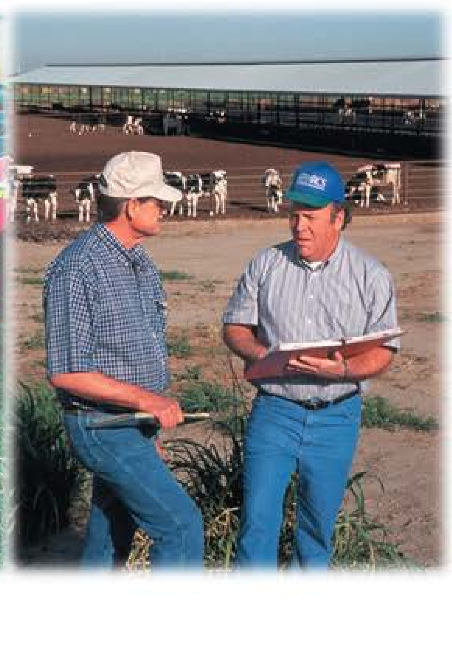
TECHNICAL GUIDANCE FOR ASSESSING PHOSPHORUS INDICES



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TECHNICAL GUIDANCE FOR ASSESSING PHOSPHORUS INDICES

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ABSTRACT

Disparate nutrient and land management recommendations generated by P Indices among states, a perceived lack of change in P-based management, and persistent P loading problems in many of the nation's waters, led to a revision of the 590 Standard. The revision requires an assessment of P Indices across the U.S. to ensure that each state Index is correctly ranking the potential for P delivery to surface water. This report describes the rationale behind P Index assessment, how assessment should be conducted, what data and models should be used, and how assessments may be interpreted and incorporated into P Index revisions. At the end of 2012, NRCS funded six CIG to assess P Indices across the U.S. This report does not review their objectives, but provides as Appendices 1, 2, and 3, regional CIG methodologies and ongoing NRCS P Index assessments using APEX.

The overarching intent of assessing Indices is to ensure they appropriately rank risk of actual P loss for any given site relative to other sites; are directionally and magnitudinally correct, in that as factors influencing P loss change to increase or reduce that loss, P Indices correctly estimate the extent of change in P loss; interpretations based on assigned risk are equivalent across state borders, given similar site and water resource conditions; and where inadequacies exist, the causes can be identified and rectified.

The main recommendations are;

- Runoff monitoring data are required to build confidence in P Index representation of site P loss potential, as well as validate nonpoint source models. Databases should include at a minimum runoff, site conditions, climate, management, and P loss over the planning / rotation period under natural rainfall.
- Several models are available, such as APEX, APLE, and DrainMod.
- Baseline management scenarios must be developed, against which to compare Index performance and source and transport factors influencing P loss ranked as locally-relevant low, medium, and high loss.
- Conditions must be defined that result in both unacceptable P loss within a model and high P Index ratings that limit or preclude P applications run under the same set of conditions.
- Determination of uncertainty or variability of Indexed risk and P loss is recommended.

PREFACE

In the early 1990's, NRCS with the help of group of scientists from across the U.S., proposed a phosphorus (P) indexing framework to identify and rank the risk of P loss from a given field. Since then, the P Index has morphed from an educational to an implementation, targeting, manure scheduling tool, and in some cases, a regulatory tool. A great deal of research was conducted to derive and support the various components of the P Indexing concept, with States modifying their Index to account for locally relevant soils, land management, physiographic, and hydrologic controls influencing P loss. However, in many cases less effort was invested in validating that P Indices were actually working by showing that Index-based nutrient and land management changes were decreasing P loss.

As a result, inconsistencies among P Indices, in terms of level of detail and scientific rigor among states, prompted NRCS and EPA to call for an independent assessment of P Indices to demonstrate that they are magnitudinally and directionally correct in assessing the risk of P loss. The need for such an assessment is heightened by a slower than expected decrease in soil P levels and P-related water quality impairment, which led some to wonder if the Indexing concept was "too farmer friendly." This report describes the efforts underway to assess P Indices.

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Executive Summary

In the years following implementation of USDA-NRCS's National 590 Standard for Nutrient Management, concerns have grown over disparate recommendations generated by P Indices of different states, a perceived lack of change in P management practices, and persistent P loading problems in many of the nation's waters. In response, the 590 Standard was revised in 2011, and now requires an assessment of P Indices across the U.S. to ensure that each state Index is correctly ranking fields by potential for P delivery to surface water and is compliant with the revised Standard. This report describes the rationale behind P Index assessment, how assessment should be conducted, what data and models should be used, and how assessments may be interpreted and incorporated into P Index revisions. Details are also given on current efforts to assess and revise the P Index.

The overarching intent of assessing Indices is to ensure they are:

- Appropriately ranking risk of actual P loss for any given site relative to other sites.
- Directionally and magnitudinally correct, in that as factors influencing P loss change to increase or reduce that loss, P Indices correctly estimate the extent of change in P loss.
- Interpretations based on assigned risk are equivalent across state borders, given similar site and water resource conditions.
- Where inadequacies exist, the causes can be identified and rectified.

Since this committee was formed, NRCS announced an RFP for, and funded six CIGs to assess P Indices in most areas of the U.S. Thus, this report does not attempt to determine or to review their objectives; but provides as Appendices 1, 2, and 3, regional CIG methodologies and ongoing NRCS P Index assessments using APEX. Our goal is to synthesize all those efforts and provide common questions that need to be answered and goals that should be met. The following questions should be answered by all Index assessments;

1. What is the appropriate time scale of Index and model assessment,
2. What models will be used,
3. Where will the data to calibrate models and populate Indices come from,
4. Which baseline management scenarios should be tested,
5. How do we set low, medium, and high categories for comparison, and
6. What methods will be used to compare Index and model output.

Recommendations

- **General**. Runoff monitoring data are required to build confidence in P Index representation of site P loss potential. Because it is unlikely that sufficient monitoring data exist to represent the range of climatic, site, and management conditions important to water quality, locally calibrated models (watershed of interest level) to ensure they reliably simulate P transport processes, are required to assess P Index predictions of P loss potential and P Index sensitivity to input variables. Therefore, the P Index assessment process entails:
  1. Compiling monitoring / field data to calibrate models and Indices.
  2. Selection of appropriate model, time scale, and land management scenarios against which Index outcomes can be compared.
  3. Calibration of a computational model with monitoring / field data, and, if necessary, testing of alternative models to represent certain processes.
  4. Comparison of computational model and P Index output, analysis of variability / uncertainty in Index input data and of sensitivity to input variables, and assessment of uncertainty.

- **Development of databases:** This should include at a minimum runoff, site conditions, climate, management, and water quality data. Measured field-scale event and annual P loss over the planning / rotation period, under natural precipitation are preferred to event-driven data and to small plots (2 -10 m^2) using simulated rainfall. An assessment of available edge-of-field runoff data from published reports is needed to build a usable data base for Index assessment. A network of sites with established monitoring at field and watershed scales should be developed to enable consistent assessment of site assessment tools (including the P Index), representing a range of current conditions (site and management), as well as anticipated conditions. For instance, manure management of cover crops and quantity of drained agricultural fields using tile drains. Substituting measured or predicted P loss data from other regions to overcome a lack of monitoring data should be discouraged.

- **Select appropriate models.** Several models are available and recommended for initial use, such as APEX, APLE, DrainMod, @RISK, and MANAGE, discussed later.

- **Study appropriate time scales.** P Index assessment is conducted to determine an annual risk of P loss, either over a crop rotation period of up to 5 years or down to an evaluation of differing seasonal risk of management decisions. Models must estimate P loss and simulate P mobilization and transport processes over the same time scale.

- **Assess locally relevant land management scenarios.** Determination must be made of locally relevant land use conditions, including representative sites (hydrology, soils) and management practices to include in any assessment. Importantly, baseline management scenarios must be agreed to and included, against which to compare Index performance. In addition, source and transport factors influencing P loss and risk must be relatively ranked to reflect locally-relevant low, medium, and high risks of P loss. As application of Indices to the planning process widens, an increasing variety of types of P sources will be need to be accounted for. States should consider including in their Indices, P source coefficients that account for differences in the potential for P release, if they don't already.

- **Calibration of computational models and P Indices**. For each region, model calibration must be conducted under appropriate conditions described above. As many of these models were developed for purposes other than assessing P movement, we need to be sure that source and transport factors correctly captured by a model. Regardless of the P loss model used, conditions must be defined that result in both unacceptable P loss within the model and high P Index ratings that limit or preclude P applications run under the same set of conditions.

- **Validation**. The relationship between assigned P risk and P loss does not have to be linear, a curvilinear relationship, where risk increases exponentially with increasing P loss can occur. For example, Indices that estimate average annual P loads should be assessed on their ability to accurately predict loads (i.e., a linear, 1:1 relationship). A P Index that predicts P loss potential and does not estimate load should be tested to make sure that the P Index correctly ranks loss in predetermined low, medium, high risk categories. Determination of an uncertainty or variability metric of Indexed risk and P loss is recommended.

- **Further challenges of testing the P Index rating system.** What are the thresholds that delineate low, medium, high, and very high risks as an outcome of an Index assessment that are protective of water quality and how should they be established? How do we relate Indices and models, which are typically calibrated at edge-of-field or edge-of-conservation practice, to an estimated in-stream water quality standard? The challenge of using models to test P Index ratings is much greater than testing the numeric output of the P Index. In the latter case, the model is beneficial as long as it is qualitatively more accurate than the P Index. Assessing the P Index rating system implies that cutoff values used as breakpoints in rating system are accurately estimated by the model. We may not be able to set up the appropriate assessment system for the P Index rating based on quantitative estimates of average annual P loss from a field. We may be able to provide feedback on whether P Indices from different states are limiting P applications from situations likely to lead to similar estimates of P loss from the model.

Introduction

Despite the widespread adoption of the P Index concept (Sharpley et al., 2003), concerns emerged about the effectiveness of the Index in attaining water quality improvement. Further, the performance of few Indices has been assessed against field data. Across the U.S., many variations of the P Index were developed, mostly to account for local differences in soil types, land management, climate, physiographic and hydrologic controls, manure management strategies, as well as policy and political requirements. Over time, concerns over a lack of uniformity in both site assessment and management recommendation components of the P Index have arisen. For instance, a survey of P Indices from 12 southern U.S. states by Osmond et al. (2006) revealed a large diversity in site assessment ratings and P application recommendations for similar conditions. Under conditions tested, some of these Indices never recommended restrictions in P application, whereas other Indices regularly restricted applications (Osmond et al., 2006). This disparity was still evident when Osmond et al (2012) conducted a similar assessment six years later. Thus, the 2011 revised National NRCS 590 Standard sought to both require validation of the site assessment component of state P Indices, ensuring that they accurately reflect water quality outcomes, and standardize the management recommendations for low, medium, and high categories (USDA-NRCS, 2011a).

As tools for nutrient management planning, P Indices include two components, site assessment and site management recommendation. These two components, while linked, are distinct, a point that is sometimes ignored and sometimes a source of confusion. As site assessment tools, P Indices identify the potential for P loss from a field on the basis of site-specific “source” factors (soil P as well as P application rate, method, timing, and form) and “transport” factors (runoff, erosion, and connection to the stream network) (Lemunyon and Gilbert, 1993; Sharpley et al., 1993). The output of the site assessment is converted into a recommendation of P management (P application allowed at rates above crop requirement, no further P application, and P application at reduced rate), just as agronomic soil tests are interpreted to generate fertilizer application recommendations. Public critique of P Indices has often applied to the recommendation components, while scientific discourse has largely focused on their site assessment.

