Simulation of Daily Flow Pathways, Tile-Drain Nitrate Concentrations, and Soil-Nitrogen Dynamics Using SWAT

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Abstract
Tile drainage significantly alters flow and nutrient pathways and reliable simulation at this scale is needed for effective planning of nutrient reduction strategies. The Soil and Water Assessment Tool (SWAT) has been widely utilized for prediction of flow and nutrient loads, but few applications have evaluated the model's ability to simulate pathway-specific flow components or nitrate-nitrogen (NO₃-N) concentrations in tile-drained watersheds at the daily time step. The objectives of this study were to develop and calibrate SWAT models for small, tile-drained watersheds, evaluate model performance for simulation of flow components and NO₃-N concentration at daily intervals, and evaluate simulated soil-nitrogen dynamics. Model evaluation revealed that it is possible to meet accepted performance criteria for simulation of monthly total flow, subsurface flow (SSF), and NO₃-N loads while obtaining daily surface runoff (SURQ), SSF, and NO₃-N concentrations that are not satisfactory. This limits model utility for simulating best management practices (BMPs) and compliance with water quality standards. Although SWAT simulates the soil N-cycle and most predicted fluxes were within ranges reported in agronomic studies, improvements to algorithms for soil-N processes are needed. Variability in N fluxes is extreme and better parameterization and constraint, through use of more detailed agronomic data, would also improve NO₃-N simulation in SWAT. Editor's note: This paper is part of the featured series on SWAT Applications for Emerging Hydrologic and Water Quality Challenges. See the February 2017 issue for the introduction and background to the series.

Keywords
tile drainage, hydrology, nitrate export, SWAT, denitrification, soil nitrogen

Disciplines

Comments

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SIMULATION OF DAILY FLOW PATHWAYS, TILE-DRAIN NITRATE CONCENTRATIONS, AND SOIL-NITROGEN DYNAMICS USING SWAT¹

Charles D. Ikenberry, Michelle L. Soupir, Matthew J. Helmers, William G. Crumpton, Jeffrey G. Arnold, and Philip W. Gassman²

ABSTRACT: Tile drainage significantly alters flow and nutrient pathways and reliable simulation at this scale is needed for effective planning of nutrient reduction strategies. The Soil and Water Assessment Tool (SWAT) has been widely utilized for prediction of flow and nutrient loads, but few applications have evaluated the model’s ability to simulate pathway-specific flow components or nitrate-nitrogen (NO₃-N) concentrations in tile-drained watersheds at the daily time step. The objectives of this study were to develop and calibrate SWAT models for small, tile-drained watersheds, evaluate model performance for simulation of flow components and NO₃-N concentration at daily intervals, and evaluate simulated soil-nitrogen dynamics. Model evaluation revealed that it is possible to meet accepted performance criteria for simulation of monthly total flow, subsurface flow (SSF), and NO₃-N loads while obtaining daily surface runoff (SURQ), SSF, and NO₃-N concentrations that are not satisfactory. This limits model utility for simulating best management practices (BMPs) and compliance with water quality standards. Although SWAT simulates the soil N-cycle and most predicted fluxes were within ranges reported in agronomic studies, improvements to algorithms for soil-N processes are needed. Variability in N fluxes is extreme and better parameterization and constraint, through use of more detailed agronomic data, would also improve NO₃-N simulation in SWAT. Editor’s note: This paper is part of the featured series on SWAT Applications for Emerging Hydrologic and Water Quality Challenges. See the February 2017 issue for the introduction and background to the series.

(KEY TERMS: tile drainage; hydrology; nitrate export; SWAT; denitrification; soil nitrogen.)


INTRODUCTION

Artificial subsurface drainage (i.e., tile drainage) allows row crop production and improves crop yields in poorly drained soils by lowering the water table to limit saturation of the root zone and prevent root aer- ation stress (Hatfield et al., 1998), and by increasing planting and harvest windows during spring and fall, respectively. Streamflow and nutrient transport are


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significantly impacted by subsurface drainage because tile drains alter the pathways and processes that govern hydrology and nutrient cycling (Schilling and Helmers, 2008). The distribution of water balance components; runoff, lateral flow, shallow groundwater flow, and aquifer recharge; differ in tiled versus nontiled watersheds (Goswami et al., 2008; Sui and Frankenberger, 2008). The presence of tile drainage also impacts water quality processes by reducing surface runoff and associated sheet and rill erosion, increasing soil aeration, thereby increasing mineralization and reducing denitrification, and increasing nitrate-nitrogen (NO$_3$-N) leaching to surface water (Dinnes et al., 2002; El-Sadek et al., 2002; Coelho et al., 2012; Boles et al., 2015). Proper identification and quantification of these pathways and processes is critically important for reliable prediction of nonpoint source pollutant loads (Goolsby et al., 2010; Stenback et al., 2008; David et al., 2011). Additionally, design and simulation of best management practices (BMPs) and strategies to mitigate negative effects of tile drainage require thorough understanding of the underlying hydrologic and water quality processes (Rozemeijer et al., 2010; Yen et al., 2014).

The Soil and Water Assessment Tool (SWAT) model is a well-established and widely utilized model for simulation of hydrology and pollutant transport in predominantly agricultural watersheds. The model explicitly accounts for both tile drainage and soil nutrient cycling and is under continuous development/improvement by U.S. Department of Agriculture-Agricultural Research Service (USDA-ARS). SWAT has been extensively applied worldwide for many types of water resource problems across a wide spectrum of watershed scales and conditions (Gassman et al., 2014; Bressiani et al., 2015; Krysanova and White, 2015). Recognizing its extensive use, Arnold et al. (2012) published guidance on the use, calibration, and validation of SWAT models and detailed performance measures and evaluation criteria were set forth by Moriasi et al. (2015).

