Modeling the Impacts of Manure on Phosphorus Loss in Surface Runoff and Subsurface Drainage


Abstract

Simulation of phosphorus (P) transfer from manured agricultural lands to water bodies via surface runoff and subsurface drainage is potentially of great help in evaluating the risks and effects of eutrophication under a range of best management practice scenarios. However, it remains a challenge since few models are capable of providing a reasonably accurate prediction of P losses under manure treatment. The Environmental Policy Integrated Climate (EPIC) model was applied to simulate the impacts on dissolved reactive P (DRP) losses through surface runoff and subsurface drainage from a solid cattle manure–amended corn ([Zea mays L.])–soybean ([Glycine max (L.) Merr.] rotation on a clay loam soil (Vertisol) located in the Lake Erie region. Simulations of DRP loss in surface runoff and tile drainage were satisfactory; however, EPIC did not consider DRP loss directly from manure, weakening its accuracy in the prediction of DRP loss in surface runoff. Having previously drawn on EPIC-predicted surface runoff to initiate SurPhos (Surface Phosphorus and Runoff Model) predictions of DRP losses strictly in surface runoff, no comparison had been made of differences in manure application impacts on EPIC- or SurPhos-predicted DRP losses—accordingly, this was assessed. The SurPhos improved the estimation of DRP loss in surface runoff (Nash–Sutcliffe coefficient, 0.53), especially when large rain events occurred immediately after or within 6 wk of manure application. Generally, EPIC can capture the impacts of manure application on DRP loss in surface runoff and subsurface drainage; however, coupling of the EPIC and SurPhos models increased the accuracy of simulation of runoff DRP losses.

Core Ideas

- Simulations of DRP loss in surface runoff and tile drainage using EPIC were satisfactory.
- Simulations of DRP loss in surface runoff between EPIC and SurPhos were compared.
- Coupling SurPhos and EPIC improved surface DRP loss prediction with manure addition.

ENVIRONMENTAL MODELS, MODULES, AND DATASETS

LONG-TERM nonpoint losses of dissolved reactive P (DRP) from agricultural lands, which accelerate eutrophication in receiving water bodies, remain a serious ongoing water quality concern (Sharpley et al., 2015). For example, the worst cyanobacterial bloom occurred in Lake Erie in 2011 (Dalglough et al., 2012; Michalak et al., 2013), and another serious bloom in 2014 left over 400,000 without potable water (Smith et al., 2015b). Manure application has been identified as one of the predominant agronomic practices leading to P loading from farmlands to Lake Erie (Smith et al., 2015b). In 2010, 48.4% of Canadian farms applied manure to their lands, of which the greatest proportion of such applications occurred in Ontario (28.2%) (Erik and Martin, 2011). Water inputs to Lake Erie include 81% from the Detroit River, 10% from precipitation over the lake, and the remaining 9% from runoff (both US and Canada) (Canada-Ontario Agreement Partners, 2017). Between 2003 and 2013, Ontario’s largely agricultural Lake Erie basin watersheds contributed approximately 18% of DRP reaching the lake, of which 71% was from nonpoint sources (Canada-Ontario Agreement Partners, 2017).

Long based on crop N demand alone, recommended manure application rates have led to over-application and buildup of P in soils (Leytem et al., 2006), since P/N ratios in manures (1:4 to 1:2) largely exceeded the ratio of P/N taken up by crops, for example, 1:8 for major grains (Sharpley, 2016). To meet crop N demand through manure application, each year up to four times more P was applied than was required by the crop, leading to a buildup of “legacy soil P” (Sharpley et al., 2013) and a high potential for excessive P loading of surface waters after manure application (Zhang et al., 2015b).

Many studies have shown that both surface runoff and subsurface drainage are important pathways for P discharge from agricultural lands (Smith et al., 2015a; Tan and Zhang, 2011; Zhang et al., 2015a). The Vertisols, typical of Ontario’s Lake Erie drainage basin (e.g., Brookston clay loam), are prone to preferential flow through macropores, such as shrinkage cracks in the dry season, as well as earthworm burrows and root

Abbrviations: DRP, dissolved reactive phosphorus; NSE, Nash–Sutcliffe efficiency; PBIAS, percentage bias; PSC, phosphorus sorption coefficient; RSR, ratio of root mean square error to observation standard deviation.
channels. These macropores funnel water from the soil surface to tile drainage, especially after a heavy rainfall (Tan and Zhang, 2011; Zhang et al., 2015a, 2015b). With such soils being predominantly dedicated to annual crops, there is a high risk of nutrient-rich subsurface runoff reaching the Lake Erie basin. Accordingly, temporal changes in soil crack volume and infiltration due to changes of soil moisture must be quantified to accurately predict surface runoff, subsurface drainage, and relevant nutrient losses in regions dominated by vertic soils (Neitsch et al., 2011).