There has been growing concern that P management recommendations based on site Indexing has not brought about as great or as quick a reduction in soil P and runoff P loss as expected or desired. For instance, recent reports related to mitigation effectiveness in the Chesapeake Bay fueled concern that site risk assessment using the P Indexing approach was inadequate (Kovzelove et al., 2010; U.S. Environmental Protection Agency, 2010). The lack of soil and water quality response undoubtedly reflects a suite of factors, including the legacy of past management and a slow ecosystem response to changes in watershed and farm level P use.

All of these factors have combined to require states to demonstrate that their P Index is accurately representing actual P loss in compliance with the revised National 590 Standard (U.S. Department of Agriculture-Natural Resources Conservation Service, 2011a, b). This report details approaches for assessing P Indices using measured or predicted P runoff. A brief summary of studies that have assessed P Indices and what was found is given in Appendix 1.

Types of P Indices

A. ***Index Formulation***

Phosphorus Indices may be grouped into three general categories based on their formulation: additive, multiplicative, and component (Table 1). Additive P Indices sum all of the ranked and weighted transport and source factors, with each weighted factor treated individually. Multiplicative P Indices combine all source factors into a single source term and all transport factors into a single transport term and calculate the final P Index value as the product of the source and transport terms. Component Indices sum individual pathway losses of P so that each loss pathway is calculated as the product of both transport and source factors. For instance, sediment-attached P loss is a different pathway than soluble P loss. Indices may also be divided into those that provide a relative rating of P loss potential by compounding individual source and transport risk factor rankings into an overall field rating and by estimating P mass delivery to the edge-of-field or to surface water.

B. ***Time-scales of risk determination***

- All P Indices are used to estimate future risk weeks, months, or years ahead of the specific P applications and management practices they are assessing as part of a nutrient management planning process.
- P Indices look at long-term average P loss for their target time step. Thus, the typical time step is long-term average annual P loss potential (assessing the expected annual average loss potential for a growing season). Examples exist of P Indices that estimate long-term average P loss for duration of plan (up to five years) or long-term average for seasonal losses.
- Typical input data for P Indices include erosion estimated by RUSLE2 (average annual sediment loss from rill erosion as tons acre^{-1} year^{-1}), and historic precipitation averages (monthly or annual), and runoff potential from event-based curve number estimates. Models need to simulate relevant P mobility and transport processes over the same time scales. Later, we discuss several models that may or already have been used, their design time scales of assessment, and how those predictions can be equated to time scales for Index assessments.

- Inventory of runoff studies demonstrates there is extensive event-based data, data collected over day, seasons, and years. Event data can be used to calibrate and/or validate models and then those models can be run over many-year scenarios to estimate average-annual losses. In this way, the model can be used to generate information that is rarely available from the scientific literature.

Table 1. Characteristics of P Indices across the U.S.

State	Formulation	Relative risk rating only	Load estimating
AL	Additive	☺	
AR	Multiplicative	☺	
AK	Additive	☺	
AR	Additive	☺	
AZ	Additive	☺	
CO	Additive	☺	
DE	Multiplicative	☺	
FL	Multiplicative	☺	
GA	Component		☺
IA	Component		☺
IL	Multiplicative	☺	
KS	Multiplicative	☺	
KY	Additive	☺	
LA	Multiplicative	☺	
MD	Multiplicative	☺	
ME		☺	
MI	Additive	☺	

MN	Component	☺	
MS	Multiplicative	☺	
MT	Additive	☺	
NE	Component	☺	
NC	Component		☺
ND	Additive	☺	
NH	Multiplicative	☺	
NJ	Additive	☺	
NM	Additive	☺	
NY	Component	☺	
OH	Additive		
OK	Additive	☺	
OR	Additive	☺	
PA	Multiplicative	☺	
RI	Additive	☺	
SC	Multiplicative	☺	
TN	Multiplicative	☺	
TX	Additive	☺	
UT	Additive	☺	
VT	Multiplicative	☺	
VA	Component		☺
WA	Additive	☺	
WV	Additive	☺	
WI	Component		☺

WY	Additive	☺	

C. *Quantitative and Qualitative Indices*

Phosphorus Indices can also be categorized as being qualitative or quantitative (Table 1). Qualitative P Indices are those Indices that provide a unit-less rating value that are not calculated as an estimate of average annual P loss (Sharpley et al., 2011). This would include the original Lemunyon and Gilbert P Index and the succeeding additive and multiplicative P Indices based on that concept. While qualitative Indices – with the exception of the Oklahoma P Index - do produce a numerical output, the numerical output is interpreted as low, medium, high, with respect to risk of P loss. Quantitative P Indices, on the other hand, incorporate physically-based relationships between source and transport factors to estimate actual P loss; though many quantitative Indices are normalized to some predetermined scale, thereby producing a relative rating based on actual estimates of P loss.

D. *Describing Hydrology in Indices*

The traditional P Index technique requires site-specific data (e.g., soil test P - STP, RUSLE) and is intended to be implemented on a case-by-case, farm-by-farm, or field-by-field basis – rendering it impractical as a watershed-scale risk assessment tool. Furthermore, many current P Indices use a fixed distance set-back from a watercourse and/or other soil wetness indicators, which do not explicitly address actual runoff potential and probability. The current P-index criteria for characterizing P transport potential in many indices are generally both poorly defined and difficult for planners and producers to implement. These difficulties arise because the underlying hydrological transport processes are distributed on the landscape in ways that are difficult to quantify via simple guidelines. Hydrologic and water quality models offer a good solution, but can often be prohibitively complex for conservation planners to use (Lane et al., 2009; White et al., 2010). Moreover, they generally require substantial parameterization and calibration data that are usually unavailable at the field scale and model outputs are often at larger scales than those relevant to individual management practices, i.e., model output is at the scale of sub-catchments or Hydrologic Response Units (HRUs), which precludes spatial targeting of single fields, or within-field hotspots.

Recognizing these limitations, several studies have developed spatially distributed topographic representations (Heathwaite et al., 2005; Easton et al., 2008) of watershed processes using GIS-based models, which rank individual polygons or grid cells within a watershed according to their propensity to generate and transport nutrient-rich runoff (Bolinder et al., 2000; Endreny and Wood, 2003; Heathwaite et al., 2003). These advances greatly improved the utility of Indices as a planning tool; but with few exceptions (Endreny and Wood, 2003; Lane et al., 2004), distributed watershed-scale P Indices ignore topographic position when determining source factors and, thus, may misrepresent source areas in regions where saturation-excess runoff is the dominant P transport concern. The value and practicality of incorporating more robust hydrology and water quality models into existing P Indices either as foundational platform (e.g., using process-based hydrological models to provide the transport component of the P Index) or as replacements to existing P Indices needs further assessment.

What Models are Available

While measured data is the preferred standard against which to assess P indices, these data are available at limited locations which do not necessarily represent the range of local conditions in producer's fields and also for limited time periods, which generally cannot be used to represent long-term average conditions. Simulation models were developed to extrapolate limited measured data at the edge of a field or stream gauge to other areas or differing conditions. Process-based models seek to simulate the physical, chemical, and biological processes defining system behavior and are used to generate long-term annual average P loss, which can be directly compared to P index ratings. However, models must contain accurate representations of the P cycle and P transport mechanisms. Many models will need to be updated to accurately represent P loss directly from applied sources (i.e., surface-applied manure or fertilizer), to simulate P sorption and desorption in soils with high STP, leaching, and managed drainage, as well as best management practice (BMP) effects.

The following models are suggested;

A. ***Daily time step*** – APEX, SWAT, AnnAGNPS, DrainMod

SWAT and APEX share a common lineage and contain many of the same components. These models are widely used to assess the effects of alternative management strategies on nutrient and sediment losses. APEX is intended to simulate smaller areas (farm-scale) in more detail than SWAT. SWAT has been successfully applied at the field scale, but is most often used at the watershed level. Consequently, SWAT may require additional detail to function at that smaller spatial scale.

AnnAGNPS is an annualized form of the earlier single event model AGNPS. It is also used to assess the effect of management practices on nutrient and sediment losses at the watershed level.

DrainMod is a subsurface model that predicts the effects of tile drainage and water management practices.

B. ***Annual time step*** – APLE

The APLE is an easy to use annualized model which is focused on P loss processes (Vadas et al., 2009). As an annualized model is it significantly less complex than models operating on a daily time step. APLE was developed for P only, and requires measured runoff and sediment losses as inputs. More detail on APLE P is given in Appendix 3.

C. ***Combined model approaches***

Daily models with the ability to generate runoff and erosion could be used in conjunction with APLE to generate annual P loss. The linkage could be either external or APLE P components could be integrated into other models.

Fate-and-transport models such as SWAT and APEX might enable both edge-of-field and watershed scale assessment of P transport processes (integrating both source and transport components). It is possible that code modifications would need to be made to both SWAT and APEX to better capture the fate and transport of P, especially with respect to land applied manures. Models such as DrainMod and APLE offer another possible solution, to edge-of-field assessment, but would require substantial revisions (DrainMod), or user defined erosion and runoff inputs (i.e., APLE). DrainMod's hydrologic transport component is thought to adequately represent the transport conditions in regions dominated by well- and artificially-drained soils, but the P chemistry routine would require modification and improvement based upon recent research. APLE represents state-of-the-science P chemical processes but runoff and erosion are user-defined and would thus require substantial user expertise or hydrologic input from some other models, such as SWAT or APEX.

Model output could be used to validate P indices in two different ways. First, annual P load estimates could be compared to P index results provided that weather-dependent transport factors were used as inputs in the P index. Second, the model could be run for many different weather scenarios to generate a long-term average annual P loss estimate. This could be accomplished by simulating P loss for multiple 1 to 5 year periods representative of the crop-rotation or the approximate nutrient management planning time period. For example, average annual P loss from a corn-soybean rotation could be estimated by running 30, 2-year scenarios, where each scenario contains different weather conditions. The resulting annual P loss estimates could be averaged over the 30-year time frame.

A thorough review of model-specific modifications that are required for P loss prediction, is beyond the scope of this report. However, the currently available widely used hydrologic contaminant transport models generally lack the following:

- simulation of P loss directly from P source,

- accurate simulation of dissolved P concentrations in runoff,
- simulation of downward P movement in the soil profile (P leaching),
- accurate simulation of P transformations and retention in concentrated flow (i.e., during transport from field edge to receiving surface waters), and
- variable source area hydrology.

Models should be tested to verify if they accurately predict:

- changes in soil P pools and soil P stratification during the time-span under consideration,
- P losses shortly following application of manures, litters, or fertilizers,
- effects of changes in STP on dissolved P concentrations in runoff, and
- effects of best management practices on P losses.

Because the P index is not a daily model, P loss models that run on an annual time-step could also generate acceptable P loss estimates for P index assessing purposes. The APLE model is an example of an acceptable annual-time step model for P loss prediction and has undergone rigorous assessment and uses a combination of process-based and empirical equations to estimate P loss from agricultural fields. APLE could also be used in combination with daily time-step models, where daily time-step models are used to estimate erosion and runoff for a wide range of weather conditions and the APLE model is used to estimate annual P loss based on erosion and runoff output of the daily time-step models.

Assessment with Modeled or Measured P Loss

A. *Model Calibration*

Model calibration is the process of adjusting model parameters within a reasonable range such that the models predictions more closely match available measured data. Though not required, calibration generally improves the predictive ability of a model.