Reliable models for simulating hydrology and nutrient transport in tile-drained landscapes are critically needed but particularly challenging. Calibration of SWAT and other watershed models often relies heavily on iterative adjustment of a large number of parameters during calibration. Calibration is typically performed to minimize differences between predicted and observed flow and/or pollutant loads at large spatial (greater than HUC-12) and temporal (monthly and annual) scales, and pathway-specific flow and daily data are often not available (Boles et al., 2015). A problem frequently encountered during the calibration process is that optimized parameter values often produce intermediate processes/flux values that are unrealistic (Malone et al., 2015). Even when this problem is recognized, observed data needed to constrain parameter values and intermediate fluxes are often lacking. As a result, performance criteria for nonpathway specific variables such as streamflow or nutrient loads may appear reasonable, but underlying simulation of surface runoff (SURQ), subsurface flow (SSF), nutrient transport, and N-dynamics (e.g., denitrification and soil-N levels) may be misrepresented (Yen et al., 2014; Arnold et al., 2015). These challenges can limit the model’s utility for accurately forecasting flow and nutrient transport across spatial scales, through varying weather patterns, with land-use changes, and with implementation of water quality improvement strategies. SWAT’s framework makes such comparative analysis relatively simple, although results may be deceiving if the baseline model is deemed accurate but is right for the wrong reasons.

This study examines the performance of SWAT in simulating hydrology and NO$_3$-N transport in small, tile-drained watersheds (200-1,000 ha) typical of drainage districts in north-central Iowa. The goals of this study were to evaluate simulation of hydrology and NO$_3$-N dynamics and to provide deeper insights into model performance. Specific objectives were to (1) develop and calibrate SWAT models for small, tile-drained watersheds, (2) evaluate model performance for pathway-specific flow and NO$_3$-N simulation at daily intervals, and (3) document important intermediate processes and N-fluxes, such as denitrification, mineralization, crop uptake, and soil-NO$_3$-N storage.

MATERIALS AND METHODS

Study Area

The two watersheds simulated in this study each drain to Conservation Reserve Enhancement Program (CREP) wetlands located in the Des Moines Lobe ecoregion in north-central Iowa (Ikenberry et al., 2017). The 309-ha KS watershed is located in Story County, Iowa, at the headwaters of a first-order tributary to Squaw Creek, a HUC-12 watershed in the South Skunk River basin. The 227-ha AL watershed is located in Kossuth County approximately 120 km northwest of the KS site (Figure 1) and drains to a first-order stream that enters Black Cat Creek, a HUC-12 watershed that discharges to the Des Moines River. Watershed characteristics for both sites are reported in Table 1. All soils in the watersheds are...
classified as somewhat poorly drained to very poorly drained, with the exception of Clarion soils, which are moderately well-drained. Therefore, hydrologic response units (HRUs) with Clarion soils were not parameterized with tile drainage, but all other HRUs include tile drain parameters.

The monitoring strategy was designed and implemented as part of the CREP wetland monitoring described by Crumpton et al. (2006). This study utilized four years of data collected upstream of the wetland at each site: 2008-2011 for the KS watershed, and 2007-2010 for the AL watershed. NO$_3$-N concentrations were measured using automated samplers that collected daily composite samples during the ice free season supplemented by grab samples collected approximately weekly throughout the year. Streamflows were estimated from stage-discharge equations developed using a combination of stage recorders, submerged area velocity meters, and point measures of discharge.

A two end-member mixing model based on NO$_3$-N concentrations was used to separate measured discharge ($Q_t$) into surface runoff ($Q_s$) and subsurface flow ($Q_{ss}$) end-members (Crumpton et al., in preparation), similar to the approach described by Tomer.

### TABLE 1. Characteristics of Study Sites.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>KS Watershed</th>
<th>AL Watershed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drainage area, DA (ha)</td>
<td>309</td>
<td>227</td>
</tr>
<tr>
<td>Row crop (% of DA)</td>
<td>93</td>
<td>80</td>
</tr>
<tr>
<td>Continuous corn (% of row crop)</td>
<td>35</td>
<td>14</td>
</tr>
<tr>
<td>Poor drainage (% of DA)$^1$</td>
<td>62</td>
<td>77</td>
</tr>
<tr>
<td>Annual rainfall (mm)$^2$</td>
<td>1,081</td>
<td>906</td>
</tr>
<tr>
<td>Annual water yield (mm)$^3$</td>
<td>395</td>
<td>279</td>
</tr>
</tbody>
</table>

$^1$Row crop areas with slopes <5% and soils classified as somewhat poor to poorly-drained.


$^3$Average annual water yield during model simulation period.