Phosphorus in crop residues, soil, and applied amendments (i.e., manure and fertilizer) represents a consistent source of nonpoint pollution in surface runoff from agricultural lands (Bennett et al., 2001; Collick et al., 2016). The latter P source can overwhelm all others when a large precipitation event follows closely after amendment application and water soluble forms of P are lost directly from the applied amendments (Withers et al., 2001). In such a case, surface runoff may contain concentrations of water soluble forms of P orders of magnitude greater than those that would originate from the soil alone (Kleinman et al., 2002). As P losses from recently applied amendments can contribute the majority of annual dissolved P losses (Owens and Shiptal, 2006), it is important to evaluate how such manure applications affect soil P content, the forms of P in the soil, and the movement of P from the field. Having made such an evaluation, if P applications exceed agronomic needs, it is critical to apply an alternative agronomic management scenario to reduce soil P losses and prevent soil P from rising to environmentally hazardous concentrations. All these issues point to a need for a complete understanding of P dynamics in manure, soil, and water fluxes. As field experiments are time-consuming and expensive, computer models are commonly used to predict P dynamics for scientific, management, and policy purposes (Zhang et al., 2018). It is therefore important to be able to reliably predict P losses in both surface runoff and tile drainage. By identifying critical source areas, targeting best management practices, and evaluating impacts of climate change, modeling—despite its inherent uncertainty—will become increasingly crucial in catchment management and policy decision making over the next decade (Sharpley et al., 2015).

Based on the original P model developed by Jones et al. (1984), the Environmental Policy Integrated Climate (EPIC) model's P subroutine has been widely evaluated for its ability to predict P losses in surface runoff and subsurface drainage (Peruta et al., 2014; Vadas et al., 2006; Wang et al., 2018a). The model's current version simplifies drainage volume by modifying the lateral subsurface flow, where depth of the tile drainage system and the time required for the tile drainage system to reduce plant stress are used for adjustment. Given the absence of preferential flow or macropore flow routine in EPIC, Wang et al. (2018a) used a crack flow coefficient of 0.4 to appropriately partition inflow into cracks. For a site receiving no P fertilization, this resulted in a reasonably accurate prediction of tile drainage and DRP loss in surface runoff and tile drainage. Similarly, Baffaut et al. (2015) set the crack flow coefficient to 0.5 to balance the surface runoff and groundwater for their Soil and Water Assessment Tool (SWAT) simulation of the Goodwater Creek Experimental Watershed and presented satisfactory calibration and validation of DRP loss. Since EPIC’s P subroutine assumes manure to be well mixed into the soil, but fails to consider P losses directly from surface-applied manure, it can be expected to provide reliable predictions when manure is well mixed into the soil but could provide poor predictions of the relatively greater quantity of dissolved P loss in surface runoff following the first significant rainfall event after surface application of amendments.

Vadas et al. (2007) developed the SurPhos (Surface Phosphorus and Runoff Model) to address direct transfer of P from manure to runoff during a rainfall event, with the aim that it be incorporated into a more complete, process-based model (e.g., EPIC or SWAT). SurPhos can estimate the dynamic fate of applied amendments P, that is, quantify different sources of P losses in surface runoff and soil by a rainfall event. The SurPhos model has been incorporated into the Integrated Farming Systems Model (IFSM) (Sedorovich et al., 2007) and the SWAT model (Collick et al., 2016) to better describe P loss from manure in surface runoff. Sen et al. (2012) compared the results of the SurPhos model with those of the 2008 version of SWAT and suggested using SurPhos to replace P subroutine in SWAT for better determination of the effectiveness of P management practices. The Annual P Loss Estimator (APLE), derived from the daily-time step SurPhos model (Vadas et al., 2009), has been tested for annual P loss prediction in surface runoff based on the ratio of annual runoff and precipitation (Vadas et al., 2012, 2015a, 2015b). Incorporating the APLE P loss subroutine into the Chesapeake Bay watershed model, Mulkey et al. (2017) showed better P loss estimation. Fiorellino et al. (2017) used predicted P loss data from APLE to assess the Maryland P Site Index and update its agreement in magnitude and direction. All these applications of the SurPhos model support its superiority against original P models in evaluating the impacts of manure on runoff P loss.

