A NEW MODEL FOR PHOSPHORUS LOSS IN RUNOFF FROM OUTDOOR CATTLE LOTS

P. A. Vadas, L. W. Good, J. C. Panuska, D. L. Busch, R. A. Larson

ABSTRACT. *Phosphorus (P) loss from agriculture can compromise the quality of receiving water bodies. For cattle farms, P can be lost from cropland, pastures, and outdoor animal lots. We developed a new model that predicts annual runoff, total solids loss, and total and dissolved P loss from cattle lots. The model requires input for annual precipitation, lot surface type, soil test P for earthen lots, cattle number and type, frequency of cleaning, and percent vegetative cover. The model estimates annual runoff using a precipitation dataset and curve number, annual solids loss based on annual runoff, annual particulate P loss based on solid loss and manure and soil P content, and annual dissolved P loss for each runoff event. Testing showed that the model reliably estimated runoff, solids loss, and P loss from a wide variety of lots and was more accurate than other, currently used models. The new model provides a valuable tool for developing whole-farm estimates of P loss and more effectively targeting P loss mitigation practices.*

Keywords. *Cattle lots, Model, Phosphorus, Runoff.*

Pollution of surface waters by phosphorus (P) and associated accelerated eutrophication continue to pose significant environmental quality challenges (Parris, 2011). Phosphorus loss from agricultural farms via surface runoff has been identified as a major nonpoint pollution source (Bennett et al., 2001). For dairy and beef cattle farms, P loss originates from cropland, grazed pastures, and open-air cattle lots, such as feedlots, barnyards, exercise lots, or over-wintering lots. From a whole-farm perspective, P loss from all of these sources should be estimated to effectively identify the major P sources and then target remediation practices (McDowell and Nash, 2012). Research has been conducted to quantify P loss from cattle lots, especially relative to the effectiveness of vegetated filter strips in reducing P loss (Gilbertson et al., 1980; Koelsch et al., 2006; Sweeten et al., 1998). This research shows cattle lots can be significant sources of P loss for two reasons. First, the high concentration of cattle leads to high rates of manure deposition and P accumulation relative to pastures and cropland (Wyngaard et al., 2011; Zhu et al., 2004). Second, cattle holding areas can be partially or completely devoid of vegetation and have a compacted or impermeable (e.g., concrete) surface, which can lead to high rates of runoff and erosion. This combination of a concentrated P source and transport pathways creates the potential for high rates of P loss.

In areas with both nonpoint-source P pollution issues and a high prevalence of cattle farms with outdoor lots, there is a need to assess the P loss impact of lots relative to other land uses on farms to see if alternative lot management is needed and cost-effective. Meeting this need through field monitoring alone is an expensive, long-term process, and it is infeasible to monitor all the variations of physical conditions and management practices that exist for cattle production. Therefore, computer models can be cost- and time-effective tools to help quantify P loss from farms and identify alternative management practices that reduce the impact of agriculture on water quality (Vadas et al., 2013). For example, in the Lake Mendota watershed in Wisconsin, the Yahara WINs pilot project is testing a new adaptive management compliance approach to meet regulatory requirements for P reduction in a cost-effective manner (www.madsewer.org/Programs-Initiatives/Yahara-WINs). For this and other similar projects, models or tools are needed to assess P loss from cattle lots on dairy farms.

Despite the research conducted on P loss from cattle lots, there has been little development of models to predict P loss from these areas. To our knowledge, the only two examples of runoff and P loss models for cattle lots are in the Agricultural Non-Point Source Pollution (AGNPS) model (Young et al., 1989) and the Agricultural Policy/Environmental eXtender (APEX) model (Gassman et al., 2010; Williams et al., 2006). In AGNPS, P loss from feedlots is estimated by combining estimates of lot runoff and a feedlot runoff P concentration (default maximum total P concentration of 85 mg L^{-1}). The 85 mg L^{-1} value comes from research by Young et al. (1982). This P con-

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centration can change in proportion to the percent "manure pack" (i.e., manure coverage of the feedlot surface), which is a function of stocking density and lot management. For example, if the percent manure pack is 100, the runoff P concentration will be equal to the maximum value. If the percent manure pack is less than 100, perhaps from lower stocking density or frequent lot cleaning, then the runoff P concentration will decrease in proportion to the percent manure pack. Barnyard runoff models, such as BARNY in Wisconsin (http://datcp.wi.gov/Environment/Livestock_Siting/Application_Materials_and_Technical_Assistance/) and Minn Farm in Minnesota (www.extension.umn.edu/ agriculture/manure-management-and-air-quality/feedlots-and-manure-storage/), use the same approach as AGNPS. In APEX, erosion of manure from a feedlot is estimated based on runoff volume and rate, erosion control practices, slope length and steepness, and the amount of manure on the surface. Feedlot P loss is then a function of erosion and the P content of eroded material. Both AGNPS and APEX have had only minimal testing for P loss in runoff from cattle lots (Kizil et al., 2006; Williams et al., 2006), especially relative to the amount of such runoff P data that are available in the published literature. Therefore, it is not clear if these and related models reliably predict P loss across a range of cattle lot conditions, locations, and management practices.

There is an increasing demand for models that (1) can quantify agricultural P loss, (2) are robust and reliably accurate, (3) incorporate state-of-the-art science, (4) remain user-friendly, and (5) require only readily available data and expertise to operate. The demand is based on the need to rapidly identify the primary areas or practices on a farm that represent significant P loss and how best to reduce that loss through alternative management practices. Two examples of such P loss models are the Wisconsin SnapPlus software (Good et al., 2012) and the Annual P Loss Estimator (APLE) (Vadas et al., 2009; Vadas et al., 2012). Both tools operate on an annual time-step, estimate P loss in runoff from agricultural fields, and use a series of process-based and empirical equations designed to rapidly estimate field-scale P loss with minimal inputs.