![FIGURE 1. Map of Watersheds and Sampling Locations. The shaded region within the state boundary is the Des Moines Lobe ecoregion. Watershed/tile flow and water quality sampling were collected at Conservation Reserve Enhancement Program (CREP) wetland inflow sites.](image)
et al. (2010). This separation relied on a water balance given by

\[ Q_t = Q_s + Q_{ss} \]  

(1)

and a NO3-N mass balance given by

\[ N_t Q_t = N_s Q_s + N_{ss} Q_{ss} \]  

(2)

In these equations, \( N \) refers to NO3-N concentration, \( Q \) refers to the discharge, and the subscripts \( t \), \( s \), and \( ss \) refer to the total flow, surface flow, and subsurface flow, respectively. Combining these equations to solve for the subsurface flow to total flow ratio \( r = Q_{ss}/Q_t \) gives

\[ r_t = (N_t - N_s)/(N_{ss} - N_s) \]  

(3)

Over the four-year periods analyzed for these two watersheds, the percent surface runoff estimated from end-member analysis of individual events ranged from near 0 to 66% and averaged 12-15% of event flow over a 10-fold range of estimated \( N_s \). These results are consistent with those reported in prior work on Corn Belt systems (Stone and Wilson, 2006; Schilling and Helmers, 2008; Tomer et al., 2010; Vidon et al., 2012).

**SWAT Model Development**

Watershed delineations were based on the Light Detection and Ranging (LiDAR) data developed for the State of Iowa in 2010. The Iowa Department of Natural Resources—GIS Section aggregated local LiDAR data to a resolution of one square meter, and hydraulically reinforced the data to incorporate culverts and bridges that convey water through embankments (e.g., roadways). Both watersheds have low topographic relief, with most slopes between 0 and 2% and many enclosed depressions.

Sources of climatic data include the National Climatic Data Center Weather Data Library database (NOAA, 2013) and the National Weather Service COOP data available through the Iowa Environmental Mesonet (Iowa State University, 2014). Weather station data included daily rainfall and maximum and minimum daily temperature. The closest weather station to the KS Wetland is located in Ames, Iowa, and data from the weather station in Algona, Iowa, was used for model input in the AL Wetland watershed. Both stations are less than 10 miles from the watersheds. Solar radiation, wind speed, and relative humidity were simulated by the weather generator within SWAT.

The USDA National Agricultural Statistics Service (NASS) cropland data layer (CDL) for the years 2005 through 2010 was obtained and used to assess land use and crop rotations. The 2010 NASS land cover was verified by windshield surveys conducted in early spring 2011. Soils data are from the Soil Survey Geographic Data (SSURGO) database developed by NRCS. Based on the area of land with soils being somewhat poorly, poorly, or very poorly drained, it is estimated that 62% of the KS watershed is tile-drained (Table 1). Hydrologic soil group B/D is dominant, with class B applied to HRUs with tile drainage. Soil data include three or four soil layers, depending on soil type, with layer-specific values for bulk density, saturated hydraulic conductivity, and percent sand/silt/clay. Soils in the KS Wetland watershed include Canisteo, Clarion, Harps, Nicollet, and Webster, with Clarion and Webster soils comprising 67% of the watershed. The AL watershed is more intensely drained, with 77% of soils being at least somewhat poorly drained. Soil classifications include Canisteo, Clarion, Nicollet, Okoboji, Storden, and Webster, with 90% of the watershed consisting of Canisteo, Nicollet, or Clarion soils.

SWAT applications typically simulate a large watershed comprised of many subbasins. Because this case study was undertaken to improve tile flow predictions at the drainage-district scale, the watershed models each have only one small subbasin, which is representative of the local drainage district. Subbasins in SWAT are divided into HRUs that have unique combinations of land use, soil type, and slope classification. Although HRUs represent real-world locations, they are not spatially contiguous and are lumped at the subbasin level within the SWAT framework. Water and pollutants generated in each HRU are aggregated at the subbasin level before being routed in the reach network of the SWAT model.

During HRU development, threshold values were used to filter areas of land use, soil, and slope. Both watershed models included thresholds of 3% for land use, 5% for soil type, and 5% for slope classification. As a result, land uses that comprise less than 3% of a subbasin were removed and the area was redistributed to the relative percentages of the remaining (non-filtered) land uses in each subbasin. Similarly, soils comprising less than 5% of any land uses were filtered, as well as slopes comprising less than 5% of any soil group. The filtering process resulted in 17 individual HRUs in the KS Wetland watershed with an average area of 18.2 ha. The AL watershed model was filtered to 26 HRUs with an average size of 8.7 ha.

**Crop Rotation and Fertilizer Application**

Land use was determined using the USDA NASS CDL for the years 2005 through 2010. The majority
of row crop production consists of two-year rotations of corn (Zea mays L.) and soybeans (Glycine max (L.) Merr.), with some continuous corn. Continuous corn was indicated by corn planted in two or more successive growing seasons per historical land use data. Planting and harvest of crops was assumed to occur on May 1 and September 30, respectively. Seventy-five percent of fertilizer-N was applied in the spring prior to planting corn, with the remaining 25% applied in the fall after soybeans. Fertilizer types consisted of anhydrous ammonia, constituting half of applied-N, urea ammonium nitrate, and diammonium phosphate. Fertilizer application rates (Table 2), types, and timing were based on practices typical in the region and are consistent with rates reported in the Iowa Nutrient Reduction Strategy (Iowa State University, 2013).

**Hydrologic Parameterization and Calibration**

Input parameterization was guided by recommended ranges reported in previous SWAT applications (Douglas-Mankin et al., 2010; Arnold et al., 2012), with particular focus on efforts in tile-drained landscapes in the Upper Midwest of the United States (Green et al., 2006; Sui and Frankenberger, 2008; Gassman et al., 2009; Moriasi et al., 2012, 2013; Yen et al., 2014). Selection of tile-drain related parameters was also informed by previous application of the DRAINMOD and RZWQM models to tile-drained field plots in Central Iowa (Thorup et al., 2007, 2009). The spin-up period for both models began in 2000, providing eight years of spin-up for the KS model and seven years for AL. The purpose of this study was to evaluate model behavior and feasibility of calibration at small spatial and temporal scales. Due to limited years of data collection and challenges encountered during calibration, neither spatial nor temporal validation was performed.

