum rainfall interception by plant canopy (mm)	U(0-30)
29	rrap	Runoff CN Residue Adjustment Parameter	U(0-0.5)
30	rrfs	Reduces NRCS runoff CN retention parameter for frozen soil	U(0.01-1)
31	rvad	Runoff volume adjustment for direct link	U(0.1-2)
32	scsc	SCS CN index coefficient	U(0.1-3)
33	secf	Soil Evaporation plant Cover Factor	U(0-1.5)
34	sevc	Soil Evaporation Coefficient	U(0.1-5)
35	ssff	Subsurface flow factor	U(1-10000)

36	STND	VSC routing used when storage > standing	U(0-500000)
37	swll	Soil Water Lower Limits	U(0-1)
38	swul	Soil water upward flow limit	U(0.01-2)
39	ulrp	Upper limit of CN retention parameters	U(0.1-4)
40	wdrm	Winter dormancy	U(0-1)
41	wswc	Water stress weighting coefficient	U(0-2)
42	wtrc	Water table recession coefficient	U(0.001-10)
43	wtre	Water table recession exponent	U(0.1-2)
44	YWI	Number of years maximum monthly 0.5 hour rainfall available (years)	U(0-50)

^a Probability distribution function and its parameters: U = Uniform distribution (left boundary, right boundary).

Table 2. APEX parameters for Nitrogen load (N) simulation

N o.	Parameter	Description	Distribution ^a
1	BME	Biological mixing efficiency	U(0-1)
2	DNSW	Denitrification soil-water threshold	U(0.9-1.1)
3	MDBM	Max. depth for biological mixing (m)	U(0-1)
4	NERC	N enrichment ratio coefficient for routing	U(0-1)
5	NERE	N enrichment ratio exponent for routing	U(0-1)
6	NFIX	Nitrogen fixation	U(0-1)
7	NLR	Nitrate leaching ratio	U(0-1)
8	PLR	Pesticide Leaching Ratio	U(0-1)
9	PNFG	Partitions Nitrogen flow from groundwater	U(0-20)
10	SRTC	Sediment routing travel time coefficient	U(0.5-10)
11	ULDN	Upper Limit of Daily Denitrification rate	U(0.0001-0.5)
12	ULNV	Upper limit of Nitrification/Volatilization	U(0-1)
13	UNFL	Upper Nitrogen Fixation Limit (kg/ha/day)	U(0.1-20)
14	VNPC	Volatilization/nitrification partitioning coefficient	U(0-1)
15	WSNL	Water Storage N Leaching	U(0-1)

^a Probability distribution function and its parameters: U = Uniform distribution (left boundary, right boundary).

Modeling framework

A modeling framework was developed to facilitate model parameterization. The framework was divided into three main parts: (I) parameterization for hydrology, (II) parameterization for contaminants (or nutrients), and (III) definition of the baseline model (Figure 3). Each part transitions to the next part through GUSA. The GUSA was used to define the variability of the outputs, identify the most important parameters that drive this variability, and identify the ranges

of these parameters that satisfied the requirements for acceptable model performance. The starting ranges for hydrology parameters were determined based on acceptable default values, field estimates, or as reported from the literature (Steglich & Williams, 2013). Uniform *pdf*'s were initially assigned to these parameters when only the base value was known, the range was considered finite, and no explicit knowledge of the distribution was available (McKay, 1995). This conservative assumption allows an equal probability of occurrence of the parameters along the probability range (Muñoz-Carpena et al., 2010).

The first GUSA (GUSA 1 in Figure 3) was performed to identify the most important hydrology parameters that controlled the variability of the water yield. The ranges of these important parameters were further narrowed down by filtering the simulations that resulted in acceptable model outcomes based on metrics used to evaluate the model, for example NSEC (Nash and Sutcliffe, 1970). The ranges of parameters from these simulations were used as basis in defining the new narrowed ranges (Figure 3; white box). The important parameters identified in GUSA 1 plus the starting nutrient parameters were used in the second GUSA run (GUSA 2; Figure 3) from which the important nutrient parameters were identified. The probability distribution functions (*pdf*) of both the important hydrology and nutrient parameters were then updated based on acceptable model requirements to define the baseline model. The baseline model is composed of a number of APEX models, each of which, has different parameter combination that resulted in acceptable model performance. Using the baseline models, hydrology and nutrient variables were simulated resulting in a family of time series each one representing the possible systemic response of the watershed.

The parameterization of the APEX model for Lake Creek watershed was performed following the three main steps of the modeling framework:

- Model run 1: *Parameterization for hydrology* was performed through global uncertainty

analysis of APEX using the 44 WYLD parameters (Table 1) to determine the spectrum of NSEC and identify the most important (sensitive) parameters for WYLD (hydrology).