A multi-level procedure to assess model performance at multiple scales would provide much needed model performance data against which various Indices could be assessed. For instance, the Chesapeake Bay regional P index team has proposed initializing various models (SWAT, APEX) in 'uncalibrated' mode (i.e., using literature based parameters), 'minimal calibration' mode (i.e., using expert knowledge) and with a more 'sophisticated calibration' mode (i.e., multi parameter automated calibration procedure) in order to test the ability of the models to assess field level responses. The comparison of calibrated and uncalibrated versions of the models can be used to assess the effect of applying these models without calibration. The later comparison would shed light on the potential for future site assessment tools to be derived from fate-and-transport models and applied without calibration, as would be expected with practitioner use. Further assessment should likely focus on the transferability of any model to fields or watershed for which there is little data available to calibrate the model against. Developing a protocol and guidelines for parameter transfer between similar physiographic or management regions, would need to be established before any of these models could reliably be utilized.

B. *Data availability*

Measured data suitable for model calibration are available (Table 2). Daily time step models require detailed management operation scheduling and weather data. These additional data must be assembled for each research site prior to calibration.

C. *Uncertainty*

All predictions contain uncertainty; the amount of uncertainty has a direct bearing on the utility of the information. Model validation provides an indication of uncertainty and a portion of the measured data should be reserved for this purpose.

There are two types of uncertainty. Input parameter uncertainty and process (model) uncertainty. Parameter uncertainty would further involve both the inherent variability associated with environmental processes and the precision with which we can measure the variable. For instance, we understand how P movement is controlled, but given the current measurement techniques we cannot fully resolve measurement of the parameters responsible with high precision and accuracy, and thus, will introduce uncertainty into the model. Process or model uncertainty is introduced by the assumptions and simplifications made in model development. As we do not fully understand all of the processes controlling runoff generation we simplify the process (e.g., the Curve Number), which also introduces uncertainty in model results.

It should be noted that there are inherent limitations associated with using simple P Indices to describe complex P loss processes. Furthermore, there exists innate variability in natural systems which can lead to significant uncertainties in P Index input variables such as runoff, erosion, and STP. As a result, a significant amount of uncertainty can be expected with any P Index output. Unfortunately, accounting for such uncertainties has not been addressed to a satisfactory degree. Because P Indices are powerful tools for extension, education, and management of agricultural P, future research must strive to reduce this uncertainty and to develop methods to include reasonable estimates of this uncertainty in P Index calculations. An example of a tool that could be used for this is @RISK commercial software which is a plug-in for Excel spreadsheets (http://www.palisade.com/decisiontools_suite/).

It must also be remembered that there is an inherent, unavoidable, and very large uncertainty in P Index inputs like STP, manure P composition, manure application rates, disturbance caused by tillage, soil characteristics from soil survey map unit descriptions, etc. These should be considered and at a minimum acknowledged.

D. **Using Measured Data for Assessment**

What data are available? We need to determine if there is really have a lack of data, or just a lack of organized or appropriate data? We have thousands of data points if we use event data, hundreds of data points if we use annual data, but very few data points if we use average annual data, realizing one would need more than 5 (generally 10 to 30) years of data to classify as a good average annual estimate. Is it acceptable to use data from outside the state or region? The Texas P Index, which predicted risk well when compared to water quality data collected in Texas, did much less well when compared to water quality data from throughout the southern United Sates (Osmond et al., 2012). To address these data questions, a group of predominantly ARS and NRCS researchers, led by Peter Kleinman (including Carl Bolster, Zach Easton, Daren

Harmel, Shaun McKinney, Lee Norfleet, Doug Smith, Mike White, and Peter Vadas), is developing a national database of existing and ongoing field data, which could be used as a source of information for this assessment. This effort builds on the MANAGE database established by Harmel et al., (2004).

Data in Table 2 are from 28 published studies that monitored P loss in runoff for at least one year. These studies provide annual rain, runoff, and erosion; initial STP; manure or fertilizer application; and field management data. Studies represent a wide variety of tillage and cropping practices, manure and fertilizer types and application methods, and geographic locations, including Ireland and Australia. These data represent a fairly thorough literature review, but there are undoubtedly more data that are available. For example, several more years of data from Harmel et al. (2004) exist beyond 2004 (Harmel et al., 2008). In addition, there are other published monitoring studies which report measured field P losses but may not contain the field management and soil characteristics information necessary for many P Indices, but this data may be obtainable from publication authors.

E. **Comparing Qualitative Risk with P Loss**

Many (but not all) qualitative P Indices assign a categorical rating to inputs such as erosion, runoff, STP, etc., even though these variables are continuous. These Indices were not intended to be an exact prediction of P loss, but rather an estimate of potential P loss under average annual conditions. One method would be to compare the qualitative index scale with ***average annual*** P loss estimates, or the average of P loss simulated for a wide range of weather conditions. Model output could be generated to represent P loss for the given management subject to a wide range of possible weather conditions, and then averaged prior to comparison with the Index.

At a minimum, the objective of assessing qualitative P Indices should be to describe the relationship between P Index rating and P loss. Comparison of P loss data to Index output will help determine if relative differences in P Index ratings are consistent (i.e., a 10% increase in the P Index rating always results in a 10% increase in P loss). Furthermore, because the P Index scale is drastically different among states, large discrepancies may exist between P management interpretations in adjacent states.

Table 2. Studies that have published data on P loss in runoff from natural rainfall for at least one year.

Source	Location	Plot Size, ha	Crop	Duration, months	P Source	Runoff Measurements
Angle et al. (1984)	MD	0.26-0.37	Corn	36	Dairy manure	Erosion, dissolved P, total P
Berg et al. (1988)	OK	2.7-5.6	Grassed, wheat	120	None	Erosion, dissolved P, total P
Burwell et al. (1975)	MN	0.009	Corn, oats, hay	72	Fertilizer	Erosion, dissolved P, total P
Cabot et al. (2006)	WI	0.01-0.03	Alfalfa	12	Dairy manure	Erosion, dissolved P, total P
Chinkuyu et al. (2002)	IA	0.4	Corn, soybean	36	Hen manure	Dissolved P
Edwards et al. (1996)	AR	0.57-1.46	Grassed	30	Poultry litter, grazing manure	Dissolved P
Gessel et al. (2004)	MN	0.007	Corn, soybean	36	Swine manure	Erosion, dissolved P, total P
Ginting et al. (1998)	MN	0.007	Corn	24	Beef manure	Erosion, dissolved P, total P
Harmel et al. (2004)	TX	1.2-8.4	Corn, pasture	36	Poultry litter, grazing manure	Erosion, sediment P, dissolved P
Jokela and Casler (2011)	WI	1.6	Corn silage	32	Liquid dairy manure	Erosion, dissolved P, total P
Jones et al. (1985)	TX	2.1-3.3	Grassed	72	None	Erosion, total P
Kimmell et al. (2001)	KS	0.006	Sorghum	24	Fertilizer	Erosion, dissolved P, bioavailable P, total P
Kurz et al. (2005)	Ireland	0.46-1.54	Grassed	15	Fertilizer, grazing manure	Dissolved P
Langdale et al. (1985)	GA	1.3-2.7	Corn, rye	12	Fertilizer	Erosion, sediment P, dissolved P
McDowell and McGregor (1980)	MS	0.01	Corn, soybean	18	Fertilizer	Erosion, dissolved P, total P

Moore and Edwards (2007)	AR	0.41	Pasture	120	Poultry Litter	Dissolved P
Owens et al. (2006)	OH	2.2-4.2	Pasture	132	Fertilizer, grazing cow manure	Dissolved P
Panuska et al. (2008)	WI	0.0146	Corn	12	Liquid Dairy Manure	Erosion, total P, dissolved P
Pierson et al. (2001)	GA	0.75	Pasture	36	Poultry litter, grazing manure	Dissolved P
Sistani et al. (2008)	MS	0.1 to 0.7	Pasture	24	Poultry litter, grazing manure	Erosion, total P
Smith and Monaghan (2003)	Australia	0.05-0.09	Pasture	36	Grazing cow manure	Erosion, dissolved P, total P
Soileau et al. (1994)	AL	3.8	Cotton, rye	72	Fertilizer	Erosion, dissolved P, sediment P
Sweeney et al. (2012)	KS	0.4	Sorghum	36	Fertilizer, turkey litter	Erosion, dissolved P, total P
Thoma et al. (2005)	MN	0.016	Corn	38	Swine manure, fertilizer	Erosion, dissolved P, total P
Vervoort et al. (1998)	GA	0.45	Grassed	30	Poultry litter	Dissolved P
Vories et al. (2001)	AR	0.6	Cotton	36	Poultry litter	Erosion, total P, dissolved P
Westerman et al. (1985)	NC	0.008	Grassed	72	Swine manure	Total P
Westerman et al. (1987)	NC	0.008	Grassed	48	Swine manure	Total P
Wood et al. (1999)	AL	0.001	Corn, rye	24	Fertilizer, poultry litter	Erosion, sediment P, dissolved P
Wortmann et al. (2006)	NE	0.004	Corn, soybean	36	Composted beef manure	Erosion, dissolved P, total P
Young and Holt (1977)	MN	0.001	Alfalfa, corn	36	Fertilizer, dairy manure	Erosion, dissolved P, total P
Zeimen et al. (2006)	KS	0.4-1.5	Sorghum, soybean	48	Fertilizer	Erosion, dissolved P, bioavailable P, total P

APPENDIX 1

What has Already Been Done to Assess Indices?

A brief summary of studies that have assessed P Indices and what was found follows.

Table A. Assessment of P Indices P loss risk assessment.

State	Source of data	Obs.	Type of data	r^2	Reference
AR	Measured P loss		Annual	0.59	DeLaune et al., 2004
AR	Measured P loss	26	Annual	0.09	Harmel et al., 2005
AR	Measured P conc. - cultivated	16	Annual	0.84	Harmel et al., 2005
AR	Measured P conc. - pasture	10	Annual	0.16	Harmel et al., 2005
GA	Measured P loss	36	Annual	Underrated risk by 2%	Butler et al., 2010
IA	Measured P conc. - pasture	26	Annual	0.31	Harmel et al., 2005
IA	Measured P conc. - cultivated	16	Annual	0.76	Harmel et al., 2005
IA	Measured P conc. - pasture	10	Annual	0.90	Harmel et al., 2005
KS	Measured P loss	90	Annual	0.79	Sonmez et al., 2009
KS	Measured P conc.	90	Annual	0.86	Sonmez et al., 2009
KY	APLE predictions	600	Annual	0.29	Bolster, 2011
MN	Stream P conc.	60	Individual samples	0.70	Birr and Mulla, 2001
MN	Lake P conc.	20	Individual samples	0.68	Birr and Mulla, 2001

NE	Measured P loss	32	Event	0.55	Eghball and Gilley, 2001
PA	SWAT predictions	22	Annual	0.79	Vieth et al., 2005
PA	Measured P loss	57	Event	0.81	Sharpley, 1995
PA	Measured P conc.	57	Event	0.79	Sharpley et al., 1995
TX	Measured P loss	9	Annual	0.20	Harmel et al., 2002
TX	Avg. P conc.	9	Annual	0.99 – 0.83	Harmel et al., 2002
TX	Measured P loss	26	Annual	0.31	Harmel et al., 2005
TX	Measured P conc. - cultivated	16	Annual	0.68	Harmel et al., 2005
TX	Measured P conc. - pasture	10	Annual	0.86	Harmel et al., 2005
WI	Measured P loss	86	Annual	0.84	Good et al., 2012

Few Indices have been assessed against field runoff data, in part because NRCS did not generally provide resources to test P Indices (Sharpley et al., 2012). A handful of studies, however, do exist which have assessed P Indices against measured P loss data (Table A). For example, Harmel et al. (2005) compared measured P runoff from a pasture and cropped watershed of the Texas Blackland Prairies with three Indices (from AR, IA, and TX). Even though the three Indices are fundamentally different, the Iowa and Texas Indices both provided reasonable estimates of P loss potential ($p < 0.01$; Harmel et al., 2005). Assessment of the Arkansas P Index by DeLaune et al. (2004) found that the Index reliably estimated P loss potential from pastures (r^2 of 0.59). The Pennsylvania P Index has been shown to be well correlated with measured P loss (r^2 of 0.79; Sharpley et al., 2001) and P loss vulnerability as determined by the Soil and Water Assessment Tool (SWAT; Vieth et al., 2005). Independent assessment of Indices in Georgia (Butler et al., 2010), Kansas (r^2 of 0.62; Sonmez et al., 2009), and Wisconsin (Good et al., 2012) all showed good agreement between risk of P loss and measured total P loss in runoff. Bolster (2011) assessed the Kentucky P Index against data generated for several hypothetical fields using APLE (Vadas et al., 2009) and found some important deficiencies in the Index.