In previous work (Wang et al., 2018b), where unavailable surface runoff data under snow melt conditions was substituted with EPIC-predicted daily surface runoff, SurPhos satisfactorily quantified DRP loss in surface runoff from soils amended with solid cattle manure; however, the SurPhos model’s limitations (i.e., without considering tile drain) prevented simulation of the equivalent DRP losses in subsurface drainage. Moreover, no comparison was made of differences in the SurPhos and EPIC models’ ability to predict the impacts of manure on DRP loss in surface runoff (Wang et al., 2018b). Since EPIC had not been tested for a Brookston clay loam soil receiving solid cattle manure, the aim of the present study was (i) to evaluate EPIC for prediction of crop yields, surface runoff, tile drainage, and relevant DRP losses under a corn (Zea mays L.)–soybean [Glycine max (L.) Merr.] rotation on a clay loam soil (Vertisol) receiving a solid cattle manure application and (ii) to compare impacts of manure on DRP loss in surface runoff predicted by EPIC with that predicted by SurPhos.

### Materials and Methods

#### Field Experiments

Field experiments were conducted at the Agriculture and Agri-Food Canada’s Hon. Eugene F. Whelan Experimental Farm at Woodside, ON, Canada. The size of each plot was approximately 0.1 ha, 67.1 m long by 15.2 m wide. The soil was Brookston
clay loam, with 25.4% clay, 26.4% silt, and 48.2% sand, which is 
defined as Orthic Humic Gleysol in the Canadian soil 
classification system (Evans and Cameron, 1983) and classified as Typic 
Haplaquolls using the USDA soil taxonomic description (Soil 
Survey Staff, 1975). The soil’s permanent wilting point and field 
capacity were 12.7 and 30.4%, respectively, and the bulk density 
was 1.27 Mg m\(^{-3}\).

The cropping system was a corn–soybean rotation. Corn was 
planted at a density of 79,800 and 79,700 seeds ha\(^{-1}\) in 2008 and 
2010, respectively. Soybean was planted at 486,700 seeds ha\(^{-1}\) both in 2009 and 2011. Details of agronomic practices can be 
found in Table 1. The corn crops were fertilized with 100 kg K 
ha\(^{-1}\) and 200 kg available N ha\(^{-1}\) prior to planting. A P application 
rate of 50 kg P ha\(^{-1}\) was achieved through two even applications of 
solid cattle manure in 2008 (2 and 3 June), and one application 
in 2010 (11 June). The total solid cattle manure application 
per plot was 53.00 Mg ha\(^{-1}\) (0.094% total P, 25% dry matter) 
in 2008 and 28.12 Mg ha\(^{-1}\) (0.178% total P, 26.9% dry matter) 
in 2010. An S-tine cultivator was used for incorporation after 
manure application. Chisel plow tillage was also conducted after 
crop harvest. Roundup (Monsanto) [N-(phosphonomethyl) 
glycine] (1.4 kg ha\(^{-1}\)) was applied before planting of both corn 
and soybean. Dual II (Syngenta) [80% (aR,S,1S)-2-chloro-6'- 
ethyl-N-(2-methoxy-1-methyl)acet-o-toluidide and 20% 
(aR,S,1R)-2-chloro-6'-ethyl-N-(2-methoxy-1-methyl)acet-o-toluidide] 
(1.4 kg ha\(^{-1}\)) and atrazine [6-chloro-N2-ethyl-
N4-isopropyl-1,3,5-triazine-2,4-diamine] (1.0 kg ha\(^{-1}\)) were 
applied after corn planting. Dual II (1.4 kg ha\(^{-1}\)) and Sencor 
(Bayer CropScience) [4-amino-6-tert-butyl-4,5-dihydro-3-methylthio-1,2,4-triazin-5-one] (0.5 kg ha\(^{-1}\)) were applied after 
soybean planting.