- Model run 2: *Parameterization for nutrient* used the identified important WYLD parameters in run 1. The ranges of these parameters were adjusted based on the acceptability of the model ($\text{NSEC} > 0.6$; Moriasi et al. 2007; 2015). Global uncertainty analysis was then performed using the adjusted important parameters plus the 15 uncertain N parameters (Table 2) to determine the spectrum of NSEC for both WYLD and N. The new set of important parameters for N were also determined.
- Model run 3: *The baseline model* was defined using the important parameters for both WYLD and N and the updated probability distribution functions (ranges and distribution) of these important parameters.

Figure 3. Modeling framework used to parameterize the APEX model. The important hydrology parameters were identified following GUSA 1. These important parameters were then combined with the starting nutrient parameters and used as inputs to GUSA 2 from which the important nutrient parameters were identified. The baseline model was derived using the important hydrology and nutrient parameters with their updated pdf.

Land management practices scenarios

The land management scenarios adopted in the study were divided into two general categories: change in management operation and change in land use (Table 3). The impacts of land management practices were quantified using six additional scenarios, two with changes in management operations (scenarios 2 and 3) and four with changes in land use (scenarios 4-7). The baseline model (scenario 1) was defined according to the land use characteristics presented in Moriasi et al. (2014). The main land uses in the Lake Creek watershed were winter wheat

crops and pasture. About one half of the watershed area is covered with winter wheat crops and the other half with pasture. For this reason, 50% of the subareas in the APEX model were assigned with winter wheat and the other 50% with pasture. The land management practices defined for the baseline model were based on a survey of agricultural land types and practices in the FCREW carried out by Storm et al. (2006). For the winter wheat, the crops from previous harvests were killed in June and then the land was prepared for new planting using tandem disk plows. In August, approximately 67 kg/ha of N (46-0-0) and 4.5 kg/ha of P205 were applied to the crops (winter wheat). Planting takes place in the middle of September. For pasture, grazing activities take place all year around.

In APEX, the agricultural management practices were simulated through the Operational Schedule file (*.OPS). APEX generates as many OPS files as there are crops defined in the model set-up process. Each file contains the dates and equipment used in each stage of crop growth and management such as planting, fertilizer application, and harvesting. The two alternative management scenarios (scenarios 2 and 3) started also in June with the killing of the previous winter wheat crops followed by land preparation for new planting (Storm et al., 2006). In scenario 2 (conventional), the land was tilled in early July using springtooth harrows and the same fertilizer and amount used in scenario 1 (approximately 67 kg/ha of N (46-0-0) and 4.5 kg/ha of P205) was applied in August. Planting occurred also in the middle September. In scenario 3 (graze out), the land was tilled in early July using springtooth harrows. Fertilizer application and planting followed the same schedule and amounts used for scenario 2, however, there was an extra fertilizer application of approximately 45 kg/ha, N (46-0-0), on the second week of February. In the case of subareas with pasture, grazing activities was assumed to take place over the entire year for both scenarios (2 and 3).

The other four alternative scenarios (scenarios 4-7) were defined considering the same management practices for winter wheat and pasture used in the baseline model, but different land use distribution. New land use percentages were redistributed into the subareas (Table 3). The OPS of the baseline models were replaced with that of the individual scenarios to simulate the effects of different land management practices on WYLD and N.

Table 3. Summary of the land management scenarios used.

No.	Scenarios	% of pasture	% of winter wheat	Tillage practices
1	Baseline	50	50	conservation
2	Conventional	50	50	conventional
3	Graze out	50	50	conventional
4	75% Pasture	75	25	conservation
5	75% Winter Wheat	25	75	conservation
6	100% Pasture	100	0	conservation
7	100% Winter Wheat	0	100	conservation

The OPS files of the baseline models were modified to incorporate the land management practices implemented for scenarios 2 and 3 while retaining their land use distribution. For scenarios 4 to 7, the OPS files of the baseline models were left unchanged while the land use distribution was modified accordingly. Each scenario, like the baseline models, is composed of several parameter combination models. The WYLD and N from scenarios 2 to 7 were compared with the baseline model and a two sample t-Test was performed using SPELLmap (Guzman et al., 2013) to quantify their differences.

Results and Discussion

Model parameterization

The probabilistic approach for model parameterization for WYLD and N was accomplished in three model runs. **Run 1** started with 44 uncertain parameters resulting in 46,080 parameter

combinations, and therefore 46,080 simulations, based on Equation 5. The model performance was evaluated for each simulation to generate the full spectrum of NSEC (Figure 4a). This spectrum ranged from negative NSEC values up to a maximum of 0.51 on a daily time step. The simulations that resulted in $NSEC > 0.5$ were segregated and their parameters were used to narrow down the starting wide ranges assigned to the parameters (Table 4).