Table 3 is the list of input parameters that were adjusted during hydrologic calibration. Various combinations of hydrologic parameter adjustments were made using both manual calibration and the SUFI2 algorithm within the SWAT-CUP software program (Abbaspour, 2011). Simulations were executed using SWAT Version 2012, Revision 634. Performance was assessed using visual assessment of daily time series data, performance criteria established by Moriasi et al. (2015) for Nash-Sutcliffe Efficiency (NSE) and percent bias (PBIAS) (Table 4), which were applied to all flow pathways, and visual analysis of flow duration curves.

Hydrologic calibration and assessment focused on simulation of daily SURQ, water yield (WYLD), and SSF, with SSF being most critical for NO3-N transport in tile-drained watersheds. SSF is the sum of tile flow, lateral flow, and groundwater flow, with tile flow being the dominant component in both KS and AL watersheds. For both watersheds, better agreement between measured and predicted hydrologic output was obtained, using the Plant ET method to calculate daily CN values. Similarly, model runs using the more recently-incorporated DRAINMOD-based tile equations (Moriasi et al., 2012, 2013) provided more accurate hydrologic predictions in both watersheds than the older TDRAIN-based algorithms. Therefore, the Plant ET curve number method and the DRAINMOD-based tile equations were used in final calibration runs.

**Nitrogen Parameterization and Calibration**

After hydrologic simulations were calibrated and assessed, NO3-N-related variables reported in Table 5 were adjusted during calibration to observed daily NO3-N concentrations using existing SWAT algorithms (Calibration A). The calibrated concentration represents the composite concentration of all flow pathways, but the vast majority of simulated and observed NO3-N is transported with tile flow. Performance assessment focused on daily concentrations rather than monthly loads. Calibration of flows and loads (and not concentrations) can mask performance deficiencies. For example, NO3-N concentrations could potentially be calibrated upwards during periods of flow underestimation in order to improve load predictions, but the appearance of improvement would be artificial and for the wrong reasons. Furthermore, calibration of daily concentration provides insights to the suitability of the model for simulation of water quality BMPs and for assessment of water quality standards, which are concentration-based. As with flow, daily concentration predictions were evaluated using NSE and PBIAS statistics (Table 4) and concentration duration curves.

After evaluating simulation of daily NO3-N concentrations using existing algorithms in SWAT, a revised executable version of SWAT (a modified version of Revision 636) was utilized to try and improve simulation of NO3-N concentrations. In both the original and revised algorithms, the concentration of NO3-N in the mobile water for a given soil layer is a linear

<table>
<thead>
<tr>
<th>Crop Rotation</th>
<th>Watershed</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn years of corn-soybean rotations</td>
<td>KS</td>
<td>170</td>
</tr>
<tr>
<td>Each year of continuous corn</td>
<td>AL</td>
<td>225</td>
</tr>
</tbody>
</table>

**TABLE 2. Estimated Fertilizer-N Application.**
The function of the amount of NO\textsubscript{3}-N (kg/ha) present in the soil layer (NO\textsubscript{3\_ly}), expressed as conc\textsubscript{NO\textsubscript{3},mobile} = NO\textsubscript{3\_ly} \times \left( 1 - \exp \left( \frac{w}{(1 - \theta)} \times SAT\textsubscript{ly} \right) \right) / w \tag{4}

where w is the amount of mobile water in the layer (mm of H\textsubscript{2}O), \( \theta \) is the fraction of porosity from which anions are excluded, and SAT\textsubscript{ly} is the saturated water content of the soil layer (mm of H\textsubscript{2}O). To calculate the concentration of NO\textsubscript{3}-N in tile flow the following nonlinear function of the amount of NO\textsubscript{3}-N in the soil profile was developed in the revised algorithm.

\[ TNO3ln = \text{N\_LNCO} \times [\ln(TNO3)]^{N\_LN}, \tag{5} \]

where, \text{N\_LNCO} is a dimensionless coefficient, TNO3 is the total NO\textsubscript{3}-N in the soil profile (kg/ha), and \( N\_LN \) is a dimensionless exponent in the nonlinear function. The concentration in the tile flow is then calculated as follows:

\[ \text{conc\textsubscript{NO\textsubscript{3},tile}} = TNO3ln \times \left( 1 - \exp \left( \frac{w_{\text{tile}}}{(1 - \theta)} \times SAT\textsubscript{ly} \right) \right) / w_{\text{tile}}, \tag{6} \]

where \( w_{\text{tile}} \) is the amount of tile flow (mm).

In addition to including a nonlinear function for tile NO\textsubscript{3}-N in the revised algorithms, the
concentration was also lagged using a digital filter technique of the form

\[ \text{concNO}_3\text{tile}_i = \frac{\text{concNO}_3\text{tile}_{i-1}(1 - N\_LAG)}{C_0^{N\_LAG}} + \frac{\text{concNO}_3\text{tile}_i}{C_3^{N\_LAG}} \]  

where the subscripts \( i \) and \( i-1 \) indicate concentrations on the current and previous day, respectively, and \( N\_LAG \) is a recession constant used to lag tile \( \text{NO}_3\text{-N} \) concentrations. These algorithms were introduced in order to evaluate impact of smoothing temporal variations in \( \text{NO}_3\text{-N} \) transported from the soil profile to tile flow, and the model was recalibrated using the new \( \text{NO}_3\text{-N} \) equations (Calibration B). The goal of revising the algorithms was not to physically represent individual processes in the transport of \( \text{NO}_3\text{-N} \) to tile drains, but to evaluate and document the need to further refine soil-N processes in the model. The parameter names, descriptions, and values of all \( \text{NO}_3\text{-N} \) calibration variables are listed in the lower section of Table 5.