We have used SnapPlus and APLE in research to estimate whole-farm P loss from cattle farms and appropriately target farm areas for P loss remediation, especially for areas like the Lake Mendota watershed. However, a well-validated P loss model was lacking for cattle lots that is compatible conceptually and operationally with SnapPlus and APLE (i.e., annual time-step, user-friendly, semi-processed based, quantitative). In Wisconsin, there is a need for such a P loss model for cattle lots. Therefore, the objectives of this research were to (1) develop a relatively simple, annual time-step model to estimate P loss in runoff from cattle lots, (2) test the model with data available in the published literature, and (3) compare the new model to existing barnyard and feedlot models. There are two important justifications for an annual time-step lot model. First, an annual model that requires only readily available data as input allows for easier adoption by policy makers, farm planners, or producers. Second, the majority of data and information in the literature available for model development and testing are for annual lot management, runoff, and P loss. An annual model makes much more of these data available across a wide range of situations. Throughout model testing, we evaluated the accuracy of model predictions using regression, Nash-Sutcliffe model efficiency, root mean square error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE) (Bennett et al., 2013; Bolster and Vadas, 2013; Moriasi et al., 2007). Finally, we intended the model to be used for both dairy and beef cattle operations.

Cattle Lot P Runoff Model Development and Testing

Annual Runoff Estimation

A flowchart of model operations is shown in figure 1. The goal of the model was to estimate annual dissolved and solids-bound P loss from lots. To achieve this, some calculations were made on an annual basis, while others were the sum of calculations made for a series of individual precipitation events.

The first step in developing the model was to estimate annual runoff from lots. We used the NRCS curve number (CN) approach (USDA-SCS, 1972). The CN was developed from an empirical analysis of runoff from small catchments and hillslope plots and is widely used to ap-

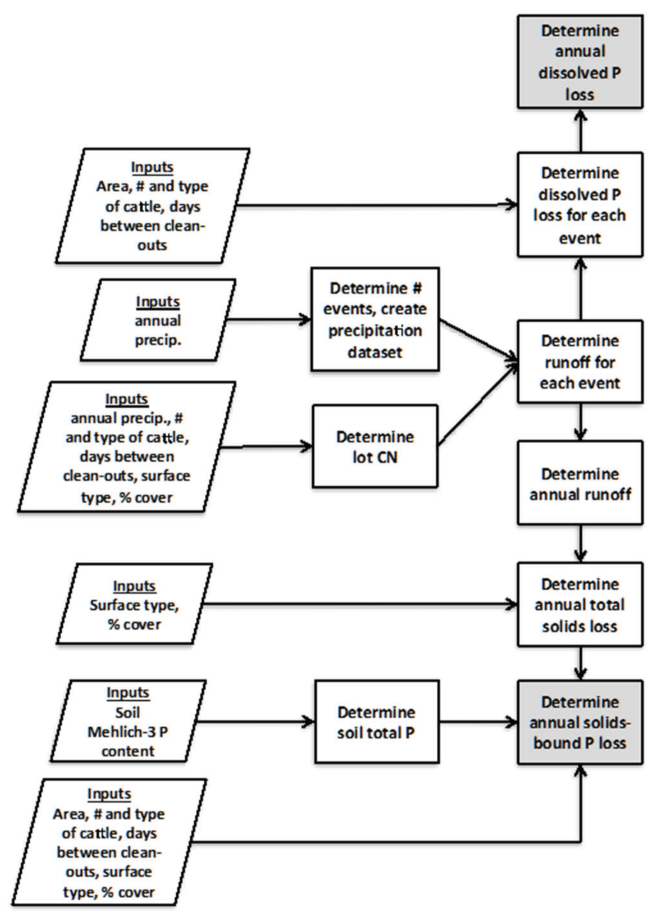

Figure 1. Flowchart of the cattle lot phosphorus runoff model.

proximate runoff from a rainfall event, given that the event is larger than a model-determined threshold value. The method requires a dataset of annual precipitation events; runoff is estimated for each event and summed for annual runoff. We were unable to obtain daily precipitation data for the exact research location of most studies used for runoff model development and testing. The alternatives were to use precipitation data from nearby locations or estimate annual precipitation datasets empirically. Due to the difficulty in obtaining local measured data, we chose the empirical option, as described below, and for consistency used this method throughout model development and testing.

For an empirical precipitation dataset for a given location, we first estimated an appropriate number of events during a year. We obtained historical precipitation data from the Western Regional Climate Center (www.wrcc.dri.edu/climatedata/climtables/citycompppt/) for 153 locations throughout the U.S. from 1949 to 2006. The data included average total annual precipitation and average number of events in an annual period for which precipitation was greater than 2.5, 12.7, or 25.4 mm. For these data, there was a nonlinear relationship between annual precipitation (mm) and the number of events with precipitation greater than 2.5 mm, expressed as:

$$\text{Number of events} = 0.578 \times (\text{annual precipitation})^{0.693} \quad (1)$$

$$(r^2 = 0.88)$$

We used this relationship to determine the number of annual precipitation events from user-defined annual precipitation.