Surface runoff and tile drainage flow volumes were recorded 
by water meters as well as from analog and digital pulse signals. A 
multi-channel data logger utilized the analog and digital signals 
to monitor, measure, and store water volumes on a continuous 
basis. Samples of surface runoff and tile drainage were collected 
automatically with each auto-sampler containing 24 1-L bottles 
(ISCO Model 2900). Sample collection was based on collection 
volume varying with the time of year and expected volumes. During the growing season, a 1-L sample of surface runoff 
or tile drainage water was collected from each plot after 1000 
L (surface runoff) and 2000 L (tile drainage) of flow volume. During the nongrowing season, a 1-L sample of surface runoff 
or tile drainage water was collected from each plot after 3000 L 
(surface runoff) and 5000 L (tile drainage) of flow volume. As such, water samples for each of the 17 periods over the 4 yr were 
collected based on agronomic practices and forecasted precipitation 
to reflect the reality of P loss. Thereafter, water samples were 
transported to laboratory, with 60-mL aliquot of each sample 
filtered through a 0.45-μm Millipore filter. Filtered samples were 
refrigerated under 2 to 4°C for DRP analysis. Additional details 
regarding to field plots layout and water sampling can be found in 
Wang et al. (2018a).

**EPIC Simulation**

Since the EPIC0810 model was calibrated and validated at 
the same site with no P fertilizer (Wang et al., 2018a), we only 
validated the model under solid cattle manure application. 
Validation was based on crop yields, periodic surface runoff 
and subsurface drainage, and relevant DRP losses from 2008 to 
2011. Simulations were driven by weather data (maximum 
and minimum temperatures, precipitation, wind speed, relative 
humidity, and solar radiation) from a Whelan weather station 
less than 0.5 km away from the experimental field. Annual average 
potential evapotranspiration in Harrow, ON, was obtained 
from Fallow et al. (2003). The Penman–Montieth equation and variable daily curve number with soil moisture 
index were used for simulating evapotranspiration and direct 
runoff, respectively. The observed DRP loss from surface runoff 
and tile drainage was compared with “labile P” estimated from 
the EPIC and SurPhos model.

**SurPhos Simulation**

Annual P uptake for crops was set to 25 kg ha\(^{-1}\) (Hao et al., 
2015). An S-tine cultivator was selected to model manure incorporation as it closely matches the soil mixing efficiency (0.1) and depth of mixing (0.075 m) of the cultivator used on the 
experimental field. The tillage implement used after harvest was a chisel 
plow with a soil mixing efficiency of 0.05 and depth of 0.25 m. Each spring, Olsen P was measured at five soil depths (0–0.15, 
0.15–0.30, 0.30–0.50, 0.50–0.70, 0.70–0.90 m) and was used to 
set labile P in three soil depths (0.02, 0.15, 0.75 m) in SurPhos. We 
assume labile P in the top soil layer (0.02 m) to be 50% greater 
than in the second soil layer (Baker et al., 2017). Soil clay, organic 
matter, and bulk density were set according to field experimental 
results. More details can be found in Wang et al. (2018b).

Statistical assessment of model accuracy used the Nash– 
Sutcliffe efficiency (NSE), percentage bias (PBIAS), and the 
ratio of root mean square error to observation standard deviation  

---

**Table 1. Agronomic practices for field experimental site at Agriculture and Agri-Food Canada’s Hon. Eugene F. Whelan Experimental Farm at Woodslee, ON, Canada.**

<table>
<thead>
<tr>
<th>Year</th>
<th>Crop</th>
<th>Plant date</th>
<th>Harvest data</th>
<th>Manure application date</th>
<th>P rate</th>
<th>Tillage date</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>Corn</td>
<td>18 June</td>
<td>5 Nov.</td>
<td>2, 3 June</td>
<td>50</td>
<td>8 Nov.</td>
</tr>
<tr>
<td>2010</td>
<td>Corn</td>
<td>26 June</td>
<td>8 Nov.</td>
<td>11 June</td>
<td>50</td>
<td>19 Nov.</td>
</tr>
</tbody>
</table>