The contribution of each parameter to the variability of the output was also computed using the Sobol's 1st order sensitivity index (S_i) (Table 4). From the 44 starting hydrology parameters, only 20 of them directly influenced the variability of WYLD. The Expands Curve Number Retention Parameter (*cnrp*) was found to be the most important parameter contributing approximately 50% to the model output variability over a total of 79%. The sum of all S_i was less than 100% which indicated that the models were non-linear and hence, interactions between parameters existed.

The WYLD equation (Eq. 1) is expressed in terms of the daily rainfall and the CN retention parameter. The role of the *cnrp* parameter, the most sensitive in this case, in the SCS CN equation is to expand the CN retention parameter. Since the computed WYLD is inversely proportional to the retention parameter, values of *cnrp* greater than 1.0 will reduce the WYLD. The initial range of *cnrp* considered in run 1 was 0 - 3 (Table 1) however, simulations with NSEC greater than 0.5 had *cnrp* values between 1.3 and 2.0.

Figure 4. Model spectrum performance for daily Water Yield (WYLD) and Nitrogen (N) at different model runs.

The **2nd run** was set-up with 20 WYLD important parameters identified in run 1 and 15 Nitrogen starting parameters (Table 2) to simulate the N. In total, 35 parameters were sampled for this second run requiring a minimum of 36,864 simulations. The ranges of the 20 WYLD parameters were redefined according to the model performance obtained in run 1 (Table 4). The model performance (NSEC) for run 2 was evaluated separately for WYLD and N (Figure 4a and 4b). After narrowing down the ranges of the 20 WYLD parameters, the highest NSEC value computed for daily WYLD estimation improved from 0.51 to 0.63 (Figure 4a). The first simulation for N resulted in NSEC ranging from negative values to 0.74 (Figure 4b). The parameters of simulations that resulted in $NSEC > 0.6$ were used as bases in redefining the ranges of the starting N parameters.

Table 4. Sobol's first order sensitivity index of important WYLD parameters from GUSA 1 and adjusted parameter ranges used for model run 2.

No.	Parameter	S_i	Initial Distribution ^a	New Distribution ^a
1	cnrp	48.60%	U(0-3)	U(1.3-2)

2	ulrp	9.50%	U(0.1-4)	U(2-3.2)
3	rgss	9.30%	U(0-3)	U(0.4-0.75)
4	scsc	2%	U(0.1-3)	U(0.3-0.6)
5	wswc	1.80%	U(0-2)	U(1.5-1.7)
6	rrap	1.60%	U(0-0.5)	U(0.3-0.5)
7	hpee	1.20%	U(0.4-0.8)	U(0.55-0.8)
8	rfic	0.97%	U(0.01-0.5)	U(0.01-0.2)
9	YWI (years)	0.76%	U(0-50)	U(15-40)
10	rcia	0.71%	U(0.01-1)	U(0.65-0.85)
11	ripc (mm)	0.66%	U(0-30)	U(2.5-26)
12	hpec	0.60%	U(0.0023-0.0032)	U(0.0023-0.003)
13	ecri	0.56%	U(0-3)	U(0.1-1.5)
14	FCW (mm)	0.52%	U(1-100)	U(15-100)
15	sevc	0.35%	U(0.1-5)	U(1.8-3.8)
16	FPSC (mm/hr)	0.12%	U(0.0001-20)	U(7-10)
17	secf	0.09%	U(0-1.5)	U(1.2-1.5)
18	ssff	0.04%	U(1-10000)	U(150-10000)
19	RFTO (days)	0.02%	U(0-365)	U(150-200)
20	swll	0.01%	U(0-1)	U(0.1-1)
TOTAL		79.20%		

^a Probability distribution function and its parameters: U = Uniform distribution (left boundary, right boundary).

GUSA 2 revealed that only 10 parameters (out of 35) directly influenced the variability of the N estimation (Figure 5a). Out of the 10 parameters, only three were exclusively N parameters and seven were WYLD parameters (Figure 5b). These three new parameters were the Nitrate Leaching Ratio (*NLR*), which is the ratio of nitrate concentration in surface runoff to nitrate concentration in percolation; the Volatilization/nitrification Partitioning Coefficient (*VNPC*), which is the fraction of process allocated to volatilization; and the Upper Limit of Daily Denitrification rate (*ULDN*), which is the maximum fraction of NO_3 in a soil layer subject to denitrification. From these three, the *NLR* had the greatest contribution to the N output (approximately 6%) which suggested that the partition between surface runoff and percolation is partly driving the estimation of N. However, the two parameters that mostly influenced N were the Hargreaves PET equation parameters, *hpee* and *hpec*. They controlled more than the 60% of output variability over a total of 73% for N (Table 4). In APEX, the Hargreaves method (Hargreaves & Samani, 1985), was used to estimate the potential evapotranspiration as a function of the solar radiation and air temperature. The estimated potential