### RESULTS AND DISCUSSION

#### Evaluation of Hydrologic Simulation

All NSE and PBIAS values for both daily and monthly WYLD meet the evaluation criteria of satisfactory or better set forth by Moriasi et al. (2015) (Table 6). NSE values for daily SSF were not satisfactory for either watershed (using Moriasi criteria for total flow), although PBIAS is very good in the KS model and satisfactory for AL. Simulation of SURQ is not satisfactory at either time step for the AL model. Average runoff in the AL watershed was only 30 mm/yr from 2007-2010, and SWAT was unable to replicate these extremely low runoff conditions. The overall water balance of both models matched observed data reasonably well. Observed SSF in the KS watershed accounted for 75% of the measured flow, with simulated SSF equal to 73% of total WYLD. Observed SSF in the AL watershed comprised 89% of total flow, whereas simulated SSF made up 85% of the simulated WYLD. Simulations of monthly WYLD were good (0.70 ≤ NSE ≤ 0.80) for both watersheds. It is noteworthy that the maximizing model agreement with observed data required calibration parameters unique to each watershed, likely due to different degrees of drainage intensity, along with other distinct watershed characteristics.

Time series plots illustrate the challenges of accurately simulating daily SSF in SWAT. The model captures the general trends/directions in SSF, but consistently underestimates peak flows and fails to reflect hydrograph recession in both the KS (top portion of Figure 2) and AL (top portion of Figure 3) watersheds. Flow duration curves (Figure 4) reveal that both models failed to simulate low flows well, although the magnitude of these flows is so small that they have little effect on the annual water balance and mass transport of \( \text{NO}_3\text{-N} \). Potential parameterization errors that contribute to deviations between observed and simulated SSF could stem from differences in localized precipitation patterns not captured by available weather stations located well...
outside the watersheds. Additionally, the presence of surface inlets is not parameterized, and there is uncertainty associated with characteristics of local tile drainage infrastructure and other hydrologic inputs.

The conceptual framework and simplifications of the SWAT model may also limit accuracy of tile flow simulation at these small scales. Such simplifications include the lumped nature of HRUs, which does not allow mechanistic routing of subsurface flow through subbasins, and simplified groundwater routines noted by Pfannerstill et al. (2014), who developed a modified version of SWAT in which groundwater storage was split into fast and slow contributing aquifers to improve hydrograph recession and low flow simulation. Additionally, the static value of many hydrological input parameters, combined with varying temporal sensitivity of hydrologic parameters, almost certainly limits model performance (Pfannerstill et al., 2015). This limitation has been evaluated and documented by others, including Guse et al. (2016), Haas et al. (2016), Herman et al. (2013), and Yilmaz et al. (2008).

NO₃-N Simulation (Calibration A)

Simulation of NO₃-N concentration prior to modification of algorithms (i.e., Calibration A) was more problematic than prediction of daily flow components, with concentrations falling steeply in June/July and remaining near zero through the end of the growing season in both KS (bottom portion of Figure 2) and AL (bottom portion of Figure 3) models in all years. Simulated NO₃-N is depleted from the soil too quickly, possibly due to misrepresentation of soil-N cycle and/or NO₃-N transport algorithms. This rapid depletion does not appear to be driven by hydrologic predictions, since the models do not significantly overestimate SSF peaks or volumes prior to and during soil-NO₃ depletion (Figure 2 and 3). Prior to depletion of soil-N, simulated concentration varied with flow, showing more short-term fluctuation than observed concentration. Additionally, there are several instances of sharp increases in simulated concentration concurrent with declines in observed concentration. This occurs in June 2008 in both watersheds, and again in July 2010 for AL, at times when both SSF and SURQ increase and SSF NO₃-N concentrations are overestimated.

Although model performance for NO₃-N concentration was not satisfactory (Table 7), the proportion of NO₃-N carried by SSF relative to SURQ was reasonable, with SSF concentrations consistently far exceeding runoff concentrations. Simulated flow-weighted average (FWA) NO₃-N concentrations in SURQ were less than 1 mg/L for both watersheds, while simulated FWA NO₃-N concentrations in SSF were over 10 mg/L. This compares well to previous measurements of NO₃-N in surface runoff in Iowa, including a study by Zhou et al. (2014), in which NO₃-N concentrations in surface runoff in the Walnut Creek watershed in Jasper County averaged 1.08 mg nitrate-N/L across all treatments and years (ranging from 0.04-3.7 mg N/L).

Time series comparisons (Figures 2 and 3) indicate that while SSF predictions may contribute to some of the deviation between observed and simulationed concentrations, hydrology alone does not explain errors in NO₃-N predictions. Concentration errors often occur during times of relatively good SSF prediction, especially well into the growing season after NO₃-N levels have dropped markedly. Further, the concentration duration curves (Figure 5) reveal that there is substantial deviation in concentration between the 30th and 60th duration intervals compared to the SSF duration curve.