---

**Journal of Environmental Quality** 41
Results and Discussion

Simulated Crop Yields

Simulated mean annual potential evapotranspiration fell into the range of the annual mean (732 ± 83 mm, Table 2) estimated by Fallow et al. (2003). Simulated mean crop yield, involving corn and soybean, was 6.33 Mg ha⁻¹ (Table 2), some 4.6% greater than the observed yield (6.05 Mg ha⁻¹). Statistical analyses showed these predictions to be reasonably accurate, with NSE of 0.97, PBIAS of −4.63%, and RSR of 0.19 (Table 2). Simulated mean corn yield was 8.76 Mg ha⁻¹, some 5.4% greater than the mean observed yield (8.31 Mg ha⁻¹). Simulated mean soybean yield was 3.91 Mg ha⁻¹, some 2.9% greater than the mean observed yield (3.80 Mg ha⁻¹). Since there was no nutritional deficiency (Table 3), water is the most important factor influencing crop yield. The higher or lower simulated (vs. actual) crop yields could be attributed to the under- or overestimated average number of water stress days for crops at each year (Table 3). For example, the simulated soybean yield in 2011 was higher than observed with no simulated water stress that could be underestimated. Overstimulated crop available water (670.7 mm, Table 3) during the growing season because of the underestimated surface runoff for Period 15 (from 23 June 2011 to 7 Sept. 2011) led to the underestimated water stress. Simulated growing season evapotranspiration and water use efficiency (water use efficiency = crop yield/growing season evapotranspiration) showed negligible differences for corn and soybean (Table 3). A significantly simulated greater temperature stress (80.2 d, Table 3) occurred for soybean during 2011 due to a late harvest (December). The minimum temperatures for plant growth for corn and soybean are 8 and 10°C, respectively, which were set as default values in the EPIC model. The temperature stress was calculated on the basis of the temperature before harvest but should be modified to better evaluate the impact of temperatures before crop maturity.

Simulated Surface Runoff and Tile Drainage

Simulated surface runoff was reasonably well modeled (NSE = 0.70, PBIAS = −3.50%, RSR = 0.55; Fig. 1A), although several overestimations and underestimations occurred. For some overestimated periods (Periods 3, 4, 6, and 17; Fig. 1A), overestimated surface runoff was tied to underestimated subsurface drainage, largely a consequence of a lower crack flow coefficient. Conversely, underestimated surface runoff was tied to overestimated tile drainage for Periods 2, 15, and 16. Similarly, a higher crack flow coefficient led to this phenomenon. For Period 4 from 23 Oct. 2008 to 11 Feb. 2009, simulated surface runoff was 11.0 mm following 1.8 mm of precipitation on 10 Feb. 2009. The minimum and maximum temperatures were 6.3 and 12°C, respectively. One possible explanation is that the model assumed snow melting to have occurred that day, which led to overestimation of surface runoff. On the next day, simulated surface runoff was 32.4 mm with precipitation of 40 mm. The overestimation of surface runoff could result from the soil having been simulated as being saturated from the previous day due to the snow melt simulation. For Period 12 from 6 Aug. 2010 to 21 Dec. 2010 (Fig. 1A), the simulated surface runoff was 15.2 mm while the observed was marginal (0.3 mm). Similarly, the simulated tile drainage (103.4 mm) was much greater than the observed (13.2 mm). Three precipitation events of approximately 30 mm in total occurred in September and early October 2010, when corn had reached or was close to its maximum leaf area index (4.9). One possible reason for the discrepancy is that crop interception of rainfall was not adequately simulated in EPIC (Williams et al., 2012), leading to an overestimation of surface runoff and

Table 2. Comparing simulated annual crop yield and PET with observed data, and relative statistical analyses.

<table>
<thead>
<tr>
<th>Year</th>
<th>Crop yield</th>
<th>PET</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observed</td>
<td>Simulated</td>
</tr>
<tr>
<td></td>
<td>Mg ha⁻¹</td>
<td>mm</td>
</tr>
<tr>
<td>Corn</td>
<td>2008</td>
<td>8.43</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>4.14</td>
</tr>
<tr>
<td>Soybean</td>
<td>2010</td>
<td>8.18</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>3.45</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>6.05</td>
</tr>
</tbody>
</table>

NSE 0.97
PBIAS (%) −4.63
RSR 0.19

† PET was obtained from Fallow et al. (2003).

Table 3. Simulated water balance and physical stress during each year.

<table>
<thead>
<tr>
<th>Year</th>
<th>WUE†</th>
<th>ETₚ</th>
<th>Pₚ</th>
<th>CAW</th>
<th>CQV</th>
<th>WS</th>
<th>AS</th>
<th>NS</th>
<th>PS</th>
<th>TS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>kg mm⁻¹</td>
<td>mm</td>
<td>mm</td>
<td>mm</td>
<td>mm</td>
<td>d</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>31.5</td>
<td>278.5</td>
<td>384.8</td>
<td>491.2</td>
<td>52.4</td>
<td>2.7</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>37.3</td>
</tr>
<tr>
<td>2009</td>
<td>14.9</td>
<td>260.6</td>
<td>318.4</td>
<td>491.9</td>
<td>9.5</td>
<td>1.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>43.4</td>
</tr>
<tr>
<td>2010</td>
<td>32.8</td>
<td>266.2</td>
<td>333.8</td>
<td>428.3</td>
<td>39.5</td>
<td>6.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>33.5</td>
</tr>
<tr>
<td>2011</td>
<td>14.9</td>
<td>263.3</td>
<td>794.6</td>
<td>670.7</td>
<td>236.4</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>80.2</td>
</tr>
<tr>
<td>Avg</td>
<td>23.5</td>
<td>267.2</td>
<td>457.9</td>
<td>520.5</td>
<td>84.5</td>
<td>2.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>48.6</td>
</tr>
</tbody>
</table>