evapotranspiration was modified for the local U.S. conditions by replacing the fixed temperature difference exponent (usually equal to 0.5) with $hpee$ and the incoming solar radiation with $hpec$. High values of $hpee$ and $hpec$ result in high evapotranspiration. Steglich & Williams (2013) suggested a range of 0.5 - 0.6 for $hpee$ and 0.0023 - 0.0032 for $hpec$. The suggested range for $hpec$ was kept but the range of $hpee$ was widened to 0.4 - 0.8 in model run 1 and narrowed down to 0.55 - 0.8 for model run 2 (Figure 5a). The acceptable simulations in model run 2 showed that the $hpee$ values were mostly ranged from 0.7 to 0.8. This indicates that evapotranspiration should be higher to fit the observed N. This can be due to the fact that during transpiration, plants are expected to take up more Nitrogen.

The two global uncertainty and sensitivity analyses performed at this point were used to determine the important parameters and their ranges to comprise the baseline model for the Lake Creek watershed. Twenty WYLD parameters were identified in model run 1 (Table 4), and 10 Nitrogen parameters were identified in model run 2 (Figure 5a). Of the 10 Nitrogen parameters, seven already belonged to WYLD (Figure 5b) and only three were exclusive to Nitrogen. The variability of the system response, as measured by NSEC, was therefore controlled by 23 parameters (Figure 5b). This indicated that the rest of the WYLD and N parameters (36 parameters) can take the default values without affecting the model performance.

The original 59 parameters (44 WYLD + 15 N) were sampled using uniform distributions since only their ranges were known. After two runs, some parameter combinations have resulted

(a)

No.	Parameter	S_i	Initial Distribution
1	$hpee$	49.80%	U(0.55-0.8)
2	$hpec$	14%	U(0.0023-0.003)
3	NLR	5.80%	U(0-1)
4	scsc	1.60%	U(0.3-0.6)
5	cnrp	1.20%	U(1.3-2)
6	secf	0.10%	U(1.2-1.5)
7	rfic	0.08%	U(0.01-0.2)
8	rcia	0.07%	U(0.65-0.85)

(b)

Figure 5. (a) Sobol's first order sensitivity index of important N parameters from GUSA 2 and their initial ranges used for model

run 3, and (b) summary of important WYLD and N parameters used to define the baseline model

in $NSEC \geq 0.6$ for both WYLD and N. Considering only

these acceptable simulations, the values of the 23 final model parameters were then plotted and their *pdfs* were re-constructed. Most of the identified distributions were either normal or triangular distributions (Table 5).

For the **3rd run** the 23 parameters were sampled resulting in 24,576 simulations considering the updated distributions listed in Figure 5a. In this run, the NSEC was estimated separately for WYLD and N (Figure 4a and 4b). The 3rd run produced 49 acceptable simulations for WYLD and 853 for N. Since the baseline model will be used to estimate both WYLD and N at different land management scenarios, it was necessary to identify the simulations that can predict both WYLD and N within the acceptable NSEC range. Twenty-seven (27) simulations were found to have satisfied the model acceptability requirements ($NSEC > 0.6$) for both WYLD and N. Therefore, the baseline model for Lake Creek was composed of 27 sets of parameter combinations resulting in 27 independent APEX models.

Output estimates and uncertainty

Once the Lake Creek watershed model was parameterized using the two-step probabilistic approach, the estimation of WYLD and N was carried out. The baseline model of Lake Creek was composed of 27 different acceptable parameter combinations, that is, 27 daily time series of WYLD and N. The purpose of considering all acceptable sets of parameters is to account for the uncertainty in WYLD and N due to parameter choices (model parameterization). For the purpose of visually presenting the

Table 5. Model parameter probability distribution function (pdf) used to define the Baseline model.