To determine the amount of precipitation (mm) for each event, we assumed that event amounts followed a lognormal distribution with a minimum of 1.0 mm and a maximum of 50.0 mm, which we chose as a reasonable average for an event maximum. Lognormal distributions are commonly used to describe precipitation patterns (Kedem and Chiu, 1987). When plotting precipitation amount and sequential event number with a lognormal curve, precipitation (mm) for a given event can be determined as:

$$\text{Event precipitation} = C_1 \times \ln(\text{event sequence number}) + 50.0 \quad (2)$$

The variable C_1 then varies with the total number of annual events as:

$$C_1 = 3.525 \times \ln(\text{number of annual events}) - 26.351 \quad (3)$$

In equations 1 through 3, as the annual precipitation increases, both the number of annual events and the precipitation per event increase. This empirical approach necessarily generated an annual precipitation amount that differed slightly from the user-specified amount. Therefore, for all events, estimated precipitation was changed proportionally so that total annual precipitation equaled the user-defined value. Through this adjustment, the maximum event value also differed from 50.0 mm in an appropriate way for different regions. For example, drier regions are less likely to have large events compared to wetter regions. In the model, a location with 100 cm of annual precipitation would have a maximum event size of 6.0 cm, whereas a location with 25 cm of annual precipitation would have a maximum event size of 3.3 cm.

We used the historical precipitation data from the Western Regional Climate Center to test if our assumed distribution between 1.0 and 50.0 mm reasonably estimated appropriate precipitation amounts per event. We entered the reported average annual precipitation for the 153 locations into the model and used equations 1 through 3 to determine a set of annual precipitation events for each location. We then compared the estimated and reported number of events that had precipitation greater than 2.5 mm, greater than 12.7 mm, or greater than 25.4 mm. The regression results were as follows:

For precipitation >2.5 mm:

$$\text{Calculated number of events} = 0.89 \times \text{reported number of events} - 0.48 \quad (4)$$

$$(r^2 = 0.78)$$

For precipitation >12.7 mm:

$$\text{Calculated number of events} = 1.03 \times \text{reported number of events} + 3.00 \quad (5)$$

$$(r^2 = 0.98)$$

For precipitation >25.4 mm:

$$\text{Calculated number of events} = 0.91 \times \text{reported number of events} + 2.44 \quad (6)$$

$$(r^2 = 0.90)$$

These results indicate that our approach generated an annual precipitation dataset that reasonably represented precipitation amounts and frequencies in many U.S. locations.

We also compared how using empirical instead of measured precipitation would impact estimated annual runoff for the study by Nienaber et al. (1974), who monitored runoff from a cattle feedlot in Nebraska during 1971 and 1972. For that study, we could not obtain event precipitation data for the exact research location. Instead, we both generated an empirical precipitation dataset and obtained measured data from five sites within 50 km of the research site. We then used all six datasets to estimate annual runoff using the CN method described above. Reported annual precipitation at the research location, and thus the total for the empirical dataset, was 708 mm in 1971 and 774 mm in 1972. Nearby annual precipitation averaged 736 and 781 mm, respectively. The number of runoff events in the empirical dataset was 42 for 1971 and 40 for 1972, with total annual runoff of 278 and 224 mm, respectively. Using precipitation data from the nearby locations, the number of runoff events averaged 43 for 1971 and 41 for 1972, with total annual runoff of 284 and 203 mm, respectively. This provided evidence that using empirical precipitation data results in similar estimates of runoff as using data measured nearby to research sites.

Determining Runoff CN

With a precipitation dataset calculated, we then determined what value to use for lot CN to calculate runoff for each event. We collected cattle lot runoff data from 11 published studies (Balogh and Madison, 1985; Clark et al., 1975; Coote and Hore, 1979; Edwards et al., 1986; Gilbertson et al., 1971a; Gilbertson et al., 1979; Gilbertson et al., 1971b; Larson et al., 1976; Madden and Dornbush, 1971; Nienaber et al., 1974; Trooien et al., 2013) representing 21 site years. All studies reported annual precipitation and runoff amounts from a variety of cattle barnyards and feedlots, including paved and earthen lots, in six different states (Minnesota, Nebraska, Ohio, South Dakota, Texas, and Wisconsin) and Canada. For all studies, we generated an empirical precipitation dataset using reported annual precipitation and equations 1 through 3. We then determined what CN was needed so that estimated annual runoff equaled reported annual runoff. With all CNs determined, we found that there was a consistent relationship between CN and measured annual precipitation in which lot CN decreased as annual precipitation decreased (fig. 2). This relationship is logical, given that less precipitation creates drier lot surfaces that absorb more water and generate less runoff. The relationship is also consistent with findings of Clark et al. (1975), who documented linear relationships between precipitation and cattle lot runoff in which the slope of the relationships decreased in proportion to the annual moisture deficit (annual evaporation – annual precipitation). We also found that there were different relationships for different lot surfaces, i.e., CN was less for earthen lots than for paved lots. The model also allows the CN for only paved lots to increase up to a maximum of 99 based on the percentage of the lot covered by manure. For example, if the paved lot is completely covered, the relationship in figure 2 is used to calculate CN. As lot coverage decreases due to low cattle density or frequent cleaning,

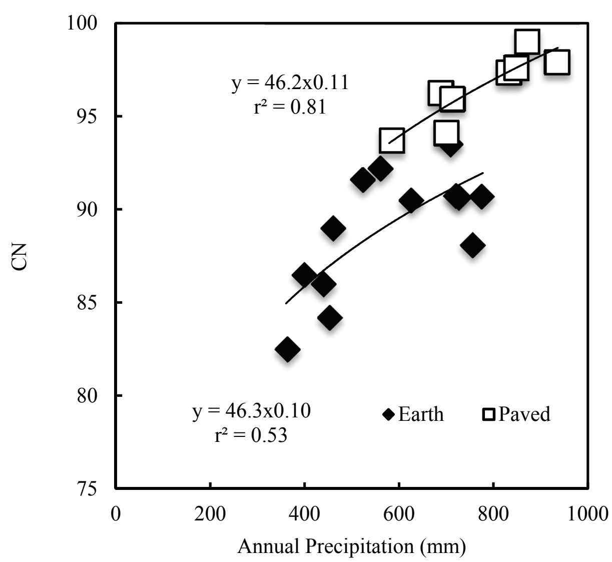

Figure 2. Data from 11 studies of cattle lots showing the relationship between estimated CN for a lot and measured annual precipitation.