The transport components of P Indices have proven difficult to completely test with measured data. Most P Indices that include erosion as a transport factor use RUSLE2 or a prior modification of the USLE all of which use average rainfall erosivities derived from long-term weather records to estimate average annual erosion. Runoff and drainage flow are also generally assessed as the most probable distribution given long term weather patterns. Erosion and runoff measured in any given year, however, will be influenced by that year's weather. For example, when the Wisconsin P Index was compared directly to annual P mass loss for a dataset that included measurements for 86 field years of measurement across 10 farms there was not a good correlation (Good et al., 2012). This was because the dataset included years of low and high precipitation and snowmelt, and this varying weather greatly influenced erosion and runoff.

Using measured sediment and runoff in this P Index calculation allowed testing of the equations estimate P mass in sediment and runoff based on soil and amendment characteristics; this is the comparison that resulted in the r^2 of 0.84 shown in Table A. With an adjustment to the particulate P component of the Index, the authors were able to get good estimations of total P yields (Nash-Sutcliffe Model Efficiency of 0.87). The erosion and runoff components of this P Index could not be assessed because there were insufficient field years under the same management at any site to obtain a long-term average measurement. In addition, the field-to-stream delivery component that estimates the effects of slope and distance of the field to surface water could not be tested with the field-monitoring results. Moreover, this comparison of field runoff with P Index rankings did not test whether the interpretation for nutrient management planning (the equivalent of 6 lbs P acre^{-1} year^{-1} delivered to surface water requires management changes) is adequate to protect water quality.

APPENDIX 2

The Regional CIG Process

The following CIGs were funded by USDA-NRCS at the end of 2012, to assess State P Indices across the U.S. For more information see http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/programs/financial/cig/?cid=stelprdb1048721

National Synthesis Project

Identify Methods to Refine Phosphorus Indices and Synthesize and Extend Lessons and Outcomes from Three Regional Indexing Efforts

Andrew Sharpley – PI

University of Arkansas (DE, MD, NY, PA, VA, WV, IA, KS, MO, NE, AR, FL, GA, KY, MS, NC, OK,

SC, TN, TX) $57,924

The overall goal of the project is to develop a national database of existing plot- and watershed-scale sites with more than three years of water quality measurement (flow and phosphorous concentration) and sufficient land management information to populate phosphorous indices and predictive models approved under the 590 Standard. This project will compare Phosphorous Index risk assessments with water quality data and validated predictive models for the combined field and watershed sites. It will also synthesize, summarize and describe the science-based information and lessons learned from the three regional Phosphorous Index assessment projects (i.e., Chesapeake Bay Watershed, the Heartland Region, and Southern States) and build a harmonized framework that yields consistent P based risk assessment across the U.S.

Chesapeake Bay States

Refining and Harmonizing Phosphorus Indices in the Chesapeake Bay Region to Improve Critical Source Area Identification and to Address Nutrient Management Priorities

Doug Beegle & Peter Kleinman – PIs

The Pennsylvania State University (DE, MD, NY, PA, VA, WV) $801,535

This regional project will coordinate the testing and revision of phosphorous management tools within the states encompassing the Chesapeake Bay watershed, with general objectives to harmonize site assessment and nutrient management recommendations with the NRCS 590 standard and to promote consistency within each of the Bay's four major physiographic provinces. This regional project is one of four (three regional, one national) proposed under coordination of SERA-17, with goals to support the refinement of state Phosphorous Indices and demonstrate their accuracy in identifying the magnitude and extent of phosphorous loss risk and their utility to improve water quality. The proposed project will promote innovations in phosphorous management at state (harmonizing Phosphorous Indices) and local (changes in behavior of farmers and/or technical service providers developing and implementing Phosphorous Indices) levels to enhance the health of the Chesapeake Bay. The project involves six objectives designed to ensure that refinement of Phosphorous Indices is grounded in the best available science, reflects local conditions and concerns and anticipates impacts to water quality and farm management.

A. ***Establish a network of 11 watersheds for foundational assessment of nutrient management site assessment tools***

We will establish a network of 11benchmark watersheds for assessing the P Indices across the Chesapeake Bay watershed, where most sites have historical water quality monitoring (edge-of-field to watershed); Mahantango Creek watershed data are available on-line from ARS's STEWARDS website (http://www.ars.usda.gov/Services/docs.htm?docid=21452; Table B). For each watershed, we will develop databases in support of activities under subsequent objectives of the project. Water flow and quality data are available at varying scales within most of the project watersheds. These data will be assembled in relational databases that enable spatial and temporal dynamics to be queried as well as annual averages to be summarized. Working with farmers, planners, conservation districts, and state nutrient management commissions, we will obtain information from representative nutrient management plans within each watershed to describe the range of conditions found in that watershed. Data will be georeferenced and compiled into a relational database for future query. In addition, we will make individual datasets (geographically aggregated to ensure confidentiality of producers) available on a per-request basis to modelers and others engaged in nutrient management evaluation.

B. ***For each physiographic province, identify site conditions and practices of priority concern and corresponding remedial practices of greatest efficacy and adaptability***

Expert panels will be established within each of the four physiographic provinces. Panels will include members of the project team, extension and action agencies (NRCS/state agencies/cooperative extension/conservation districts), farmers, local environmental groups and tributary action teams, and private sector farm advisors (CNMP planners). Panels will be charged with identifying site conditions and management practices of priority concern within a province. Specifically, what conditions (source, transport, management) are recognized as priority concerns, what conditions have been under-addressed, and what conditions require additional consideration? Panels will also establish a list of priority manure and fertilizer management practices that, if implemented, are expected to lower the potential of P loss from fields (i.e., BMPs where implementation should be incentivized by a P management tool).

Each panel will review representative nutrient management plans as well as pertinent studies related to P fate-and-transport in order to establish a common understanding of both the state of P management and the state of P science in each province. The priority site conditions and priority management practices identified by the panels will be used to (a) assess strengths and shortcomings in existing site assessment tools (P Indices and models) and (b) provide a list of core management recommendations that should be addressed by P site assessment tools. The first outcome is needed to ensure confidence in results generated by P Indices and fate-and-transport models. The latter outcome is critical to ensuring that nutrient management planning incentivizes the appropriate BMPs needed to enhance water quality.

Table B. Characteristics and data availability at field sites used for the Chesapeake Bay states P-Indices assessment.

Project watersheds	Agriculture	Watershed monitoring		Edge-of-field monitoring		Topography	Field mgt. / Nutrient mgt. plan
		Flow	Water quality	Flow	Water quality		
Atlantic Coastal Plain							
Manokin River Watershed (MD)	Poultry, crop	USGS	USDA-ARS, Del, NREC, Naticoke Creekwatchers	UMES/USDA-ARS	UMES/USDA-ARS	LiDAR DEM	Cooperating farms, Univ. Maryland
Naticoke River Watershed (DE/MD)	Poultry, crop, intensive irrigation	USGS, Del, NREC		- -	Naticoke Creekwatchers	LiDAR DEM	Cooperating farms, Univ. Del, Univ. Maryland, Del Nutrient Mgt. Commission
Appalachian Piedmont							
Antielem Creek Watershed (MD)	Dairy, crop	--	--	--	--	LiDAR DEM	Univ. Maryland
Conewago Creek Watershed (PA)	Dairy, poultry, swine, crop	USGS	USGS	USDA-ARS	--	LiDAR DEM	Penn State, cooperating farms and planners

Appalachian Valley and Ridge								
Anderson Run (WV)	Poultry, crop	--	--		--	--	USGS DEM	Cooperating farms and planners
Mahantango Creek (PA)	Dairy, poultry, swine, crop	USDA-ARS Penn State, USGS	USDA-ARS Penn State, USGS		USDA-ARS Penn State,	USDA-ARS Penn State,	LiDAR DEM	ARS database/cooperating farms
Spring Creek (PA)	Dairy, crop						LiDAR DEM	Cooperating farms and planners
Allegheny Plateau								
Glade Run Watershed (WV)	Dairy, crop	--	--		--	--	USGS DEM	Cooperating farms and planners
Anderson Run Watershed (PA)	Dairy, crop	--	--		--	--	LiDAR DEM	Cooperating farms
Town Brook Watershed (NY)	Dairy, crop	USGS	USGS SWCD			USC and local farm	USGS DEM	Cornell database, cooperating farms, SWCD
Elk Creek Watershed (NY)	Dairy, crop	USGS	USGS SWCD		--	USC	USGS DEM	Cornell database, cooperating farms, SWCD

C. ***Assess P site assessment tools by comparing their output with water quality monitoring data and fate-and-transport models***

We will assess the accuracy of state P Indices in predicting P loss potential within individual physiographic provinces, focusing on select watersheds to compare output from components of a P Index and the entire P Index with observed (monitored; Table B) and modeled P loss. The suite of models coupled with measured data will allow us to better understand which component of the P Index (source or transport) is critical to consider in each region.

Three fate-and-transport models will be applied to at least one project watersheds in each of the physiographic provinces: SWAT (Neitsch et al., 2011); APEX (Wang et al., 2011); and a coupling of the *transport* model, Drainmod, with a *source* model, APLE (Vadas et al., 2009). In upland watersheds, SWAT and APEX will be applied, enabling both edge-of-field and watershed scale assessment of P transport processes. Both a SWAT model with variable source area hydrology (VSA hydrology) developed by Easton et al. (2008) and conventional hydrology will be compared against each other and the existing P Indices. Variable source area hydrology predominates in much of the Chesapeake Bay watershed, so an initial effort will be made to assess the advantages and limitations of employing SWAT with and without its VSA. Past research has shown that the VSA-approach allows managers and producers to more easily manage farm units (e.g., fields) at finer resolutions both spatially and temporally, which will increase the options for managing nutrients on fields.

In the Atlantic Coastal Plain, DrainMod will be applied, coordinating closely with the Southeastern regional P Index initiative that will also be applying DrainMod to coastal plain conditions. While DrainMod is thought to adequately represent hydrologic transport processes, its representation of P chemistry requires modification and improvement based upon recent research. Therefore, APLE, a spreadsheet based P routine where runoff and erosion are user defined will be employed to represent P chemical processes.

We will calibrate the fate-and transport models with existing data from at least one watershed in each of the four physiographic provinces. When local data are not available (e.g., edge-of-field runoff is missing from many watersheds), comparable data from an adjacent watershed or from another project watershed within the same physiographic province will be employed. Calibrated and uncalibrated versions of the models will be compared to assess the effect of applying these models without calibration. The later comparison is expected to shed light on the potential for future site assessment tools to be derived from fate-and-transport models and applied without calibration, as would be expected with practitioner use.