No.	Parameter	Description	Distribution ^a
1	hpee	Hargreaves PET equation exponent	N(0.76, 0.04)
2	hpec	Hargreaves PET equation coefficient	T(0.0024, 0.0027, 0.003)
3	NLR	Nitrate leaching ratio	T(0.015, 0.9, 1.1)
4	scsc	SCS CN index coefficient	T(0.38, 0.58, 0.63)
5	cnrp	Expands CN Retention Parameter	T(1.3, 1.65, 2.1)
6	secf	Soil Evaporation plant Cover Factor	T(1.2, 1.4, 1.6)
7	rfic	Rainfall interception coefficient	N(0.15, 0.02)
8	rcia	Runoff CN Initial Abstraction	T(0.7, 0.83, 0.89)
9	VNPC	Volatilization/nitrification partitioning coefficient	T(0, 0.9, 1.1)
10	ULDN	Upper Limit of Daily Denitrification rate	T(0, 0.3, 0.55)
11	ulrp	Upper limit of CN retention parameters	T(2, 2.3, 3.1)
12	rgss	Root Growth Soil Strength	U(0, 3)
13	wswc	Water stress weighting coefficient	N(1.65, 0.03)
14	rrap	Runoff CN Residue Adjustment Parameter	T(0.35, 0.45, 0.55)
15	YWI	Number of years maximum monthly 0.5 hour rainfall available (years)	N(33, 5)
16	ripc	Maximum rainfall interception by plant canopy (mm)	T(4, 15, 26)
17	ecri	Exponential coefficient used to account for rainfall intensity on CN	T(0.4, 0.7, 2)
18	FCW	Floodplain width/channel width (m/m)	T(15, 30, 95)
19	sevc	Soil Evaporation Coefficient	N(3.4, 0.2)
20	FPSC	Flood saturated hydraulic conductivity (mm/hr)	N(8.5, 0.8)
21	ssff	Subsurface flow factor	T(1500, 9000, 11500)
22	RFTO	Groundwater residence time (days)	N(190, 8)
23	swll	Soil Water Lower Limits	T(0.3, 1, 1.1)

^a Approximate distributions and their parameters: N = Normal distribution (mean, standard deviation); T = Triangular

distribution (minimum, peak, maximum); U = Uniform distribution (left boundary, right boundary).

results of the baseline model, the monthly time step was used to plot the mean, the upper, and the lower thresholds of simulated WYLD and N from the 27 models for the whole period of simulation, 2007-2013 (Figure 6a and 6b). The band bounded by the lower (minimum) and upper (maximum) thresholds defines the uncertainty band propagated to the model outputs (WYLD and N) due to model parameterization. If traditional calibration were conducted, wherein the best fitting model is determined by optimization, the values of the WYLD and N loads were expected to fall within this uncertainty band (Figure 6a and 6b). The band also represented the possible responses of the system. Note that other sources of uncertainty such as the uncertainty linked to measurements of input data, land management and use, or model representation and conceptualization (structural uncertainty) were not accounted for.

The average monthly total WYLD for the simulation period was approximately 7 mm. The uncertainty due to parameter estimation can reach up to 2 mm (Figure 6c) which suggested that parameter calibration to obtain the best fitting model can add an uncertainty of up to 29% of the average WYLD. The most likely uncertainty for WYLD was 0.7 mm or approximately 10% of the mean WYLD value (approximate probability of 0.35; Figure 6c). For N, the uncertainty can reach up to 0.34 kg/ha which was more than 400% of the mean N at 0.08 kg/ha. The most likely uncertainty value for N was 0.03 kg/ha or approximately 38% of the average monthly N (approximate probability of 0.35; Figure 6d). The 10 important parameters that controlled N (Figure 5) introduced more uncertainties than the 13 parameters used to estimate the WYLD.

Based on these results, target research that focused on improving the measurement and estimation of identified key model parameters may help tighten the uncertainty band. For example, improved quantification of parameters or processes controlling N estimation can be prioritized to address this uncertainty resulting in more efficient use of resources. Furthermore, exploring the entire spectrum of responses can give realistic insights on the behavior of the system and hence environmental managements and decisions can be formulated accordingly based on this behavior. Future research is also needed to expand the presented GUSA approach to include the unaccounted uncertainty driven by input variables.

(a) Uncertainty band: WYLD

(b) Uncertainty band: N

(c) Uncertainty distribution: WYLD

(d) Uncertainty distribution : N

Figure 6. Range of simulated values of the monthly total WYLD (a) and N (b) from the baseline model and the corresponding uncertainty distribution (c and d) due to parameter estimation

Land management impacts and uncertainty

The impacts of six land management scenarios on WYLD and N were quantified by comparing their total monthly WYLD and N loads to that of the baseline model. In general, the WYLD from the different land management scenarios did not show any significant changes from that of the baseline model ($p > 0.05$). The difference between the mean WYLD of the six scenarios and the baseline model for the entire period of simulation was found to be less than 0.5% except for the 100% pasture scenario which was 1%. In the case of N, the differences between the baseline model and the scenarios, and between the scenarios themselves, were more visually evident. A comparison of the total monthly N load with the baseline model was carried

out by taking the mean, minimum, and maximum values of the 27 simulations comprising each scenario and contrasting them with the banded baseline N (Figure 7). The deviation of the maximum (red dots) and minimum N (yellow dots) of each scenario from the baseline scenario (band) represents the impacts of the land management practices taking into account the uncertainties brought about by parameter selection. In general, the uncertainties in N loads due to parameter estimation for the different land management practices can reach up to 0.36 kg/ha which is from the conventional scenario (scenario 2). The lowest uncertainty is for 100% pasture at 0.24 kg/ha (scenario 6) while the rest of the scenarios remained the same as the baseline uncertainty.