CN can increase up to a maximum of 99. The increase is in direct proportion to the percent of the total lot area covered. The logic is that paved lots with more manure have a more uneven surface with greater depressional water storage and thus less runoff. Finally, research has shown that increasing vegetative cover can decrease runoff amounts (Butler et al., 2006; Mwendera and Saleem, 1997; Mwendera et al., 1997; Owens et al., 2003; Owens and Shipitalo, 2009). Accordingly, for earthen lots, the regression coefficient in figure 2 was allowed to vary linearly between 46.3 for no vegetation and 38.9 for full vegetation. The value estimated between these two extremes is determined in direct proportion to the percent of vegetative cover. The 38.9 value is taken from lot runoff data of Vadas and Powell (2013).

Figure 2 shows there was greater variability in CN for earthen lots than paved lots, most likely due to more variables contributing to surface conditions, such as vegetation or soil depressions, that are not present in paved lots. The proportion of the CN variance explained by the regressions in figure 2 was not very great, especially for earthen lots. This represents a situation in which the desire to maintain model simplicity (e.g., annual runoff is estimated from only annul precipitation data, which is easily known) introduces uncertainty in model predictions, which could be accounted for in future model development (Bolster and Vadas, 2013).

Testing the Runoff Model

Overall, the model uses user-defined annual precipitation, type of lot surface, and percent vegetative cover to estimate lot CN and an empirical precipitation dataset. The model then uses the CN to determine runoff for each event in the dataset and sums runoff for all events to determine total annual runoff. We tested this runoff prediction approach using data from 12 studies that were independent of those used to develop the runoff model (Bond, 2010; Busch et al., 2013; Coote and Hore, 1979; Cramer et al., 1976; Edwards et al., 1983; Edwards et al., 1972; Komor and Hansen, 2003; Madden and Dornbush, 1971; Miller et al., 2004; Powers et al., 2010; Uusi-Kamppa et al., 2007; Westerman and Overcash, 1980). The studies represented 37 site years and reported lot characteristics, annual precipitation, and annual runoff. Lots varied widely in size, number and type of cattle, surface type (including paved and earthen), management (including frequency of cleaning), and geographic location (Iowa, Minnesota, Nebraska, Ohio, Wisconsin, South Dakota, North Carolina, Ontario, Alberta, and Finland), which resulted in a variety of climates with annual precipitation ranging from 130 to 1025 mm. We used the precipitation dataset and CN approach described earlier to predict annual runoff and compared the predicted to measured annual runoff.

Results in figure 3 show that the slope of the regression equation relating measured and predicted annual runoff was not significantly less than 1.0 ($p = 0.05$), but the intercept was significantly greater than 0.0. The standard error values for the intercept and slope were 21.07 and 0.09, respectively. We also calculated a model efficiency of 0.69 for the data (Nash and Sutcliffe, 1970), which Moriasi et al. (2007) would classify as satisfactory. Nash-Sutcliffe (NS) effi-

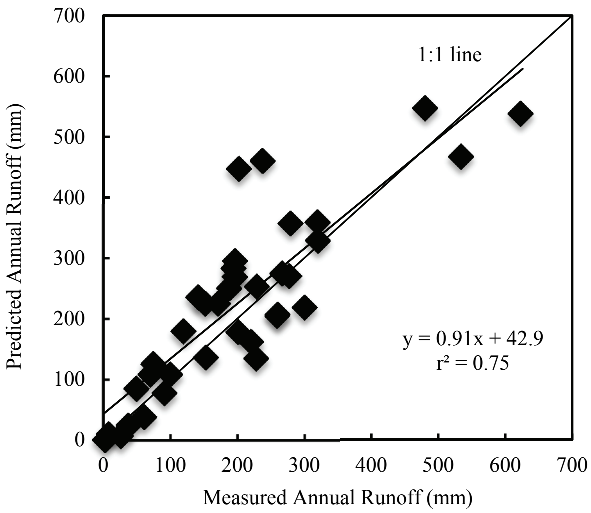

Figure 3. Data from 12 studies representing 35 site years showing the relationship between measured annual runoff from cattle lots and predicted runoff using the new model.

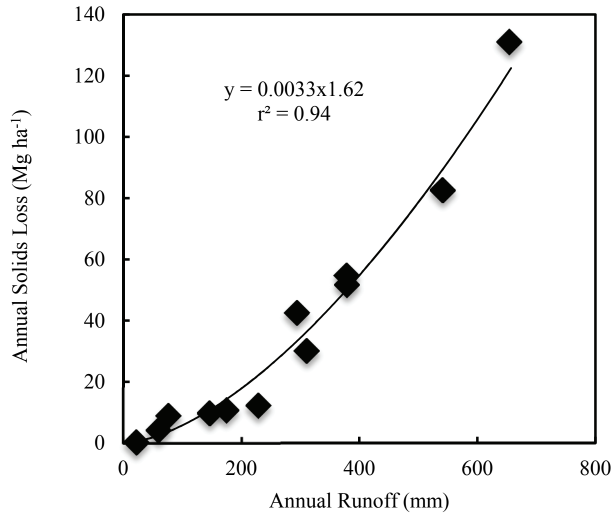

Figure 4. Data from six studies showing the relationship between annual runoff (mm) and annual total solids loss (Mg ha^{-1}) from cattle lots.

ciencies can range from -∞ to 1. An NS efficiency of 1 corresponds to a perfect match of modeled and observed data. An NS efficiency of 0.0 indicates that model predictions are as accurate as the mean of observed data, whereas an NS efficiency less than zero occurs when the observed mean is a better predictor than the model. The model also had an RMSE of 75.5 mm, an MAE of 54.8 mm, and an MAPE of 35%. Given the minimal model inputs, the overall runoff estimates were reasonably robust and reliable predictions of measured annual runoff. Although the regression in figure 3 suggests that predicted runoff was generally less than measured runoff, underprediction was not systematic. Only 15 of the 37 site years had underpredicted annual runoff, and the average difference between measured and predicted runoff was positive 19%.