NO₃-N Simulation Using Modified Algorithms (Calibration B)

Due to problems simulating daily NO₃-N concentrations, modifications were made to the SWAT source code to improve NO₃-N loss from the soil profile by smoothing temporal variations in NO₃-N export via tile drains using the N_LAG, N_LN, and N_LNCO parameters. The updated models were calibrated by adjusting ANION_EXCL, CDN, and SDNCO, along with the new lagging parameters (Table 5). The addition of the new algorithms improved simulation of daily NO₃-N fluctuations for both the KS (Figure 2) and AL (Figure 3) watersheds, but there remained periods of significant divergence between simulated and observed NO₃-N concentrations.


<table>
<thead>
<tr>
<th></th>
<th>Daily NSE</th>
<th>Daily PBIAS¹</th>
<th>Monthly NSE</th>
<th>Monthly PBIAS¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>KS Watershed</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WYLD</td>
<td>0.68 [S]</td>
<td>−2.7 [VG]</td>
<td>0.79 [G]</td>
<td>−5.0 [G]</td>
</tr>
<tr>
<td>SURQ</td>
<td>0.55 [S]</td>
<td>−10.0 [S]</td>
<td>0.87 [VG]</td>
<td>−11.1 [S]</td>
</tr>
<tr>
<td>SSF</td>
<td>0.36 [NS]</td>
<td>−0.3 [VG]</td>
<td>0.55 [S]</td>
<td>−2.9 [VG]</td>
</tr>
<tr>
<td>AL Watershed</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WYLD</td>
<td>0.51 [S]</td>
<td>9.2 [G]</td>
<td>0.71 [G]</td>
<td>9.2 [G]</td>
</tr>
<tr>
<td>SURQ</td>
<td>−0.25 [NS]</td>
<td>−21.5 [NS]</td>
<td>0.10 [NS]</td>
<td>−21.5 [NS]</td>
</tr>
<tr>
<td>SSF</td>
<td>0.46 [NS]</td>
<td>12.9 [S]</td>
<td>0.66 [S]</td>
<td>12.9 [S]</td>
</tr>
</tbody>
</table>

Notes: VG, very good; G, good; S, satisfactory; NS, not satisfactory. ¹A negative PBIAS result indicates overestimation.
FIGURE 2. Daily Subsurface Flow (SSF) and NO₃-N Concentration for the KS Watershed. Observed and simulated SSF shown in top half of plot with solid gray and dashed black lines, respectively. In bottom half of plot, blue lines represent observed NO₃-N concentrations, red dashed lines show simulated concentrations (Calibration A), and green dashed lines illustrate concentrations simulated using the new lagging algorithms (Calibration B).

FIGURE 3. Daily SSF and NO₃-N Concentration for the AL Watershed. Observed and simulated SSF shown in top half of plot with solid gray and dashed black lines, respectively. In bottom half of plot, blue lines represent observed NO₃-N concentrations, red dashed lines show simulated concentrations (Calibration A), and green dashed lines illustrate concentrations simulated using the new lagging algorithms (Calibration B).
Performance statistics with the new algorithms (Table 8) were improved significantly by lagging the release of NO$_3$-N from the soil profile compared with predictions obtained, using the original SWAT algorithms (Table 7). Times series results (green-dashed lines in bottom portion of Figure 2 and Figure 3) illustrate this improvement, with delayed reduction in predicted NO$_3$-N concentrations later into the growing season and elimination of sharp peaks of NO$_3$-N concentrations predicted using the original SWAT equations. Substantial improvement was obtained in the distribution of NO$_3$-N concentrations, as illustrated by the concentration duration curves (Figure 5).

Despite improved predictions using the new equations, NSE remained unsatisfactory for daily concentrations but was satisfactory for daily loads in both models. Concentration PBIAS was very good for the KS model but not satisfactory for AL. Simulated concentrations did not drop as sharply in mid-summer months as with the original equations, but short-term fluctuations continued to exceed fluctuations in observed concentration, and overall, SWAT still underestimated NO$_3$-N loss from these small watersheds. Despite challenges in simulating daily concentrations and loads, monthly statistics are categorized as “good” or better for all performance criteria except PBIAS in the AL model. If model calibration and assessment had focused on monthly NO$_3$-N loads, it would have been possible to obtain good results, despite poor performance at the daily time step.

**TABLE 7. Performance Statistics for NO$_3$-N Simulation (Calibration A).**

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Daily Concentration</th>
<th>Daily Load</th>
<th>Monthly Load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>PBIAS</td>
<td>NSE</td>
</tr>
<tr>
<td>KS</td>
<td>-1.90</td>
<td>50.6</td>
<td>-0.23</td>
</tr>
<tr>
<td>AL</td>
<td>-2.35</td>
<td>66.3</td>
<td>-0.15</td>
</tr>
</tbody>
</table>

Note: All performance criteria are not satisfactory (NS) per Moriasi et al. (2015) unless otherwise indicated.

**FIGURE 4. SSF Duration Curves for the KS (top graph) and AL (bottom graph) Watersheds.**

**Evaluation of Soil NO$_3$-N Processes**

To better understand and document intermediate N-related processes, simulated soil-NO$_3$-N concentrations for several soils in corn-soybean rotations are plotted for the KS model (Figure 6) and AL model (Figure 7). For comparison, measured data for similar soils in Central Iowa (Cambardella et al., 1999) are shown with the simulated soil-NO$_3$ levels. Simulated soil-NO$_3$-N considers the depth of the soil layers in model, which extends 1,524 mm into the soil profile. Cambardella et al. (1999) measured soil-N to a depth of 1,050 mm. Although the depths differ, the comparison of soil-NO$_3$-N levels is reasonable because soil-NO$_3$-N levels are highest in the upper layers and decrease significantly with depth. Another distinction between the Cambardella et al. (1999) study and the model is the timing of N-application. In the study, all
N was applied in the fall as anhydrous ammonia, but in the model, various forms of N fertilizer were utilized, and application was split between spring and fall.