The rise and fall in N loads for both the conventional and graze out scenarios (2 and 3) follow the same pattern as the baseline model where increases happened during the early fall following fertilizer application for the winter wheat (Figure 7a and b). The ranges of N from these scenarios fell within the bands of the baseline scenario indicating that uncertainty was generated from parameter choices rather than the implementation of the scenarios themselves. Increasing the amount of winter wheat in the area also increased N (Figure 7d and f) higher than the baseline model while the opposite happened when pasture cover was increased (Figure 7c and e). In general, changes in land use (Figure 7c to f) had more notable impacts on the N loads than the conservation practices did (Figure 7a and b). Furthermore, results from the statistical tests revealed that the lower and upper bounds of N in all scenarios except the 100% pasture were not significantly different from that of the baseline model which indicated that the different land management scenarios, except scenario 6, did not affect the uncertainty of N.

The difference in N between the baseline and the different land management scenarios was quantified by computing the difference in the mean monthly N of the 27 simulations of the

baseline model and the different scenarios (Figure 8). Contrary to what was expected, the N loads under the conventional scenario showed an average increase of approximately 2%. Although there were fluctuations in the changes in N with respect to the baseline scenario, these fluctuations were minimal resulting in a more consistent change in N load for the entire period of simulation (Figure 8). The N in the graze out scenario posted an average decrease of approximately 2%, however, spikes in N load were observed in February of 2008, 2010, and 2012 (Figure 8). It can be recalled that an additional 45 kg/ha of N (46-0-0) was applied in February for the graze out scenario. Inspection of the WYLD for these months revealed that they were not significantly higher than the other months that did not result in spikes following the second fertilizer application. In fact, the WYLD for 2010 and 2012 were below the all-time mean for Lake Creek (see Figure 6). Further investigation revealed that the spikes in N can be associated with the high total daily rainfall (more than 30 mm in a week) that occurred a few days after the application of fertilizer on the second week of February. Results showed that despite the second application, spikes were not always present and an overall decrease in N can even occur, for example in 2009 and 2011, if rainfall following fertilizer application did not exceed a certain threshold. Unfortunately, sub-daily rainfall data were not used in this study to determine the intensity and duration that can produce these spikes.

In the land use change scenarios, increasing the winter wheat coverage generally increased the N load due to additional fertilizer application. For instance, changing from 50% winter wheat in the baseline model to 75% increased the N load by 3%. However, increasing to 100% winter wheat coverage will more than triple the increase in N load indicating nonlinear N production of the system. Despite the fact that increasing the land use to pasture resulted in animal grazing all year round in the watershed, N load had the highest decrease at approximately 12 and 31% for

75% pasture and 100% pasture, respectively. The highest decrease (negative spikes in Figure 8) was observed during early fall when fertilizer applied on winter wheat in the baseline scenario is no longer present in the 100% pasture scenario.

Figure 7. Comparison of the six land management scenarios with the baseline model. The band represents the 27 parameter combination of the baseline model while the dots the maximum (red) and minimum (yellow) values of the 27 models comprising each scenario.

The changes in N load under different land management scenarios can provide useful insights when considering the tradeoffs between increased productivity such as yield or animal production, and environmental impacts like the change in water quality. For instance, increasing winter wheat production by 50% can increase N load by up to 3%. Whether or not this tradeoff is within the existing water quality regulations, this information can help stakeholders decide if the change in land use to increase yield is plausible. The risk involved in increasing the N load can also be determined since the uncertainty of each scenario were considered in these results. A multi criteria decision analysis can then be implemented to explore the different alternatives that can possibly increase productivity while keeping the environmental impacts minimal.

Figure 8. Changes in the N load from the baseline model of the six land management practices

Conclusions

The most challenging aspect of environmental modeling is understanding the capabilities and limitations of the model and converting the results into tangible decisions given the uncertainties involved in the process. Despite the rigorous efforts of calibrating and validating a model, it can be argued that it cannot be accepted in the sense of “being true” or “being accurate”. Rather, it is more appropriate to say that the model has survived a series of test – be they formal, of internal consistency, or relative to the model’s capacity to explain the “real world” in a convincing parsimonious way (Saltelli et al., 2008). Presenting the full spectrum of model outputs in lieu of the traditional calibration-validation approach can give light to inflection points of system responses that are otherwise unknown. These inflections points, for example extremely high or extreme low values, are important indicators of how the system represents the “real world”.