† WUE, water use efficiency; ETₚ, growing season ET; Pₚ, growing season rainfall; CAW, crop available water; CQV, growing season runoff; WS, water stress; AS, Aeration stress; NS, nitrogen stress; PS, phosphorus stress; TS, low temperature stress.
The overestimated tile drainage could also be due to a higher settled crack flow coefficient. The accuracy of simulated subsurface drainage was reasonable (NSE = 0.51, PBIAS = -8.05%, RSR = 0.70) although several periods were either overestimated or underestimated. Generally, all over- and underestimation could be linked to the constant crack flow coefficients that were higher or lower than actual representative crack flow coefficients, which lead to greater or lesser downward water flux to subsurface drains. Another reason of overestimation may be the simplification of tile drainage that forces all lateral subsurface flow above tile drain as tile drainage in this study. The crack flow coefficient, which performs a function akin to that of simulating macropores, can redistribute the total quantity of runoff between surface and subsurface (Neitsch et al., 2011) and thereby contribute to better statistical accuracy of periodical surface runoff and tile drainage. However, this coefficient was set to a constant value of 0.4, whereas in reality, crack volume can change depending on weather conditions, thereafter contributing to a less accurate simulation of some periods (Wang et al., 2018a).

Simulated Impacts of Manure Application on Dissolved Reactive P Loss Using EPIC

Consistent with overpredicted surface runoff, DRP loss in surface runoff was overestimated (0.14 kg ha⁻¹) for Period 6 from 28 Mar. 2009 to 26 May 2009. Conversely, underestimation of surface runoff was the major reason for underestimated DRP loss in surface runoff for Periods 5, 11, and 15 (Fig. 2A). A further possible explanation for underestimation of DRP loss in Period 11 (12 June 2010 to 5 Aug. 2010) is that EPIC did not simulate P loss directly from manure. Since solid cattle manure

---

**Fig. 1.** Periodic natural precipitation, and observed and simulated periodic (A) surface runoff and (B) tile drainage flow volumes using EPIC.

**Fig. 2.** Simulated periodic DRP losses in (A) surface runoff using EPIC and SurPhos and (B) tile drainage using EPIC. *Only statistical analysis of SurPhos was displayed, as the statistical analysis of simulated P loss in surface runoff by EPIC was less accurate (NSE of 0.31).
was applied on 11 June in 2010 and a large rainfall event (73.8 mm) occurred on 24 July, heavy losses from manure itself could have occurred. This is addressed below by comparing DRP losses in surface runoff simulated with EPIC or SurPhos.

For Period 16 from 8 Sept. 2011 to 9 Nov. 2011 (Fig. 2A), simulated DRP loss in surface runoff was zero while the observed loss was 0.49 kg ha\(^{-1}\). Similarly, for Period 17, prediction of P loss in surface runoff was 0.05 kg ha\(^{-1}\), much lower than observed loss (0.24 kg ha\(^{-1}\)). One possible reason for these discrepancies is that a higher set crack flow coefficient led most of DRP downward to lateral flow or even deep percolation (Williams et al., 2015). This finding was similar to previous results (Wang et al., 2018a), where these two periods had negligible predicted P loss compared with the observed data. Without considering Period 16, simulated P loss in surface runoff was acceptable (NSE = 0.55, data not shown).

Simulated DRP loss in subsurface drainage water was satisfactory (NSE = 0.67, PBIAS = −5.39%, RSR = 0.57; Fig. 2B). Consistent with overestimated tile drainage, DRP loss in tile drainage was overestimated for Periods 2, 7, 12, and 15, possibly as a result of an overly high crack flow coefficient resulting in an overestimation of tile drainage and therefore of DRP loss. The obvious underestimation of P loss in tile drainage that occurred in Period 4 (23 Oct. 2008 to 11 Feb. 2009) was consistent with underestimated tile drainage. As mentioned in surface runoff section, lower set crack flow coefficients led to this underestimation.