Heartland Region States

Validate, Improve and Regionalize Phosphorus Indices to Reduce Phosphorous (P) Loss across the Heartland Region

John Lory – PI

The Curators of the University of Missouri (IA, KS, MO, NE) $531,622

This project will advance phosphorous management in the U.S. by developing and demonstrating procedures that ensure Phosphorous Indices are appropriately tested in accordance with the 2012 NRCS 590 Standard by meeting the following objectives:

- Identifying the most effective strategies for using the Agricultural Policy Environmental Extender, an existing fate-and-transport model, to assess P Indices using data from existing watershed and large-plot studies;
- Assessing and improve current P Index formulations in Iowa, Kansas, Missouri and Nebraska; assess and compare potential P Index formulations for use as a regional P Index in the humid regions of Iowa, Kansas, Missouri and Nebraska;
- Engaging farmers, technical service providers, stakeholder groups, state and regional regulators and state NRCS staff to facilitate acceptance of recommendations in each state, facilitate more consistency across state borders, and demonstrate the utility of validated, calibrated P-indices for reducing P loss and protecting water quality; and
- Collaborating with similar projects in Chesapeake Bay, the South, and the national overarching CIG project to facilitate application of results to humid regions of the U.S.

A. ***Demonstration the effectiveness of three strategies for using APEX***

The project will first establish the degree of rigor and specificity of location needed in calibrating the APEX model for generating data for testing P Indices. We will compare the outcome of three potential calibration strategies to measured flow and phosphorus loadings from five sites in the region (referred to as “Tier 1” sites) that have sufficient data to calibrate APEX in 34) small watersheds representing 27 management systems (Table C). These five Tier 1 sites will have four to 20 years of data. For each of the three calibration strategies, the error will be quantified with the root mean square error (RMSE) between measured and simulated results.

The three calibration strategies will be:

1. APEX out-of-the-box strategy using limited local data to calibrate APEX

Scientists and modelers involved with the CEAP cropland modeling have expended considerable efforts developing a methodology to parameterize APEX for the Natural Resources Inventory sites (Wang et al., 2011). We will rely on their methodology and the corresponding version of the model as our out-of-the box parameterization strategy. Typically, site specific input data will be derived from national or regional databases. Soil information will be extracted from SSURGO soil maps and associated characteristics. Topographic parameters will be determined from USGS 10-meter digital elevation models (DEM). Management will be site specific as we assume that one would want to assess P losses associated to a specific management. Management includes dates and types of tillage, dates and information on fertilization operations, grazing periods and characteristics, dates of planting and harvest operations. Model options, control and global parameters will be set to values identified during the cropland CEAP project and outlined by Wang et al. (2011).

2. Rigorous calibration strategy for APEX for each local dataset

We will test the different options of the model (curve number estimation, erosion prediction equation, estimation of field capacity and wilting point, denitrification equation) and identify those best suited for each site. Measured flow, crop yields and P loadings will be compared to model results on an event or monthly basis using quantitative criteria such as the percent bias, coefficient of determination, and Nash-Sutcliffe efficiency, which are described in Moriasi et al. (2007). The comparison during the calibration period will drive parameter adjustments while a similar comparison during the validation period will ensure that the model is not over-parameterized. Parameter adjustments will be informed by published sensitivity analyses (Wang et al., 2006, Mudgal et al., 2010, Wang et al., 2012) and the experience of the modelers.

Table C. Characteristics and data availability at field sites used for the Heartland P-Index assessment.

Name	Location County, State	Monitoring period	Management of field-scale watersheds[1]			Water measurements[2]	Contact	Relevant publications
			Trts[3]	Fields. (average size)	Details			
TIER 1 SITES								
Greenley	Knox, MO	1991-present	3	3 (3 Acres)	C-SB, NT with grass and agroforestry buffers.	Q, Sed, TP, TN	R. Udawatta	Udawatta et al., 2002; 2004; 2011
HARC	Howard, MO	2000-present	3	3 (~1 Acre)	GP with grass and agroforestry buffers	Q, Sed, TP	R. Udawatta	Udawatta et al., 2010; Kumar et al., 2011
Neal Smith	Jasper, IA	2007-present	4	12 (3 Acres)	C-SB, NT with prairie filter strips	Q, Sed, TP, TN, NO_3	M. Helmers	Zhou, et al., 2010
Franklin	Franklin, KS	2001-2004 2006-2009	3 2	6 (2 Acres)	GS-SB and C-SB, T, NT, surface and sub-surface fertilizer application	Q, Sed, TP, DP	N. Nelson (K. Janssen manager)	Zeimen et al., 2006; Maski et al., 2008; 2010; Anand et al., 2007; Sonmez et al., 2009
Crawford	Crawford, KS	2001-2004 2005-2007 2011-present	4 5 3	10 (1 Acre)	GS-SB and GS, T, NT, surface and incorporated poultry litter and fertilizer	Q, Sed, TP, DP	D. Sweeney & N. Nelson	Zeimen et al., 2006; Sonmez et al., 2009; Sweeney et al., 2012

TIER 2 SITES								
Treynor	Pottawattamie, IA	1976-1995 1998-2003	1	4 (75 Acres)	C-SB, CT then NT with conservation practices	Q, Sed, TP, TN, NO_3,	M. Tomer	Schuman et al., 1975; Wang et al., 2008; Karlen et al., 2009
Sutherland Farm	O'Brien, IA	2007-2011	5	5 (0.3 Acre)	C-C, C-SB, T, NT, fertilizer P and liquid manure	Q, Sed, TP, DP,	A.P. Mallarino	Mallarino et al., 2010a; 2010b
Centralia	Boone, MO	1992-2002	3	3 (30 Acres)	C-SB, T, NT, surface vs. incorporated and uniform, vs. variable rate fertilizer	Q, Sed, DP	C. Baffaut	Ghidey et al., 2010 Mudgal et al., 2011
Missouri MRBI	Audrain (2), Chariton (2), and Linn (3), MO	Initiated 2010 or 2012	7	7 (1 Acre)	C-SB, w/wo terrace, w/wo grass waterway	Q, Sed, TP, TN	R. Udawatta	
McPherson	McPherson, KS	2008-2010	2	2 (4 Acres)	GS, T, NT	Q, Sed, TP	P. Barnes & N. Nelson	
Washingto n	Washington, KS	1999-2001	2	2 (2 Acres)	GS, T, NT	Q, Sed, TP	P. Barnes & N. Nelson	Rector, 2001
U.S. Meat An. Res. Center	Clay County, NE	1976-1978	1	1 (100 Acres)	Seasonally GP	Q, Sed, TP, TN, NO_3	J. Doran M. van Liew	Doran et al., 1978; 1981

[1] Management abbreviations: C-C=continuous corn; C-SB=corn-soybean rotation; GP=grazed pasture; GS=grain sorghum; T=tilled, NT=notill; w/wo=with and without.

[2] Water measurement abbreviations: Q=surface water flow; Sed=sediment; TP=total P, TN=total nitrogen, NO_3=nitrate-N, DP=dissolved P.

[3] Treatments affecting P loss.

3. Regional parameterization of APEX

The objective of this step is to develop a regional calibration of APEX for the Heartland region based on a comparison of the parameter sets and model options obtained in steps 1 and 2, specifically the identified parameters requiring calibration in those steps. Regional values will be developed for those parameters.

We have also identified 24 small watersheds in the region with sufficient data to parameterize APEX but not to calibrate the model (Table C). The regional model will be further validated by applying it to the Tier 2 sites and comparing simulated results to measured data using RMSE.

B. ***P Index assessment with APEX***

The field-scale P loss data that will be assembled for the APEX calibration and validation represent a unique dataset that could be used to directly assess the P Index. This dataset is impressive in size (over 200 site years of data) but it is limited by the fact that it represents only 27 soil-cropping-management systems of which only 3 sites have greater than 5 years of runoff data under constant management. The losses for these datasets are for the specific weather sequences that occurred during monitoring whereas P Indices are designed to rank the relative risk of P loss from sites for unknown future weather sequences, not for a specific past year or even past 5-year sequence. APEX simulations will be used to overcome the inconsistency between the limited time-scale and weather sequence of the observed data and the intent of the P Index to assess potential P losses over unknown future weather sequences. The APEX simulations will also be used to increase the number of soil-cropping-management scenarios from 27 to over 70, thereby allowing assessing of the P Index over a wider range of P loss conditions.

Tier 2 sites will be utilized to generate datasets for the purpose of assessing and improving the P Indices (Table C). The revised P Indices will then be assessed based on datasets generated at the Tier 1 sites using the fully calibrated models. Specifically, the following steps will occur sequentially:

1. Generation of datasets at Tier 2 sites

We will use the out-of-the-box (see step 1 above) and the regionally parameterized (see step 3 above) APEX models to estimate average-annual P losses for a range of management scenarios and STP values at all Tier 2 sites (Table C). Management scenarios will be adapted to each site and include changes in P source application methods and timing; tillage systems; and field buffers. Soil test P will be changed between a range of low (i.e., 10 ppm) and very high (i.e., 500 ppm). The APEX model will be used to simulate P loss from these soil-cropping-management systems for 30 simulation periods of a duration to be determined in accordance with the permitting cycle for which the Index is intended to operate. This duration typically varies from 1 to 5 years, depending on the state. By representing 30 such cycles, we can assess a wide range of weather scenarios and determine an average estimated P loss given the uncertainty of future weather.

2. Assessment and improvement of the state P Index at Tier 2 sites

A P Index rating will be determined for each of the simulated soil-cropping-management systems at each Tier 2 site using the corresponding state P Index currently in use. Effects of the changes in management and initial soil P will be assessed individually for each site and collectively for all sites. Resulting average annual P loss estimated with each of the two APEX models, i.e., out-of-the-box and regional parameterization, will be compared to current P Index values or ratings using trends and correlation analysis tools, e.g., single and multiple regression analysis, analysis of variance. The comparison will be used to determine if the P Index structure and weights are appropriate for representation of P loss under the tested conditions and to adjust them using systemic search guided by the investigators expertise and the model results. It will also lead to the identification of P Index factors that need to be incorporated into a regional Heartland P Index as well as corresponding weights. This process will lead to two sets of updated P Indices for each state and two regional P Indices; one set developed using the out-of-box version of APEX and one set developed using the regionally calibrated version of APEX. Given the number of sites and the proposed number of runs, the process of altering input files on one hand, and reading and synthesizing output files on the other hand, will be automated.

3. Generation of P Index validation datasets at Tier 1 sites

The fully calibrated APEX models at the Tier 1 sites are those in which we expect to have the most confidence; we will therefore use them to generate P loss values that cannot be obtained through experiments and water quality monitoring. For each site, we will automatically generate average annual P losses for a range of management scenarios and STP values. Similarly to what was done in step 1, management scenarios will be adapted to each site and will include changes in STP, P source application methods and timing, tillage systems, and field buffers. The APEX model will be used to simulate P loss from these soil-cropping-management systems for 30 simulation periods of a duration adapted to the rotation and the permitting cycle for which the P Index is intended to operate.

4. Assess the performance of the P Indices developed in step 2

The four improved state P Indices and the two regional P Indices will be assessed using the data generated in step 3 using methods similar to those used in step 2. Average annual P losses will be compared to P Index values using trends and regression analysis tools. Performance measures for these P Indices will be used to validate the proposed state P Indices, determine what proposed regional P Index performs best, and simultaneously determine what level of APEX calibration is needed to develop a P Index.

From this analysis we will be able to compare the performance of P Indices assessed and improved using out-of-the box and regionally calibrated APEX.