Annual Total Solids Loss Estimation

The next step in model development was to estimate annual eroded solids loss from a cattle lot. One study investigating nutrient loss in runoff from feedlots observed a consistent increase in solids transport with increasing runoff volume (Gilbertson et al., 1972). From the perspective of an annual-based model, this suggests that physical surface conditions remain consistent enough through time so that solids loss can be described as a function of how much water is moving across the surface. This idea is consistent with the results of Gilley et al. (2011), who found that erosion from feedlots was a function of transport capacity (i.e., runoff amounts) and not the characteristics of the feedlot surface materials. We investigated data from six published studies (Coote and Hore, 1979; Edwards et al., 1986; Edwards et al., 1972; Gilbertson et al., 1971b; Madden and Dornbush, 1971; Younos et al., 1998) that monitored annual runoff and erosion from cattle lots. There was a strong relationship between annual runoff (mm) and annual solids loss (Mg ha^{-1}) (fig. 4), which the model uses to estimate annual solids loss from estimated annual runoff. For earthen lots, the model also allows total solids loss to fluctuate down to a minimal amount (~0.15 Mg ha^{-1} at 100 cm of annual precipitation) based on the user-defined percentage of vegetative cover of the lot. This minimal amount is taken from field plot research of Vadas and Powell (2013) for well-vegetated cattle lots. Figure 4 shows a nonlinear relationship between runoff and total solids loss. While we decided to use a nonlinear equation because that was what fit the data well, a nonlinear relationship may also be logical conceptually. Greater runoff volumes are likely due to a greater occurrence of larger storms, which may generate proportionately more runoff (Ramos-Scharron and MacDonald, 2007) and related sediment transport.

During model development, we found that the method described above overpredicted solids loss for paved cattle lots that have manure consistently removed by cleaning. Assumedly this is true because such lots have less manure on the surface and therefore less manure solids loss in runoff. To account for lot cleaning, the model first estimates how much lot area is covered by manure from cattle between cleanings, with time between cleanings specified by the model user. The model uses the user-defined cattle information and the manure production information in table 1 and assumes that each 250 g of manure (dry weight) covers an area of 659 cm^2 (James et al., 2007). The data in table 1 are from Nennich et al. (2005). The model then estimates how much of the lot area is covered between cleanings. If less than the full lot area is covered between cleanings, the model reduces the estimated annual solids loss in proportion to how much of the lot is covered with manure be-

Table 1. Fecal production and P content for dairy and beef cattle.

Animal Type	Daily Fecal Production (kg)	Fecal Total P Content (kg kg^{-1})
Lactating dairy cow	8.9	0.0088
Dairy heifer	3.7	0.0054
Dairy dry cow	4.9	0.0061
Dairy calf	1.4	0.0054
Beef cow	6.6	0.0067
Beef calf	2.7	0.0092

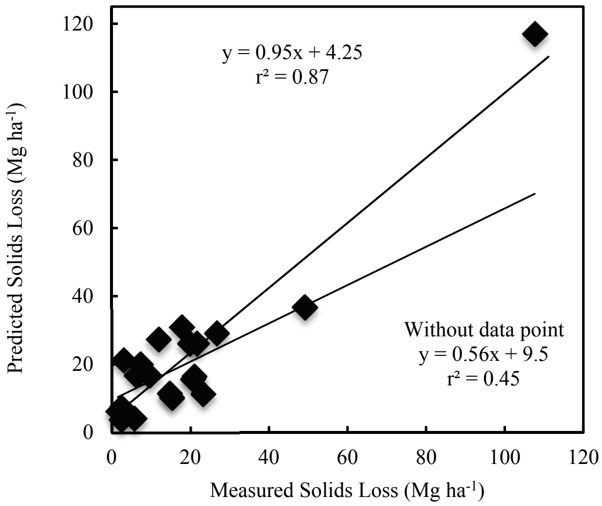

Figure 5. Data from five studies representing 20 site years showing the relationship between measured annual total solids loss from cattle lots and predicted solids loss using the new model.

tween cleanings. For example, if a lot is cleaned once per week, and only 23% of the total lot area is covered in a week, annual solids loss is reduced by multiplying by 0.23.

We tested the model's ability to predict annual solids loss in runoff using data from five studies that were independent of those used to generate the erosion relationship in figure 4 (Bond, 2010; Busch et al., 2013; Coote and Hore, 1979; Edwards et al., 1983; Madden and Dornbush, 1971). These studies constituted five sites with 20 site years and were a subset of the 12 studies used to test the model for runoff predictions. For these studies, we predicted annual solids loss from measured annual runoff using the regression equation in figure 4. We used measured runoff to eliminate error in erosion predictions introduced by first predicting runoff. Results in figure 5 show the model predictions for annual solids loss for the five studies. The slope and intercept of the regression line relating measured and predicted total solids loss were not significantly different ($p = 0.05$) from 1.0 and 0.0, respectively. The standard error values for the intercept and slope were 2.57 and 0.09, respectively. We also calculated a model NS efficiency of 0.85 for the solids loss data. Regression results were influenced by one site year with very high solids loss (>100 Mg ha^{-1}) (Edwards et al., 1983), although the model reliably predicted solids loss for this data point. Without this point, the regression slope was significantly less than 1.0 (0.56), the intercept was greater than 0.0, and the model NS efficiency decreased to 0.35. For all data, the model had an RMSE of 9.06 Mg ha^{-1}, MAE of 7.71 Mg ha^{-1}, and MAPE of 101%, all of which suggest moderate model performance. However, removing the very high data point did not affect these statistics (RMSE = 8.80, MAE = 7.23, MAPE = 101), suggesting that these statistics are better indicators of model predictions than the regression coefficients.