Model estimates of DRP loss in both surface runoff (<0.8 kg ha\(^{-1}\)) (NSE of 0.55) and subsurface tile drainage (<1.3 kg ha\(^{-1}\)) (NSE of 0.67; Fig. 2) under manure treatment were more accurate than those for plots receiving no P fertilization at the same site reported previously (Wang et al., 2018a); DRP losses in surface runoff (<0.4 kg ha\(^{-1}\)) (NSE of 0.54) and subsurface tile drainage (<0.6 kg ha\(^{-1}\)) (NSE of 0.58). This is consistent with the finding that a narrow range of DRP loss with relatively low variability would generally result in lower model accuracy (NSE) than those observed for predictions with manure application and a wider range of DRP losses (Vadas et al., 2017). Indeed, manure application increased the range of DRP loss when followed closely by a large rainfall event, thereby typically leading to better accuracy statistics. Generally, EPIC can adequately simulate the impacts of manure on DRP losses in surface runoff and subsurface drainage.

The concentration of labile P in the soil is the main factor influencing DRP loss. The P incorporation routine developed for EPIC by Jones et al. (1984) predicts changes in DRP with time. The DRP loss in surface runoff is based on the concept of partitioning pesticides into solution and sediment phases. The DRP loss in tile drainage is partitioned among tile drainage, lateral flow, and percolation according to their relative flux ratios. Four parameters were used to adjust P loss: PARM (8)-P partition between runoff and sediment, PARM (43)-upward movement by evaporation, PARM (77)-coefficient regulating P flux between labile and active pools, and PARM (78)-coefficient regulating P flux between active and stable pools. The up limit of PARM (8) is 20 for EPIC and 100 for APEX. While in our previous study (Wang et al., 2018a), PARM (8) was set to 100 to strongly link P loss and sediment levels, in this study, PARM (8) was set to 40 in EPIC. Thus, the linkage between P loss both in surface runoff and drainage and sediment was increased. The PARM (77) and (78) were set to 0.1 to increase P desorption as in Wang et al. (2018a). Without changing the P flux among labile, active, and stable P pools, PARM (43) only can partition P upward or downward. We set PARM (43) to 1 to drive most P to tile drainage. Irrespective of weathering, the P sorption coefficient (PSC) of the plots’ calcareous soil (11% calcium carbonate content) was set at 0.51. While this showed more accurate results than other PSC equilibriums (Wang et al., 2018a), the fact of having a constant PSC value limited the P sorption-desorption process (Vadas et al., 2006). Thereafter, to improve the simulation of P loss in surface runoff under solid cattle manure treatment, we used predicted daily surface runoff as an input to SurPhos.

Comparing EPIC- and SurPhos-Predicted Impacts of Manure Addition on Runoff Dissolved Reactive P Loss

Because of the sensitivity of the SurPhos model to surface runoff (Vadas et al., 2008), predicted daily surface runoff drawn from EPIC was used in SurPhos to eliminate the impact of snow melt in winter and early spring (Wang et al., 2018b). Statistical assessment of SurPhos’s prediction accuracy for DRP loss in surface runoff (NSE = 0.53, PBIAS = −17.86%, RSR = 0.69) showed it to be greater than that of EPIC (NSE = 0.31), which performed particularly poorly in Period 16, from 8 Sept. 2011 to 9 Nov. 2011 (Fig. 2A). The overestimation by SurPhos occurring in Periods 4, 6, 12, and 17 was consistent with the overestimation of surface runoff predicted by EPIC. The underestimation of DRP losses during Period 11, from 12 June 2010 to 5 Aug. 2010 (0.28 kg ha\(^{-1}\) and 0.01 kg ha\(^{-1}\) for SurPhos and EPIC, respectively, compared with the measured value of 0.51 kg ha\(^{-1}\)) was consistent with an underestimation of surface runoff. For Period 11, the lower accuracy of the EPIC model’s DRP loss simulation compared with that of the SurPhos model may be tied to EPIC only considering manure P as part of soil P after manure application, and therefore ignoring manure decomposition and P loss directly from manure. This assumption was valid when manure was well mixed into the soil and no large precipitation event happened shortly after manure application; however, if a large rainfall event occurred, EPIC simulations underestimated P loss. Immediately after manure application on 11 June 2010, a large loss of DRP in surface runoff occurred as the result of the heavy rainfall of 24 July 2010 (73.8 mm; Fig. 3) in Period 11. This interpretation is consistent with the work of Vadas et al. (2011), who found that P loss 30 d after manure application could equal or exceed those occurring when precipitation closely followed application. While in this case (Period 11) EPIC did not reflect the increase of P loss directly from manure, EPIC (and SurPhos) did reflect the two increases of DRP loss in surface runoff after manure applied on 2 and 3 June when rainfall events occurred on 21 June (45 mm) and 28 June (61 mm) 2008 (Fig. 3). Why EPIC could reflect P loss after one large rainfall event but not another may be because manure P loss in surface runoff was strongly influenced by a precipitation event’s rainfall and runoff.
characteristics (e.g., quantity and intensity of precipitation, runoff-to-rain ratio) (Vadas et al., 2011). The SurPhos model’s obvious overestimations of DRP loss in surface runoff from 27 Mar. to 26 May 2009 (Period 6) and 22 Mar. to 22 June 2011 (Period 14) were due to underestimated surface runoff (Fig. 1).