Southern Regional States

Refine and Regionalize Southern Phosphorous (P) Assessment Tools Based on Validation and State Priorities

Deanna Osmond – PI

North Carolina State University (AR, FL, GA, KY, MS, NC, OK, SC, TN, TX) $472,962

The major objective of the project is to coordinate and advance phosphorous management in the South by ensuring that most southern phosphorous assessment tools have been tested based on guidance in the 2011 NRCS 590 standard and compared to water quality data. The project will also use these tools to produce more consistent results across physiographic regions in order to promote greater similarity between regional Phosphorous Index ratings and recommendations.

A. ***Collect pre-existing quality and land treatment data from watershed or plot-scale (11) sites where nutrient management site assessment tools can be reliably assessed for accuracy in predicting site P loss potential and in generating nutrient management recommendations that will improve water quality.***

Twenty-one water quality data sets are available from multiple agroecological and physiographic regions throughout the south (Table D). We will use existing water quality monitoring sites to establish a network of benchmark sites that will provide a foundation for current and future testing of nutrient management tools (P Index) as most of these plots and/or watersheds provide both land use and water quality information. We are NOT requesting funds to establish new monitoring sites or to carry out water quality monitoring. Rather, we have identified watersheds/plots where project members or associates have a history of on-farm or on-station nutrient management research.

Water quality data has been collected in Arkansas, Georgia, Mississippi, North Carolina, Oklahoma, and Texas (Table D). At some of these sites there exists substantial historical water quality monitoring data (edge-of-field to watershed). These sites represent a range of agro-ecological areas, cropping systems, nutrient application rates, and tillage. In addition, we will identify studies included in the data set used to validate the APLE model (Vadas et al., 2009) that can be used as part of our model and P Index assessment process. This data set includes values of annual P loss measured from field plots of varying size under a variety of climatic and land management conditions. The data have a twofold purpose; 1) we will compare southern P Index assessments against water quality data (Objective B) and 2) the data will be essential for model calibration and validation (Objective C).

Table D. Characteristics and data availability at field sites used for the Southern states P-Indices assessment.

State	Region	Cropping system	Number of locations	Acre(s)	Year(s)	Measured parameters	Treatment(s)
AR	Ozark Highland	Pasture	6	1	4	Runoff volume, P and N forms	Check; continuous grazing & 1.5 t/ac litter; hay & 1.5 t/ac litter injected; hay & 3 t/ac litter injected
AR	Ozark Highland	Soybean/rice	2	20/70	1	Runoff volume, P and N forms	Land-grant fertilizer recommendations to no-till and conventional
AR	Ozark Highland	Rice	3	75	1	Runoff volume, P and N forms	Land-grant fertilizer recommendations
AR	Ozark Highland	Corn	1	75	1	Runoff volume, P and N forms	Land-grant fertilizer recommendations
AR	Ozark	Pasture	4	1.5-3.8	4.5	Runoff volume, P and N forms	Grazed, poultry litter or commercial fertilizer application
GA	Piedmont	Pasture	9	6-109	1.5-2.0	Runoff volume, P and N forms	Producer dependent
GA	Piedmont	Forest	3	6-109	1.5-2.0	Runoff volume, P and N forms	None
GA	Piedmont	Pasture	6	2	2	Runoff volume, P and N forms	Variable rates of poultry litter
NC	Piedmont	Pasture	2	133-193	4	Runoff volume, P and N forms	Variable rates of poultry litter, fertilizer, and/or biosolids
NC	Piedmont	Corn/ soybeans	2	17-123	4	Runoff volume, P and N forms	Variable rates of fertilizer
NC	Mountains	Sweet corn	20	0.07	2	Runoff	No fertilizer; poultry

						volume, P and N forms	pellets; conservation tillage and plow
MS	Delta	Cotton/ soybeans	2	28-35	4	Runoff volume, P and N forms	Fertilizer, conservation tillage
OK	Ozark	Pasture	8	1-5.4	1	Runoff volume, P forms, sediment	Grazed, hayed, poultry litter and no poultry litter
OK	Southern Central Semi-arid Prairie	Pasture	12	10	6	Runoff volume, sediment	Grazed, no fertilization
OK	Southern Central Semi-arid Prairie	Cropland	6	10	6	Runoff volume, sediment	Cultivated wheat with commercial fertilizer
OK	Southern Central Semi-arid Prairie	Pasture	4	20-27	3.5	Runoff volume, N and P forms, sediment	Rangeland, no fertilization, grazed
OK	Southern Central Semi-arid Prairie	Cropland	5	13-45	4.2	Runoff volume, N and P forms, sediment	Cultivated small grains and irrigated cotton
OK	Southern Central Semi-arid Prairie	Cropland	2	7	5.5	Runoff volume, P forms, sediment	Grazed native range, no fertilization
OK	Southern Central Semi-arid Prairie	Pasture	6	7-14	10	Runoff volume, P forms, sediment	Cultivated wheat, commercial fertilizer
TX	Southern Central Semi-arid Prairie	Cropland	6	10-20	2.5	Runoff volume, N and P forms, sediment	Cultivated row crops and small grains, animal manure application
TX	Southern Central Semi-arid Prairie	Pasture	6	3-20	4.7	Runoff volume, N and P forms, sediment	Grazed, animal manure application

B. ***Compare predictions of P Index assessment tools to water quality data derived from the benchmark sites***.

Project participants will provide not only water quality data but also land use data. The southern P Indices require over 40 land use and field site characteristics although any individual P Index uses no more than 10 parameters (Osmond et al., 2006). The necessary parameters to run the P Indices will be collected for each watershed. This information will be transferred to each state in order to run the P Indices for each given watershed. State P Index ratings will be regressed against water quality data to determine goodness of fit (Osmond et al., 2012). Then southern P Indices will be compared to each other to determine if the type (component or relative) of P Index matters. For instance, are component P Indices (more processed based by loss pathway) or qualitative P Indices (based on Lemunyon and Gilbert model) better able to represent P losses? In addition, as a group we will begin to assess our P Indices to consider how they could be changed.

C. ***Compare predictions of P Index assessment tools against fate and transport water quality models (APEX, EPIC, and SWAT/PPM) for both calibrated and uncalibrated model conditions. Use APLE to better predict source contributions from manure pools. Use DrainMod to better predict leaching and overland losses in drained soils. Compare the fate and transport models against the water quality data. Use water quality data (monitored or predicted by model) to guide refinement of P Indices.***

We will use five models to compare to P Indices in our region: APLE, APEX, DrainMod, EPIC, and PPM Plus. These models were chosen because they simulate P losses at the field to small-watershed scale and they have been used successfully in our region. Although DrainMod does not simulate P transport, it could be used to test the ability of some P Indices to estimate the amount of water lost to drainage. This is especially important for use of P Indices in coastal plain physiographic regions, such as North Carolina and Florida, where P leaching occurs.

The models and P Indices will first be compared using the data from the benchmark sites. The input data for running the models varies but in general it includes soil physical and chemical properties by horizon, STP, weather data (rainfall, temperature, and potential evapotranspiration), and management information (crop, fertilizer and manure applications, grazing, and tillage operations). Some of these properties can be estimated using soil texture (for example water holding capacity, saturated hydraulic conductivity, and P adsorption coefficient).

For the Modified APLE model, runoff and erosion will be calculated using the SCS curve number method and RUSLE2, respectively. Measured data from the benchmark sites for comparison to the model predictions include runoff, erosion or suspended sediment concentration, forms of P in runoff, and in some cases tile drain or ditch discharge and forms of P. Models will be run in three modes; uncalibrated (using default parameter values, SSURGO soil data, USGS 10-m digital elevation model data, and site-specific management), regionally calibrated (using regional values for parameters that are unlikely to vary from field to field), and site-specific calibrated (full calibration of all parameters). This should show the extent to which the models have to be calibrated for fields that are not typical of the benchmark sites.

The benchmark sites will be grouped by physiographic region (Piedmont, Coastal Plain, and Ozark Plateau). Where there are multiple benchmark sites within a region, we will use some of the sites for calibration, making adjustments to the model parameters to provide the best fit to observed data. Then we will use the other sites for validation, running the calibrated models from the other sites without adjusting the model parameters to see how well they do. This process will tell us which of the models are most accurate and should be used to modify P Indices. We may be able to perform the model validation in cooperation with the other regional projects which have benchmark sites in the same physiographic regions as our project (Piedmont and Coastal Plain in the Chesapeake project; Ozark Plateau in the Heartland project).

The benchmark sites typically contain different treatments such as manure application rate, STP, or crops and the models will be run for all of these scenarios. The accuracy of the models will be quantified using scatter plots of predicted vs. observed output (runoff, P loss, erosion, etc.). The trend line will be compared to the 1:1 line and R^2 for model fit to the data will be determined. Model efficiency and root mean squared errors will also be compared. The models will also be compared to the various P Indices for the benchmark site scenarios.

Scatter plots of model predicted output and the P Index output will be used for comparison. Outputs will include total P loss from the models vs. P Index numerical rating, but other outputs of the models will be compared to transport and source components of the P Indices. For example, since DrainMod does not predict P it will not be possible to compare P losses with P Indices. However, it will be possible to compare DrainMod predicted water loss via drainage to the drain loss component in APEX and in some P Indices (such as the Georgia P Index which estimates deep drainage water loss as a transport component).

The APLE predicted P loss and the EPIC predicted P loss can be compared to measured loss to see if there is an advantage in using the additional P source processes in APLE. Note that the P Indices will be predicting a long-term average annual P loss or risk for the benchmark site scenarios whereas the models will be predicting a loss for the particular year (using the weather for that year) when the measurements were made. To address this difference, we also run the models for a 30-year weather scenario that will provide the long-term predicted losses for comparison to the P Indices.

Ideally, accurate models could be used to expand the test data for P Indices beyond the benchmark sites. That is, a model that is shown to produce accurate results at the benchmark sites could be used to run scenarios (soils, crops, weather) that were not represented in the benchmark site datasets. Bolster et al. (2012) did this by using a Monte Carlo approach to run APLE and the Pennsylvania P Index for a wide range of inputs including precipitation, STP, soil clay content, soil organic matter content, manure incorporation %, mineralization rate, and total fertilizer P applied. They used MATLAB to run the Monte Carlo system and programmed APLE into MATLAB.

We will use a similar approach to run APLE and the P Indices in our proposal. We will also investigate the possibility of running PPM Plus and EPIC using MATLAB. These models are too complex to program in MATLAB so we will need to call the executable file for each model and write the input file and read the output files of the models. At this point, we are not certain we will be able to do this. Alternatively, we may use the PEST (Parameter Estimator; Doherty, 2004) program to run the models. PEST is designed to run FORTRAN models in batch mode. However, this would require programming the P Indices in FORTRAN. The Monte Carlo results will be used to make scatter plots of the model predictions and the P Index predictions as described above. The Monte Carlo results will also be used to measure the uncertainty in the model and P Index predictions (95% confidence limits).

The results of the model and P Index comparisons will be used to guide refinement of the P Indices. We expect to find that some models are more accurate than others, overall or in predicting certain processes. The best P loss models will be used to determine which P Indices are better predictors of P loss risk and be used to guide changes to improve the P Indices. Some of the questions we will address are:

- Are there important differences in P Index accuracy based on how a P Index is formulated?

- Are the weights assigned to different sources and processes appropriate?
- Are there important processes that are not part of P Indices (drainage) or that are poorly modeled?
- How well do P Indices estimate transport and source components?