Annual Solids-Bound and Dissolved P Loss Estimation

With solids loss estimated, the next step in model development was to estimate solids-bound P loss. In the model, annual solids P loss (kg ha^{-1}) is determined by multiplying annual solids loss by solids P content (mg kg^{-1}). For paved or concrete lots, the dominant source of eroded solids is cattle manure, and the eroded solids P content is the same as the manure P content. The model estimates manure P content based on user-provided information about the type and number of cattle on the lot and the information in table 1 for cattle type, daily manure production, and manure P content. While the model uses constant manure P content values, research shows that manure P can change as a function of animal diet and metabolism (Bernier et al., 2014; Luebbe et al., 2012). Future versions of the model could consider these variables, which would be important with the inclusion of cattle diet ingredients like distillers grains that can alter manure P content (Bernier et al., 2014).

On earthen lots, both manure and soil are sources of solids P loss, and the P content of eroded solids is generally less than the P content of manure. For example, Cramer et al. (1976) measured the P content of eroded solids in settling basins draining paved and earthen cattle lots in Wisconsin. They found that the solids P content from the paved lot was 2.4 times greater than the solids P content from the earthen lot. Thus, for earthen lots, the model assumes that eroded solids are 30% from manure and 70% from soil. The model estimates soil total P content based on the approach in the APLE soil P model (Vadas et al., 2012), which requires Mehlich-3 P content of the lot soil as an input. Vadas and White (2010) present methods to convert other soil test P values (e.g., Bray-1, Olsen, Mehlich-1) to Mehlich-3. The model then calculates eroded solids P content based on manure P content, soil total P content, and the 30/70 ratio. The model also allows this 30/70 ratio to fluctuate between 30/70 and 0/100 in direct proportion to percent of the lot area covered by manure. For example, if manure covers 50% of the lot area, the ratio is 15/85. At 75% manure coverage, the ratio is 25.5/74.5.

For dissolved P loss estimation, the model uses the approach described by Vadas et al. (2007) to estimate P loss in runoff from manure applied to agricultural fields. This approach first estimates how much P is released from manure during a precipitation event using an empirical relationship that relates P release to the ratio of manure mass to rainfall volume. An estimate is then made of how much of that released P infiltrates into soil and how much is lost in runoff. This is done using an empirical relationship that relates P movement to the ratio of runoff volume to precipitation volume. For the cattle lot model, for each event in the precipitation dataset, dissolved P released (kg ha^{-1}) from manure on the lot surface is estimated based on the precipitation to manure dry matter ratio (W, cm^3 g^{-1}) as:

Dissolved P released =

$$[1.2(W/(W + 73.1)] \times (\text{manure WEP}) \quad (7)$$

where manure WEP is manure water-extractable P (kg ha^{-1}). The origin of this equation is based on laboratory extraction data as described by Vadas et al. (2004). The value of W is calculated as:

W = precipitation / manure mass

$$\times \text{ manure cover area} \times 100{,}000 \quad (8)$$

where precipitation is in cm, manure mass is in kg, manure cover area is in ha, and 100,000 ensures units of cm^3 g^{-1}. If runoff occurs, some released manure P is transferred to runoff, with the amount of dissolved P in runoff (kg ha^{-1}) calculated as:

Runoff dissolved P = dissolved P released

$$\times \text{ (runoff/precipitation)} \times \text{PDfactor} \quad (9)$$

where PDfactor is a P distribution factor that varies between 0.0 and 1.0 and is calculated as:

$$\text{PDfactor} = (\text{runoff/precipitation})^{0.225} \quad (10)$$

The origin of equations 9 and 10 is based on field-plot rainfall simulation data as described by Vadas et al. (2005). The model then sums the estimates of runoff dissolved P for all runoff events in the precipitation dataset to estimate annual loss of dissolved P from manure on the lot surface.

Three important variables for calculations in equations 7 and 8 are manure WEP, manure mass, and manure cover area. All of these variables are in reality very dynamic, depending on animal diet, lot management, cattle density, and climate, but the model uses representative values for the sake of simplicity and compatibility with an annual time-step approach. To estimate these variables, the model first determines how much manure cattle deposit during the lesser number of days either between lot cleanings or between runoff events. The model user specifies time between cleanings. Time between runoff events is determined as 365 divided by the number of runoff events as determined during runoff estimation. While this is a necessary simplification given how the model generates a precipitation dataset, it obviously does not represent reality. Future model versions that could import measured precipitation datasets would better represent time between runoff events. The model then takes the user-defined cattle information and manure production information in table 1 to estimate the manure applied, manure total P applied, and lot area covered by the manure applied during the specified time period. Maximum values are set for the amount of manure that covers the total lot area. The model assumes that 64% of total manure applied is manure WEP. This 64% represents initial manure WEP and manure P that becomes WEP through mineralization processes (Vadas et al., 2009).