The trend for simulated soil-NO$_3$-N is similar to the measured pattern using both original (Calibration A) and modified (Calibration B) algorithms with an important distinction: in Calibration A, soil-NO$_3$-N is fully depleted by mid-summer in both corn and soybean years, whereas Calibration B and measured mid-summer residual levels off at 30-40 kg-NO$_3$/ha in corn years and remains steady at approximately 45 kg-NO$_3$/ha in soybean years. The increase in soil-NO$_3$-N from fertilizer application and/or mineralization in the spring and after soybean harvest in the fall is reflected by the models and the observed data. Simulated soil-NO$_3$-N levels are much lower in the Canisteo soil than the Webster or Clarion soils in the KS watershed, but this difference is not observed in the AL model.

Modeled corn yields using the original algorithms (Calibration A) were 8,713 kg/ha (139 bu/ac) in the KS watershed and 10,335 kg/ha (164 bu/ac) in the AL watershed, which are 16% and 10% lower than reported countywide yield data, respectively (ISU, 2015). Yields were little-changed with modified algorithms in Calibration B. The fact that simulated yields are higher in the AL watershed than KS is consistent with the countywide yield data. Simulated depletion of soil-NO$_3$-N levels to zero in the middle of the growing season may be partly responsible for lower than expected corn yields, based on the number of N-stress days in model output. However, this depletion occurs in both wet and dry years and in years in which simulated denitrification is zero. This suggests that simulation of N mineralization may also be problematic and partially responsible for errors in prediction of NO$_3$-N loss. Model prediction of crop growth processes may also contribute to over-depletion of soil. Nair et al. (2011) noted the

![Concentration Duration Curves](image)

**FIGURE 5.** Concentration Duration Curves for the KS (top graph) and AL (bottom graph) Watersheds. Observed concentrations represented by blue line, simulated concentrations shown using red dotted line (Calibration A), and concentrations simulated using the new lagging equations are illustrated with the green dashed line (Calibration B).

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Daily Concentration</th>
<th>Daily Load</th>
<th>Monthly Load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>PBIAS</td>
<td>NSE</td>
</tr>
<tr>
<td>KS</td>
<td>0.20 [NS]</td>
<td>8.9 [VG]</td>
<td>0.40 [S]</td>
</tr>
<tr>
<td>AL</td>
<td>-0.55 [NS]</td>
<td>38.1 [NS]</td>
<td>0.45 [S]</td>
</tr>
</tbody>
</table>

**TABLE 8.** Performance Statistics for Modified Algorithm NO$_3$-N Simulation (Calibration B).


FIGURE 6. Simulated Soil Profile NO$_3$-N for Corn-Soybean Rotations in the KS Watershed Using Existing (Calibration A) and Modified (Calibration B) Algorithms. Dashed green line is soil-NO$_3$-N for Canisteo soil, dotted purple line is for Webster, and solid brown is for Clarion. Observed and simulated SSF is shown in the top portion of each graph. Squares and circles represent soil-NO$_3$-N measured in similar Central Iowa soils in corn and soybean years, respectively (Cambardella et al., 1999).

FIGURE 7. Simulated Soil Profile NO$_3$-N for Corn-Soybean Rotations in the AL Watershed Using Existing (Calibration A) and Modified (Calibration B) Algorithms. Dashed green line is soil-NO$_3$-N for Canisteo soil, dotted purple line is for Webster, and solid brown is for Clarion. Observed and simulated SSF is shown in the top portion of each graph. Squares and circles represent soil-NO$_3$-N measured in similar Central Iowa soils in corn and soybean years, respectively (Cambardella et al., 1999).
importance of crop yields when simulating nitrogen transport in SWAT, and it is likely that plant growth parameters for corn in the SWAT plant database are outdated and do not reflect current crop genetics.

Simulated soil-N dynamics for a tile-drained Webster soil are reported in Table 9. With the exception of several zero-nitrification years, the magnitude of simulated fluxes were generally within ranges reported in regional guidance and literature, but these fluxes are highly variable and there is large uncertainty associated with estimates of N-fixation and denitrification (Christianson et al., 2012). In Webster soil HRUs, the average simulated denitrification was 28 kg-N/ha/yr \(^{-1}\) for the KS model and 20 kg-N/ha/yr for AL, using the original tile NO\(_3\)-N algorithms (Calibration A). David et al. (2009) simulated denitrification rates ranging from 3.8 to 21 kg-N/ha/yr \(^{-1}\) using a variety of models to estimate denitrification rates in a tile-drained corn and soybean rotation in Illinois. In well-drained Clarion soils in the KS and AL models, the simulated denitrification rate was zero and large magnitudes of NO\(_3\)-N were lost to deep seepage because of the absence of a restrictive soil layer. N-fixation by soybeans was somewhat higher than reported in other studies in Iowa (Jaynes et al., 2001; Christianson et al., 2012) and near the upper-end of fixation rates summarized in a meta-analysis of published data (Salvagiotti et al., 2008), and N-uptake was near or above the high end of rates estimated for high yielding corn crops in Iowa (ISU, 2006).