This study demonstrated that quantification of input-output uncertainties and equifinality can be incorporated in the model parameterization process. This coupled processes facilitated the adjustment of parameters as well as the accountability of model uncertainties. The use of probabilistic inputs resulted in a more efficient way of dealing with the many input/parameters considered in hydrologic models. In the case of the APEX model developed for the Lake Creek watershed, 20 parameters were found to control the estimation of WYLD and 10 the estimation of N loads (7 of them were also WYLD parameters). However, the computation of the Sobol’s 1st order sensitivity index (S_i) also revealed that only one parameter for WYLD and only two parameters for N loads controlled over 50% (out of 80%) of the full spectrum of responses of each output. The most important parameter that controlled WYLD was the Expands CN

Retention Parameter (*cnrp*) while for Nitrogen were the two Hargreaves PET equation parameters (the Hargreaves PET equation exponent, *hpee*, and the Hargreaves PET equation coefficient, *hpec*).

Results showed that 27 sets of parameter combinations can acceptably represent the hydrologic responses of Lake Creek watershed. Using these 27 models, the total monthly WYLD was estimated to vary from 0.17 to 17 mm while the total monthly N can range from 0 to 0.5 kg/ha. Uncertainty in WYLD can reach up to 2 mm or approximately 29% of the average monthly total WYLD. Uncertainty in the N, on the other hand can reach up to 0.33 kg/ha which is more than 400% of the average monthly total load. Changing the land cover to pasture manifested the highest decrease in N to up to 30% for a full pasture coverage while changing to full winter wheat cover can increase the N up to 11%.

The methodology developed in this study was able to quantify the full spectrum of system responses, the uncertainty associated with them, and the most important parameters that drive their variability. The full spectrum of model outputs can provide robust information on the achievable responses of the watershed given the different land management practices in place and planned. Similarly, by knowing the parameters that drive the variability of the outputs, future research can be prioritized to collect more information about these parameters resulting in a more efficient use of resources. Results from this study can be used to develop strategic decisions on the risks and tradeoffs associated with different management alternatives that aim to increase productivity while also minimizing their environmental impacts.

Acknowledgements

Funding for this research was provided by the U.S. Department of Agriculture – Agricultural Research Services Research, education and Economics (REE) Cooperative Agreement (No. 59-3070-5-001).

References

- Beven, K. J. (2006). A manifesto for the equifinality thesis. *J. Hydrol.* 320(1-2), 18-36.
- Cariboni, J., Gatelli, D., Liska, R., & Saltelli, A. (2007). The role of sensitivity analysis in ecological modelling. *Ecol. Model.*, 167-182.
- Chu-Agor, M. L., Muñoz-Carpena, R., Kiker, G., Emanuelsson, A., & Linkov, I. (2011). Exploring sea level rise vulnerability of coastal habitats through sensitivity and uncertainty analysis. *Environ. Modell. Softw.* 26, 593-604.
- Chu-Agor, M. L., Muñoz-Carpena, R., Kiker, G. A., Aiello-Lammens, M. E., Akcakaya, H. R., Convertino, M., & Linkov, I. (2012). Simulating the fate of Florida Snowy Plovers with sea-level rise: Exploring research and management priorities with a global uncertainty and sensitivity analysis perspective. *Ecol. Model.* 224, 33-47.
- Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The soil and water assessment tool - historical development applications, and future research directions. *Trans. ASABE* 50(4), 1211-1250.
- Guzman, J. A., Ma, L. Chu, P. J. Starks, D. N. Moriasi, J. L. Steiner, C. A. Fiebrich, and A. G. McCombs (2014). Upper Washita River Experimental Watersheds: Data Screening Procedure for Data Quality Assurance. *J. Environ. Qual.*, 43: 1250-1261.

- Guzman, J. A., Shirmohammadi, A., Sadeghi, A., Wang, X., Chu, M. L., Jha, M. K., Parajuli, P. B., Harmel, R. D., Khare, Y. P., Hernandez, J. E. (2015a). Uncertainty Considerations in Calibration and Validation of Hydrologic and Water Quality Models. *Trans. ASABE*, 58(6): 1745-1762.
- Guzman, J.A., Moriasi, D.N., Chu, M.L., Starks, P.J., Steiner, J.L., Gowda, P.H. 2013. A tool for mapping and spatio-temporal analysis of hydrological data. *Environ. Modell. Softw.* 48: 163-170.
- Guzman, J. A., Moriasi, D. N., Gowda, P. H., Steiner, J. L., Starks, P. J., Arnold, J. G., & Srinivasan, R. (2015b). A model integration framework for linking SWAT and MODFLOW. *Environ. Modell. Softw.* 73: 103-116.
- Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Applied Engr. Agric.*, 1, 96-99.
- Mausbach, M.J., and A.R. Dedrick. (2004). The length we go: Measuring environmental benefits of conservation practices. *J. Soil. Water Conserv.* 59(5):97–103.
- McKay, M. D. (1995). Evaluating prediction uncertainty. *U.S. Nuclear Regulatory Commission*. Washington, DC.
- Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Binger, R. L., Harmel, R. D., & Veith, T. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE* 50(3), 885-900.
- Moriasi, D. N., Guzman, J. A., Steiner, J. L., Starks, P. J., & Garbrecht, J. D. (2014). Seasonal sediment and nutrient transport patterns. *J. Environ. Qual.*, 43: 1334-1344.