MODEL TESTING FOR P LOSS IN RUNOFF

We tested the complete model, including runoff, solids loss, and P loss predictions, with barnyard and feedlot P loss data from the same 12 studies cited for annual runoff testing. These data were independent of any data used to develop the model. Most studies measured only total P loss, while some measured both total and dissolved P loss. Model testing results are shown in figure 6 for total P loss and figure 7 for dissolved P loss. The model was able to reliably predict total

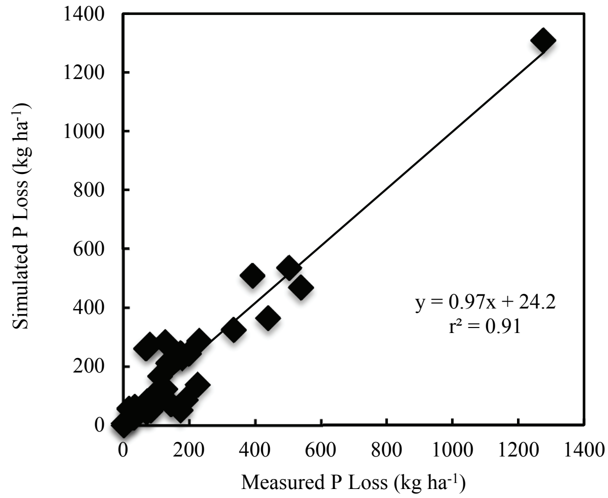

Figure 6. Data from 12 published studies showing the relationship between measured annual total P loss from cattle lots and predicted total P loss using the new model.

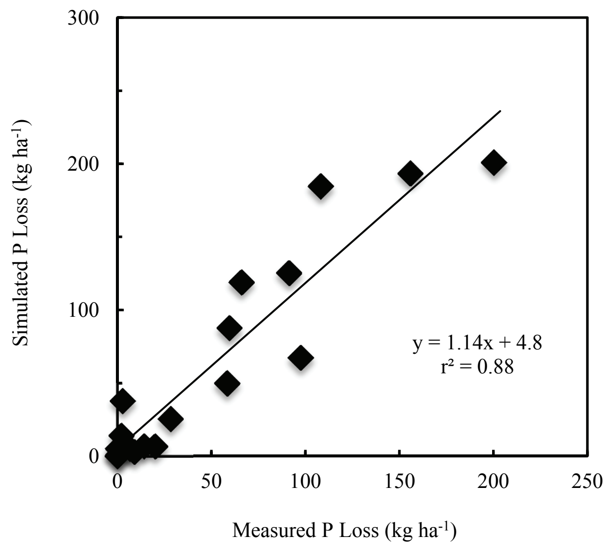

Figure 7. Data from 12 published studies showing the relationship between measured annual dissolved P loss from cattle lots and predicted dissolved P loss using the new model.

P loss for the 12 studies. The slope and intercept of the regression line relating measured and predicted total P loss were not significantly different ($p = 0.05$) from 1.0 and 0.0, respectively. The standard error values for the intercept and slope were 15.62 and 0.05, respectively. We also calculated a total P model NS efficiency of 0.91. As with the total solids loss data, these total P prediction results were influenced by one site year with very high P loss (>1200 kg ha^{-1}) (Edwards et al., 1983). However, without this point, the model predictions were still strong. The regression slope was 0.90 (not different from 1.0; $p = 0.05$), the intercept was 34.4 (not different from 0.0), and the model NS efficiency was 0.73. For all data, the model had an RMSE of 74.7 kg ha^{-1}, MAE of 55.9 kg ha^{-1}, and MAPE of 73%, all of which suggest satisfactory model performance.

Results in figure 7 show that, for dissolved P runoff da-

Table 2. Results of a sensitivity analysis of the major input variables for the P loss quantification tool. Input variable values were changed by +10%, -10%, +25%, and -25%.

Variable	Initial Value	Change in Total P Loss Prediction			
		+25%	+10%	-10%	-25%
Earthen lots					
Precipitation (cm)	11.8	94.0	32.7	-25.5	-55.0
Cover (%)	15	-11.9	-4.4	5.6	13.7
No. of cows	20	11.0	4.4	-4.4	-11.0
Area (ha)	0.4	-8.8	-4.0	4.9	14.7
Days between cleanings	30	4.3	1.7	-1.7	-4.3
Mehlich-3 soil P (mg kg^{-1})	750	0.3	0.4	-0.8	-2.9
Paved lots					
Precipitation (cm)	11.8	74.2	26.1	-22.3	-49.0
No. of cows	20	16.4	6.8	-7.4	-19.4
Area (ha)	0.4	-15.2	-6.8	7.5	21.3
Days between cleanings	30	13.6	5.6	-6.3	-16.4

ta, the slope and intercept of the regression line relating measured and predicted dissolved P loss were also not significantly different ($p = 0.05$) from 1.0 and 0.0, respectively. The standard error values for the intercept and slope were 8.67 and 0.11, respectively. We also calculated a model NS efficiency of 0.75 for the data. For all data, the model had an RMSE of 31.3 kg ha^{-1}, MAE of 23.0 kg ha^{-1}, and MAPE of 344%. All of these statistics except MAPE suggest satisfactory model performance. The MAPE statistic was influenced by six data points with relatively very low measured dissolved P loss (<3 kg ha^{-1}) because of either low annual runoff (Miller et al., 2004) or low stocking density (Uusi-Kamppa et al., 2007). Without these points, the MAPE was 29.8%.

Overall, these regression results suggest that the model can reliably predict both dissolved and total P loss from lots. This is especially encouraging given the minimal input data required to run the model, which consist of only soil test P content, annual precipitation, lot size and surface type, cattle type and numbers, frequency of cleaning, and percent vegetative cover. On average, predicted dissolved P loss was 48% of predicted total P loss, with a standard deviation of 19%. These data compare well with measured results from three studies (n = 12) (Busch et al., 2013; Coote and Hore, 1979; Miller et al., 2004) in which dissolved P loss averaged 37% of total P loss with a standard deviation of 15%.