D. ***Refine P Indices to ensure better consistency in ratings across state boundaries and within physiographic provinces***

The southern states represent multiple physiographic areas and cropping systems. Some states have similar regions – such as Florida, Georgia, and North Carolina – but other states cross physiographic boundaries with multiple states. For instance, Texas has Blacklands (more common with MS), coastal plain, but also prairies (more similar to OK).

Objectives B and C allow project participants and relevant NRCS and state-partners the opportunity to compare state P Indices against water quality data and other models in order to determine the magnitude and directionality of P Index results. This will help project participants to determine if state P Indices need changes and also to improve cross-state P Index ratings based on physiographic regions. Thus, the project investigators, in association with state and federal partners, will meet yearly to discuss potential changes to state P Indices to encourage better standardization, while maintaining unique state characteristics and needs. The P Indices will be refined, when possible, to reflect input from Objectives B and C and to ensure better consistency within physiographic provinces across state boundaries.

Ohio

Evaluating/Updating the Ohio Phosphorus Risk Index Using Field-Scale, Edge-of-Field Monitoring Data

Libby Dayton – PI

The Ohio State University (OH) $999,987

This project proposes to assess and as necessary revise and update the current Ohio Phosphorous Risk Index through use of field-scale, edge-of-field monitoring data. It will quantitatively, integrate additional best management practice (BMPs) options into the Ohio Phosphorous Index and develop a web-based, easy to use, interactive geographic information system (GIS) tool (web-based tool) that allows producers to easily calculate their Ohio Phosphorous Index scores. The project will also choose from a suite of additional BMP options to aid with management decisions to reduce their risk of phosphorous transport (Ohio Phosphorous Index scores). This web-based tool will also be used for education purposes and to actively promote increased implementation of the revised/enhanced Ohio Phosphorous Index. Significant statistical analyses will be required to assess/revise the Ohio Phosphorous Index, integrate additional BMP options and to develop the on-line web-based interface.

A. ***Project Summary***

The objective of this work is to assess and as necessary revise the Ohio P Risk Index (Ohio P Index) by establishing field-scale, edge-of-field (EOF) monitoring facilities around Ohio. Data from these facilities will be used to 1) validate and as necessary revise the Ohio P Risk Index 2) Quantitatively, integrate additional best management practices (BMPs) into the Ohio P Index and 3) An online, web-based, interactive GIS tool (online tool) will be developed and used to actively promote the revised/enhanced P Index. With increased degradation of surface water in Ohio, agriculture is being cast in the role of the villain. A robust functioning Ohio P Index will give farmers a tool to manage field scale P transport, while sustaining agricultural productivity and protecting surface water quality. The Ohio P Index is used to develop nutrient management plans (NMPs) for both manure and commercial fertilizer. Ensuring that these plans are scientifically valid and sufficiently protective of surface water quality, demonstrates good stewardship by the agricultural community. This work will increase the utility and implementation of the Ohio P Index beyond a tool used merely to assess risk of P transport, into a tool producers can use to make management decisions to reduce their risk and thus, their Ohio P Index score.

B. ***Project Objectives***

The objective of this work is to validate and as necessary revise the Ohio P Risk Index (Ohio P Index) by establishing field-scale, edge-of-field (EOF) monitoring facilities around Ohio. Data from these facilities will be used to 1) validate and as necessary revise the Ohio P Risk Index 2) Quantitatively, integrate additional best management practices (BMPs) into the Ohio P Index and 3) develop an online, web-based, interactive GIS tool (web-based tool) to calculate Ohio P Index scores, and actively promote the revised/enhanced Ohio P Index.

In Ohio, the risk of agricultural P transport to surface water is assessed by the Ohio USDA-NRCS P Index Assessment Procedure (Ohio P Index) within the Nitrogen and P Risk Assessment Procedures.
http://efotg.nrcs.usda.gov/references/public/OH/Nitrogen_and_Phosphorous_Risk_Assessment_Procedures.pdf

Why focus on improving the Ohio P Risk Index? The answer is implementation. The Ohio P Index is used for every nutrient management plan (NMP) for manure or commercial fertilizer issued in Ohio. These plans are required if a producer wants to participate in USDA conservation programs and for concentrated animal feeding operations (CAFOs). This work is especially timely considering the increased emphasis on using P Indices and minimum requirements for P Indices discussed in the revised 590 Nutrient Management Standard. A precedent has already been set in the Grand Lake St Marys watershed for imposing additional rules on farmers once a watershed is deemed "distressed". Including the western basin of Lake Erie in the "distressed" category is a looming possibility. Additional rules include increased documentation which includes NMPs.

Further, in the current Ohio P Risk Index farmers are given credit, as reflected by reduction in their P Index scores, for only a very few BMPs. Increased BMP options in the Ohio P Index will allow credit for conservation efforts and allow farmers to make management decisions that will be reflected in lower P Index scores as well as actual lower P transport risk. Requested for this project are up to 32 Ohio farm fields, with a special emphasis on the **Grand Lake St. Marys,** and the **Western Lake Erie Basin**. However any Ohio farm field could be considered.

This work will increase the utility and implementation of the Ohio P Index beyond a tool used merely to assess risk of P transport, into a tool farmers can use to make management decisions to reduce their risk of P transport and thus, their Ohio P Index score. Specific objectives of this project are:

C. ***Objective 1 - Evaluate and as necessary revise the Ohio P Risk index so we are confident that it accurately predicts/quantifies risk of P loss (transport) at the edge-of-field***

Both source and transport factors (and weighting) used in the Ohio P Index to calculate the risk of P transport or score need to be assessed/revised. There must be a mathematical relationship between Ohio P Index scores and **edge-of-field endpoints (EOF), runoff and tile drainage water P concentrations/load, and in-field management practices (Ohio P Index score)**. To provide information to build quantitative models (objective 2), long-term (minimum 3yr) **EOF** sampling instrumentation (ISCO samplers) to monitor both runoff and tile drainage water will be installed on representative fields (5 to 15acres). Throughout a rain event, the sampler dispenses a flow proportional aliquot to a collection bottle. Thus for each event, an event mean concentration will be determined.

The event mean concentration and volume of runoff can be combined to calculate a P load for each rainfall event. This will provide EOF, long-term, monitoring data, at the field-scale, for each site across the year. Included will be all storm events, “first flush” after fertilizer/manure applications, effects of tillage, planting, harvesting, dormant times (winter) and effects of current and additional BMPs. **In-field management** will be evaluated as related to EOF water samples and be used in statistical modeling (objective 2). Measurements made will include: All parameters used in the current Ohio P Index: 1) Soil erosion potential, 2) Slope/Soil Hydrologic Group, 3) Connectivity to water, 4) Soil test P, 5) Fertilizer/manure application amount , 6) Fertilizer/manure application method (incorporation/field residue), 7) Filter Strip (yes or no), 8) plus data from additional BMPs (objective 2).

D. ***Objective 2*** **- Additional BMPs will be evaluated to assess their effectiveness compared to each other and quantified so they can be integrated into models developed through this work**

Many best management practices (BMPs) affect P transport but the current Ohio P index only credits a few. Additional BMPs must be quantified so that they can predict a percent reduction in EOF P loss and be integrated into the P Index. The ability to quantify reductions in P loss will allow producers to prioritize time and resources (bang for the buck) when choosing BMPs. Additional BMPs that may improve the predictive power of the Ohio P Index include: soil compaction/infiltration, Controlled traffic, alternative soil test P methods, P source coefficient, soil testing depth, tillage, cover crops, drainage water management, conservation crop rotation, and other appropriate practices.

Significant statistical analyses will be required to quantify and revise the Ohio P Index and to quantitatively integrate additional BMPs for producers to choose from to reduce their Ohio P Index scores (risk). Statistical analyses will be conducted in three phases:

a. Assess current Ohio P Index parameters and modifiers. Determine which independent variables (parameters), or combinations of variables, best predict risk of P transport.
b. Quantitatively integrate additional BMP options into the Ohio P Index. This will allow producers to choose BMPs to reduce their risk of P transport (P Index score).
c. Adapt the developed models to work together as the enhanced Ohio P Risk Index and be delivered through an online, web-based interactive GIS tool (objective 3).

The power of this project is that true measures of P transport (EOF, surface runoff and drainage water, objective 1) will serve as the dependent variable in these models, while the candidate variables, possibly interacted, will serve as the fixed independent variables. Since repeated measures of fields will be made over time, random effects will be included for each field in the study. Variables identified as significant ($p < 0.05$) in these models will be evaluated to assess the match of coefficient directions and magnitudes to other research findings and their role in the current Ohio P Index.

E. ***Objective 3 - An online, web-based, interactive GIS tool (web-based tool) will be developed so farmers can calculate their Ohio P Index scores***

The tool will automate the process following the Ohio P Risk Assessment Procedure outlined in the Ohio NRCS, electronic Field Office Technical Guide. Use of this tool will require minimal input from producers and will require working closely with the statistician (objective 2). The online tool with enhanced BMP options for producers to choose from will increase the utility of the Ohio P Index beyond a tool used merely to assess risk of P transport, into a tool producers can use to make management decisions to reduce their risk of P transport and thus, their Ohio P Index score. The online tool will be used to **actively promote the use of the enhanced Ohio P Index** through significant outreach efforts, such as: workshops, field days and fact sheets. Additionally, promotion and implementation will be accomplished, through changes in Ohio NRCS policy, technical manuals and guides used by producers and other stakeholders.

F. ***Project Team Members***

We have assembled a team that provides a high level of expertise in all areas.

Dr. Elizabeth (Libby) Dayton, Research Scientist, Soil and Environmental Chemistry (Ohio State University) will act a principal investigator and coordinate activities and be responsible for project management, data analysis, data summary, and recommendations and reporting. Ohio State University will assist with site (field) selection, be responsible for soil sampling and analysis of soil and water samples.

Dr. Kevin King, Agricultural Engineer (USDA-ARS) will act as collaborator. All hydrology and edge-of-field runoff and drainage water collection, will be the responsibility of USDA-ARS. Also, USDA-ARS will contribute to site selection, project management, data collection, data analysis and summary, and recommendations and reporting.

Dr. Christopher Holloman, Director of The OSU Statistical Consulting Service and Auxiliary Assistant Professor, will serve as the lead statistician on the project taking primary responsibility for designing databases for recording data, performing statistical modeling to validate the Ohio P Index.

Dr. Sakthi Subburayalu, Research Scientist, SENR, (OSU), will develop the web-based interface for adaptation of the Ohio P risk index into an online tool, and create and maintain a project website.

Mr. Greg LaBarge, OSU Extension, will assist with education and outreach of project information as well as ongoing communication with participating farmers.
Mr. Mark Scarpitti, State Agronomist, and head of the Ohio P Risk Index Revision Team (Ohio NRCS) and **Mr. Kevin Elder**, Executive Director of the Environmental Livestock Permitting Program (ODA), will assist with producer participation, data analysis, recommendation and reporting. They will have a strong role in information dissemination (outreach/education), as described in objective 3 with support from Drs Dayton and King. Collaborating with the agencies that mandate P management in agriculture ensures adoption, of revisions resulting from this work.

It is important to collect data from diverse parts of the state and a wide variety of land management systems. This will be especially true as we collect data on BMPs and will need sufficient replication to make decisions. Therefore we will rely on our **Producer Partners** to allow us access to their fields for data collection and to share their field management practices with us. The privacy of these producers will be protected. At no time will field or EOF data be linked to a producer. In fact, in order to get statistically valid data, representative of a wide range of management practices, we may ask producers to employ or refrain from employing management practices in areas we are collecting data. While we will strive to be as unobtrusive as possible we will be looking for flexible producers and have budgeted some funds to compensate them for any inconvenience.