Soil-NO\(_3\)-N levels simulated using the modified algorithms (Calibration B) were more representative of Central Iowa soil data (Cambardella et al., 1999). However, calibration using modified algorithms eliminated denitrification in these HRUs, which is not realistic and resulted in much higher NO\(_3\)-N losses via SSF (Table 9) and deep seepage in soils without tile drainage (e.g., Clarion soils). While the modified algorithms and subsequent calibration improved predictions of NO\(_3\)-N concentrations and loads compared with the original algorithms, the basis for the modifications is not well established and problems simulating important N processes and NO\(_3\)-N transport remain. Nevertheless, the modifications provide insight to the possible causes of error and reveal the need for improved soil-N and crop growth processes in the simulation of NO\(_3\)-N transport in tile-drained watersheds. Our work suggests simulations of nitrification, mineralization, and denitrification need further evaluation and more physically-based modifications than the empirical lagging algorithms presented here.

Pohlert et al. (2007) identified similar limitations of SWAT, and found improvement in the prediction of NO\(_3\)-N transport using lysimeter data after the

### Table 9. Simulated Soil-NO\(_3\) Dynamics for Webster Soil HRUs with Tile Drainage.

<table>
<thead>
<tr>
<th>Soil/Crop</th>
<th>Positive Fluxes (kg-N/ha (^{-1})(^{1}))</th>
<th>Negative Fluxes (kg-N/ha (^{-1})(^{2}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>App(^{3})</strong></td>
<td><strong>Atmos</strong></td>
</tr>
<tr>
<td><strong>KS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008 Soy</td>
<td>49</td>
<td>13</td>
</tr>
<tr>
<td>2009 Corn</td>
<td>122</td>
<td>9</td>
</tr>
<tr>
<td>2010 Soy</td>
<td>49</td>
<td>13</td>
</tr>
<tr>
<td>2011 Corn</td>
<td>122</td>
<td>8</td>
</tr>
<tr>
<td><strong>AL</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2007 Corn</td>
<td>135</td>
<td>10</td>
</tr>
<tr>
<td>2008 Soy</td>
<td>49</td>
<td>8</td>
</tr>
<tr>
<td>2009 Corn</td>
<td>135</td>
<td>8</td>
</tr>
<tr>
<td>2010 Soy</td>
<td>49</td>
<td>9</td>
</tr>
</tbody>
</table>

1Inputs: App, fertilizer-N; Atmos, rainfall-N; Fix, N-fixation; Min, mineralization of organic-N.
2Outputs: Denit, denitrification; Uptake, plant uptake; Runoff and SSF, N lost to surface water; Seep, N lost to deep aquifer via seepage.
3Fertilizer application occurs in fall after soybean harvest and in spring in corn years.
integration of a detailed biogeochemical model into SWAT. However, the updated model is not publically available, and to our knowledge, has not been applied at the watershed scale. The time-varying nature of the sensitivity of nitrate-related model parameters has been documented by others (Haas et al., 2015, 2016). Evaluation of this phenomenon as it relates to simulating soil-N dynamics may facilitate the development of more physically descriptive modifications to the algorithms revised for the AL and KS watersheds studied here.

CONCLUSIONS

Model assessment revealed that it is possible to meet generally accepted performance criteria (Moriasi et al., 2015) for simulation of monthly WYLD, SSF, and NO$_3$-N loads in both case study watersheds, while not accurately capturing the daily fluctuation of pathway specific flows or NO$_3$-N concentrations. For the KS and AL watersheds, NSE values were 0.79 and 0.71, respectively, for monthly WYLD; 0.55 and 0.66 for monthly SSF; and 0.72 and 0.60 for monthly NO$_3$-N load (using the modified NO$_3$-N algorithms). Simulation of daily SURQ and SSF proved more challenging and were generally not satisfactory (NSE < 0.50). Simulation of daily NO$_3$-N concentration was not satisfactory even after modifying NO$_3$-N algorithms to lag NO$_3$-N transport from the soil profile via tile drainage, with the KS watershed NSE of 0.20 and AL watershed NSE value of 1.12.

Differences in hydrology and NO$_3$-N transport between watersheds were not reflected by the model, as evidenced by distinct calibration parameters and parameter values. This suggests that parameterization may not be transferable across watersheds with similar characteristics, and also that models calibrated at larger scales may not accurately reflect hydrology and nutrient transport at small watershed (e.g., drainage district) scales, as noted by Baffaut et al. (2015). These limitations are especially important in cases where the model is intended to help locate, design, and/or estimate NO$_3$-N removal capabilities of water quality BMPs, as indicated by impacts on NO$_3$-N simulation wetlands at the outlet of these case study watersheds (Ikenberry et al., 2017).

Investigation of intermediate N processes revealed SWAT has the capability to simulate various N fluxes and soil-NO$_3$ levels, but overestimates depletion from the soil during summer months. Simulated mineralization and plant uptake rates are generally reasonable compared to literature values; however, these fluxes are highly variable in space and time and heavily influence NO$_3$-N transport via tile drainage. Soil-N fluxes such as mineralization and denitrification should therefore be evaluated and reported as standard practice when applying the SWAT model for simulation of NO$_3$-N transport, and more physically-based improvements to soil-N algorithms than those presented here is warranted. Additionally, better parameterization methods and supporting data for model inputs related to these processes are needed to improve and appropriately constrain soil-N fluxes and associated prediction of NO$_3$-N transport.

ACKNOWLEDGMENTS

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LITERATURE CITED