Table 2 shows results of a sensitivity analysis for the major model input variables, which were Mehlich-3 soil P, lot area, annual precipitation, number of cows in a lot, percent vegetative cover, and days between lot cleanings. Results are presented separately for earthen lots and paved lots. Annual P loss estimates were least sensitive to Mehlich-3 soil P, and more sensitive to variables that influenced how much manure accumulates on the lot surface and how much of the lot area is covered by manure (lot area, number of cows, percent cover, days between cleanings). These latter variables influenced paved lots more than earthen lots. Model estimates were most sensitive to annual precipitation, which ultimately controls P transport pathways in runoff and erosion. Precipitation had a somewhat greater influence for earthen lots than paved lots.

COMPARING THE NEW AND EXISTING CATTLE LOT PHOSPHORUS RUNOFF MODELS

Two barnyard P loss models currently used in Wisconsin and Minnesota are BARNY and MinnFarm, which are both based on the prediction approach used in AGNPS. These models estimate runoff using local precipitation datasets and the CN approach, and estimate P loss by combining estimates of lot runoff and a runoff P concentration (default total P concentration of 85 mg L^{-1}). This default P concentration can change in proportion to the percent manure pack on the lot surface, which is a function of lot cattle density and management. We compared the performance of BARNY and MinnFarm with that of our new lot P runoff model using data from the same 12 studies cited above that measured total P loss from barnyards and feedlots. We entered the required model information, including lot area, surface type, and animal numbers. We used the same precipitation data and CNs for BARNY and MinnFarm as we did when testing our new lot P runoff model. We did this because BARNY and MinnFarm use Wisconsin and Minnesota precipitation datasets, which would not give comparative representation of the climates in all 12 studies, particularly the drier ones. Thus, this test compared P loss predictions for BARNY, MinnFarm, and our new model for similar runoff data.

Regression equations relating measured and predicted annual total P loss for BARNY and MinnFarm are shown in table 3. Results for both models were similar, which is expected since they are based on the same prediction approach. The regression between measured and predicted P loss was strong for both models (r^2 of 0.73 and 0.71), suggesting that the models can reasonably simulate the relative difference in P loss between different types of lots, runoff amounts, and management practices. However, the regressions were not as strong as that of our new lot P model (r^2 = 0.91), the slopes of the regression equations were significantly less than 1.0, and while the intercepts were not significantly different from 0.0, they were greater than the intercept for our new P runoff model (fig. 6). Based on the data used, results show that BARNY and MinnFarm overpredicted at low observed rates of P loss and significantly underpredicted at high rates of P loss. In fact, of the eight observations with less than 50 kg ha^{-1} of measured annual total P loss, six were overpredicted (75%), with the average and standard deviation of overprediction at 2.12 and 1.81, respectively. On the other hand, of the 28 observations with greater than 50 kg ha^{-1} of annual total P loss, 22 were underpredicted (79%), with the average and standard deviation of underprediction at 0.65 and 0.37, respectively. These trends are because BARNY and MinnFarm use a constant concentration of runoff total P (85 mg L^{-1}) to estimate total P loss. This constant underpredicts at high rates

Table 3. Regression results for measured and predicted total P loss (kg ha^{-1}) from barnyards and feedlots for the BARNY and MinnFarm models.

Model	Regression Equation	r^2
BARNY	Predicted TP = 0.42(measured TP) + 56.19	0.73
MinnFarm	Predicted TP = 0.40(measured TP) + 41.32	0.71

of P loss and overpredicts at low rates of loss. Absolute P loss predictions seem to be fairly accurate at about 50 to 100 kg ha^{-1} of annual total P loss. In contrast, the new lot P runoff model predicted P loss more reliably across a wide range of measured loss rates. Thus, the new model provided a more robust, dynamic simulation of P loss for a variety of lot types, management practices, and climates.

CONCLUSIONS

We developed a new, user-friendly spreadsheet model that predicts annual runoff, total solids loss, and total and dissolved P loss from beef and dairy cattle barnyards and feedlots. The model requires input for only soil Mehlich-3 P content, annual precipitation, and lot characteristics, including surface type (paved or earthen), cattle number and type, frequency of lot cleaning, and percent vegetative cover. The model estimates annual runoff using a dynamic dataset of precipitation events and a lot CN, which is estimated empirically based on annual precipitation and lot surface characteristics. The model estimates annual solids loss empirically based on annual runoff, and annual particulate P loss based on solids loss and P content of soil and manure in the lot, where manure P is a function of animal type and lot surface type. The model estimates dissolved P loss for each runoff event in the precipitation dataset based on the model of Vadas et al. (2007). Testing with data from 12 published studies in the literature showed that the new model was able to reliably estimate annual runoff, total solids loss, and P loss from cattle barnyards and feedlots representing a variety of lot types, climates, and management practices. The new model also gave more reliable predictions than the MinnFarm and BARNY models, which are currently used in Wisconsin and Minnesota for barnyard and feedlot P loss estimates.

The new P runoff model provides a reliable, user-friendly tool than can be used to develop whole-farm estimates of P loss and more effectively target P loss mitigation practices for watershed management and/or total maximum daily load (TMDL) projects. However, the model is intended for annual estimates and relies on empirical equations. Therefore, it cannot be used for event-based purposes, such as retention basin design, and does not consider runoff or P loss variables that may vary between events, such as changes in lot surface, manure, and weather characteristics. We are currently developing more advanced software for using the model in Wisconsin, including options for specifying rooftops and other run-on contributing areas, lots with variable surface types, and lot management options such as settling basins or vegetated filter strips.

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