- Moriasi, D.N., Gitau M.W., Pai N., and P. Daggupati, (2015). Hydrologic and water quality models: Performance measures and criteria. *Trans. ASABE* 58(6): 1763-1785
- Muñoz-Carpena, R., G.A. Fox and G.J. Sabbagh. (2010). Parameter Importance and Uncertainty in Predicting Runoff Pesticide Reduction with Filter Strips. *J. Environ. Qual.* 39(1):630-641. doi:10.2134/jeq2009.0300.
- Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models: Part 1. A discussion of principles. *J. Hydrol.* 10(3), 282-290.
- Richardson, C. W., Bucks, D. A., & Sadler, E. J. (2008). The Conservation Effects Assessment Project benchmark watersheds: Synthesis of preliminary findings. *J Soil Water Conserv.* 63 (6), 590-604.
- Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models. Chichester, UK.: John Wiley and Sons.
- Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S. (2008). Global Sensitivity Analysis: The Primer. The Atrium, Southern Gate, Chichester, West Sussex, England.: John Wiley & Sons Ltd.
- Sobol, I. M. (1993). Sensitivity estimates for non-linear mathematical models. *Math Modell. Comput. Exp.* 4(I), 407-414.
- Starks, P. J., C. A. Fiebrich, D. L. Grimsley, J. D. Garbrecht, J. L. Steiner, J. A. Guzman, and D. N. Moriasi (2014a). Upper Washita River Experimental Watersheds: Meteorologic and Soil Climate Measurement Networks. *J. Environ. Qual.*, 43: 1239-1249
- Starks, P. J., Steiner, J. L., Moriasi, D. N., Guzman, J. A., Garbrecht, J. D., Allen, P. B., & Naney, J. W. (2014b). Upper Washita River Experimental Watersheds: Nutrient water quality data. *J. Environ. Qual.*, 43: 1280-1297.

- Steglich, E. M., & Williams, J. W. (2013). Agricultural Policy/Environmental eXtender Model User's manual. Temple, Texas: Blackland Research and Extension Center.
- Steiner, J. L., Starks, P. J., Daniel, J. A., Garbrecht, J. D., Moraisi, D., McIntyre, S., & Chen, J. S. (2008). Environmental effects of agricultural conservation: A framework for research in two watersheds in Oklahoma's Upper Washita River Basin. *J. Soil Water Conserv.* 63(6), 443-452.
- Storm, D. E., Busteed, P. R., & White, M. J. (2006). Fort-Cobb Basin. Modeling and land cover classification. Retrieved from Draft reported to the Oklahoma Department of Environmental Quality: Available at: http://www.deq.state.ok.us/WQDnew/tmdl/fort_cobb/osu_fort_cobb_modeling_jan_2006.pdf. Accessed on January 2016.
- Tomer, M. D., & Locke, M. A. (2011). The challenge of documenting water quality benefits of conservation practices: a review of USDA-ARS's conservation effects assessment project watershed studies. *Water Sci. Tech.* 64(1), 300-310.
- USDA. (2016). The Web Soil Survey (WSS). Available at: <http://websoilsurvey.sc.egov.usda.gov/App/Home Page.htm>. Accessed on March 2015
- USDA-Soil Conservation Service. (1972). National Engineering Handbook. In Hydrology Section 4 (pp. Chapters 4-10).
- USGS. (2016). The USGS Store. Available at: <http://www.usgs.gov/pubprod/>. Accessed on March 2015.
- Wang, X., Williams, J. R., Gassman, P. W., Baffaut, C., Izaurralde, R. C., Jeong, J., & Kiniry, J. R. (2012). EPIC and APEX: model use, calibration, and validation. *Trans. ASABE* 55(4), 1447-1462.

Williams, J. R., Jones, C. A., Gassman, P. W., & Hauck, L. M. (1995). Simulation of animal waste management with APEX. In *Innovations and New Horizons in Livestock and Poultry* (pp. 22-26). College Station: J. McFarland, ed. Austin, Tex.: Texas A&M University, Texas Agricultural Extension Service.

Williams, J.R., Izaurrealde, R.C., Steglich, E.M. (2012). Agricultural Policy/Environmental eXtender Model, Theoretical Documentation (Version 0806). Agrilife Research, Texas A&M systems.

Zhou, X., & Lin, H. (2008). Global Sensitivity Analysis. In *Encyclopedia of GIS* (pp. 408-409). Springer US.