The first advantage of SurPhos is in its simulation of direct DRP loss from manure. In ignoring this portion of DRP losses, the EPIC model was unable to quantify DRP loss from dairy manure applications when a significant rainfall event occurred immediately (Collick et al., 2016) or 30 d after manure application (Vadas et al., 2011). Collick et al. (2016) further indicated that the SurPhos P routine captured over 50% of the variation in DRP losses, whereas the routine that ignored direct P loss from manure (EPIC) captured less than 20% of the variation under different scenarios. Using manure P assimilation into soil (SurPhos) rather than direct adsorption of manure to soil (EPIC) also improved the estimation of DRP loss in surface runoff (Vadas et al., 2011).

A further reason why SurPhos showed better simulation of DRP loss in surface runoff is rooted in its use of a dynamic PSC (Vadas et al., 2012), allowing labile P to be included in the calculation. In contrast, the PSC value used in EPIC is either based on soil properties or user defined (Williams et al., 2015). With the dynamic PSC in SurPhos, labile P increases when P is added into the soil system, resulting in an increase in PSC. This results in a greater quantity of P remaining as labile P and PSC increasing even more. This feedback loop guarantees a relatively rapid PSC and labile P increase under amendments. Thus, a dynamic PSC was necessary to maintain the equilibrium between different P pools (Collick et al., 2016).

SurPhos also uses dynamic P sorption and desorption rate factors related to the PSC rather than the constant factor value (0.1) used in EPIC. Vadas et al. (2006) showed that the dynamic rate factors implemented in SurPhos provided greater accuracy in predicting P sorption and desorption than EPIC, resulting in differences in predicted P losses in the short and long term. Similarly, our prediction based on SurPhos showed greater accuracy in DRP loss in surface runoff than did EPIC, indicating that SurPhos is better in modeling the impacts of manure on runoff DRP.

Conclusions

The EPIC model was reliable in predicting crop yield, surface runoff, subsurface drainage, and relevant DRP losses from a Brookston clay loam soil (Vertisol) of the Lake Erie region under a corn–soybean rotation receiving a solid cattle manure amendment. Although EPIC reliably simulated DRP loss in tile drainage, it did not consider DRP loss directly from manure, thereby decreasing its accuracy in the prediction of DRP loss in surface runoff following a large rainfall event immediately or up to 6 wk after manure application. SurPhos has the capability to offset this limitation. Improved PSC, P sorption–desorption rate factors, and manure assimilation into soil all contributed to the reliable simulation of impacts of manure on DRP loss in surface runoff by SurPhos. A full comparison of the impacts of manure on DRP loss in surface runoff from soil amended with cattle manure supports the hypothesis that coupling SurPhos and EPIC would increase the overall accuracy in estimating the impacts of manure on DRP loss (Wang et al., 2018b).

Simulated crop yields were higher than those observed because of the underestimated water stress resulting partly from underestimated surface runoff and consecutively the overestimated crop available water. However, this result needs to be addressed with further studies. Misestimation of high temperature stress implies that the model should be modified to reflect the impact of such stresses on the crop prior to maturity rather than before harvest. The lower accuracy of surface runoff and subsurface drainage estimates was mainly due to the use of a constant crack flow coefficient. The lack of simulating crop leaf rainfall interception also contributes to the overestimation of surface runoff. Another limitation of EPIC is that it does not simulate leaf drop before harvest for annual crops, thereby potentially limiting organic P sources that contribute to P loss after the crop has reached maturity. These limitations will be the focus of continued efforts to improve P loss modeling.

References