G. ***Deliverables***

This project will deliver an updated/revised Ohio P Index. Additional BMPs will be integrated into the Ohio P Index. The ability to quantify reductions in P loss, through BMP options will allow producers to prioritize time and resources (bang for the buck) when choosing BMPs. The easy to use on-line tool developed through this work will allow farmers to calculate their Ohio P Index scores, evaluate alternative management practices that could be implemented to reduce their scores and therefore their risk of P transport.

Data, resources and effort from these EOF facilities will be integrated to revise the Ohio P Index. Therefore our primary partner is Ohio NRCS. Collaborating with the agencies that mandate P management in agriculture ensures adoption, of revisions resulting from this work. Implementation and promotion of validated and enhanced Ohio P Index will be accomplished, through changes in NRCS policy, technical manuals and guides for use by producers and other stakeholders including:

- NRCS comprehensive nutrient management plans (CNMP)
- Purdue Manure Management Planner (MMP) utilized by ODA
- NRCS (633) Waste Utilization and (590) Nutrient Management Practice Standards
- Appendix G of OCES Bulletin 604 Ohio Livestock Manure Management Guide
- Ohio NRCS Electronic Field Office Technical Guide on-line posting
- Utilization by NRCS and SWCD Certified CNMP Specialists

Wisconsin

Phosphorous (P) Index and Snowmelt Runoff Risk Assessment: Demonstration and Refinement

Anita Thompson – PI

Board of Regents of the University of Wisconsin System (WI) $134,850

This project proposes to demonstrate the ability of a process-based Phosphorous Index formulation to assess management effects on runoff phosphorous losses from fields under frozen soil conditions. The project will test and refine the method used in a process-based Phosphorous Index to determine the effect of field management practices on frozen soil runoff volume and adapt the refined frozen soil runoff risk assessment method (within the process-based Phosphorous Index) to identify field conditions and management practices capable of minimizing runoff when animal manure is applied to frozen soils. This project will promote NRCS Conservation Practice Standard Code 799 Monitoring and Evaluation by demonstrating the prototype flow measurement gage on farm fields under winter conditions observed in Dane County, Wisconsin. It will also improve the functionality of the prototype flow gage by adding a user-friendly interface that will allow landowners to easily access gage data.

A. ***Project objectives***

This project has multiple objectives, and only the components related to P Index testing and refinement are discussed below. The project focuses on the method used in Wisconsin's process-based P Index to determine the effect of field management practices on frozen soil runoff volume. Current formulations within Wisconsin's (WI) P Index (Good et al., 2010) estimate average annual winter runoff from snowmelt and rain on frozen soils. This project will evaluate, and, if warranted, refine the winter runoff assessment method and incorporate any refinements into the WI P Index.

B. ***Background***

The WI P Index assesses runoff P loss risk by estimating average annual runoff P loads from a field and delivery to the nearest surface water. The load estimates account for P in runoff from soil, applied manures and fertilizer. Average annual loads are estimated separately by crop year and P transport pathway. Individual crop year P loads from the field are summed for sediment-bound and dissolved P losses from soil, manure and fertilizer in snowmelt runoff and rainfall runoff. The field loss equations have been validated with relevant field runoff data from Wisconsin, and are capable of providing an accurate assessment of runoff P loss risk when good estimates of average annual runoff and erosion are available (Good et al., 2012).

In the WI P Index, average annual erosion and rainfall runoff are currently estimated using standard NRCS methods. RUSLE2 (NRCS, 2008) is used for erosion, while a modification of the runoff curve number formula with field-specific curve numbers generated by RUSLE2 is used for rainfall runoff. Currently, however, there is no widely accepted method for estimating average runoff from snowmelt and rainfall on frozen and thawing soils that is appropriate for a field-scale management planning tool like the P Index. Therefore, an empirical method was developed for the WI P Index using long-term average frozen soil period runoff from representative U.S. Geological Survey (USGS) monitored agricultural watersheds in Wisconsin, with adjustments made for estimated over-winter field surface depressions for storing meltwater (Good et al., 2010).

The adjustments are an adaptation of the Fall Soil Condition Factors used in the Minnesota P Index (Moncreif et al., 2006). The resulting average frozen soil runoff volume estimates are sensitive to field location within Wisconsin (climate), soil texture, slope, and tillage-induced surface roughness. One concern about this method is the use of watershed-scale measurements as the basis for estimating average field-scale runoff. Existing field runoff data are not adequate to validate the frozen soil runoff volume method in the WI P Index, but these runoff data do show that the volume estimates are directionally correct; e.g., fall tilled fields have less snowmelt runoff than nearby untilled fields (Bohl Borhman et al., 2012).

Monitoring specific to this project will be in the Sixmile (Dorn/Spring) Creek (HUC12: 070900020602; 15,760 acres) watershed, the location of a pilot project to test the feasibility of using an adaptive management approach to reduce agricultural non-point P loading to the Yahara chain of lakes by 50%. In this part of the Upper Mississippi River Basin, accurate estimates of management and site effects on snowmelt runoff are important to delineate high P loss areas and evaluate suitable management options. USGS monitoring of adjacent Pheasant Branch from 1990 through 2010 (USGS, 2012) showed that, on an average, 36% of the annual total P loading occurred during the melt months of February and March. The average P load during these two months was approximately equal to the average load from May through July, a period with higher sediment losses. These watersheds have erodible (i.e. sloping) silt loam soils where no-till and minimum till practices are often adopted to reduce sediment-bound P losses. However, these practices result in fields with less surface roughness and fewer surface depressions after crop harvest as well as a tendency for snow to accumulate in over-winter crop residue, leading to higher snowmelt runoff volumes than fall-tilled fields. For some field conditions, fall tillage may result in lower annual total surface runoff P losses. Thus, quantifying the effects of management (fall tillage in particular) on snowmelt runoff allows for the selection of management scenarios that can lower total average annual P loads from specific fields.

C. ***Project methods***

- Continuous in-stream flow monitoring operated by the USGS were established for agricultural subwatersheds of Sixmile Creek and Dorn Creek in the summer of 2012.
- Flow gages to measure winter runoff volume will be installed on four fields within the monitored subwatersheds beginning in November, 2012. The selected fields will have tillage systems, soil and slope conditions leading to differences in expected snowmelt runoff volume. The flow monitoring equipment will be installed at field locations with concentrated flow representing edge-of-field losses. The project will continuously monitor edge of field

flow during three frozen soil periods before freeze-up until after thaw is complete (approximately November - April).

- Project partners will coordinate with the producers to identify planned management on gaged fields over the project period to verify tillage and soil condition effects on frozen soil runoff. They will measure field surface roughness in November prior to snow cover and again in April following melt and prior to field operations. Vertical offset measurements will be taken at 2-4 inch intervals along a 5 ft leveled line at multiple representative locations throughout the field. They will also measure snow depth using transects and snow cores to determine snow pack water equivalent and variability among fields and within fields. The timing of snowpack analysis will vary depending on imminent melt as indicated by the Wisconsin Runoff Risk Advisory System (http://www.manureadvisorysystem.wi.gov/app/runoffrisk).
- Project partners will conduct a baseflow separation analysis for the entire period of record and focus on the frozen soil period stream flow for the two gaged watersheds, similar to the baseflow separation analysis of agricultural watersheds used to derive the current WI P Index average annual snowmelt runoff volumes. This procedure will allow them to test assumptions about the relationship between watershed and field-scale snowmelt runoff.
- Measured in-field snowmelt runoff will be compared to stream snowmelt event flow and the runoff volume estimates from the WI P Index method, other simple methods (e.g. the degree day method (USDA-NRCS, 2004)) and mechanistically modeled (e.g. Water Erosion Prediction Project (USDA-ARS, 2010)) snowmelt runoff volume. The project will investigate the assumptions in the WI P Index regarding the relationship between watershed event flow and field runoff volume. They will compare the monitored edge-of-field and watershed outlet snowmelt runoff volume to quantify scale effect and test the factors currently used in the WI P Index.
- Should the project determine measured surface roughness to be a good predictor of relative snowmelt runoff volume, they will compare measured surface roughness with calculated surface roughness factors derived from RUSLE2. They will determine if calculating field depression storage from RUSLE2 field roughness using the method of Molling et al. (2005) improves frozen soil runoff potential over the method currently used in the WI P Index. They will also investigate the potential use of other readily accessible nutrient management planning information (e.g. soil type, drainage, slope, landscape position, or curve number

condition factors from RUSLE2) to improve field-scale snowmelt runoff estimation. After two years of snowmelt monitoring, they will develop a model using the RUSLE2 surface roughness and appropriate additional factors and subsequently test it with a third year of monitoring data. Snowmelt flow measurements from 18 fields at the UW-Platteville Pioneer Farm as well as two fields in the Waunakee/Sixmile Creek that are already continuously monitored by this project's partners will also be used to test the refined snowmelt runoff volume model.

APPENDIX 3

The NRCS Process using CEAP and APEX Platforms

This is based on an assessment conducted by Moffitt et al., (2012).

Texas

Documentation for the P Indices used in Texas is found in Texas NRCS Agronomy Technical Note 15 (USDA-NRCS, 2005). Texas uses two P Indices – one for East Texas and another for West Texas. While primarily the same, there are some minor alterations between East and West to better reflect resource concerns in the different parts of the state. The Texas P Index for each part of the state was detailed on an EXCEL Spreadsheet – one for each part of the state. Each spreadsheet contains the P Index itself as well as data and work sheets necessary to support the P Index calculations. While done separately, all the various files were combined in one spreadsheet file – Combined Texas P Index.xlsx to accompany this paper. Appropriate multipliers and other factors were programmed into the spreadsheet as needed so the results would be identical as if the Technical Note 15 worksheet was used. The CEAP-APEX modeling reflected 47 years of climate data, and conceivably there could be a numerically different P Index for each year of the simulation for each field. Since the crop rotations for a specific field are repeated through-out the 47 year simulation, the EXCEL sheets were developed to reflect the average annual condition.

Data sets were populated from CEAP data collected during on-farm interviews, from previously collected field information from NRCS's Natural Resources Inventory (NRI), and from the results of the CEAP cropland field modeling. Data was supplied primarily by Dr. Jay Atwood, with USDA-NRCS in Temple, TX. For Texas, data from 922 cropland fields, which includes 271 fields in East Texas and 651 fields in West Texas.

One of the larger tasks was to assemble the fertilizer P and organic P applications into a useful form. It should be noted only 27 Texas cropland fields had organic P applications, three in east Texas and 24 in West Texas. The CEAP questionnaire data for each field was summarized by rotation, most often with multiple years and often multiple applications in the same year. The fertilizer and organic P application data were added for the rotation and then divided by the length of the rotation to arrive at an average annual value. The East and West Texas P Indices provided a system for relating timing and application method to numeric values. Since applications within a rotation often had different timing and application methods, each application within the rotation was weighted to aid in determining the 'weighted' timing and application method numeric value for the rotation. The weighting and subsequent use of the weighted values in calculating the appropriate P Index input was done separately and not included here. Should be noted the Texas P Index did not account for P availability which could vary with source.

Chesapeake Bay States

For the Chesapeake Bay states, P Index for Delaware, Maryland, New York, Pennsylvania, Virginia, and West Virginia were used and appropriate multipliers and other factors were programmed into the spreadsheets as needed. Some states have an electronic version of their P Index available, but the use of the state version would be unwieldy for the analysis of hundreds of fields. The data needs for each P Index was determined from the state's technical material. Data sets were populated from CEAP data collected during on-farm interviews, from previously collected field information from NRI and the results of the CEAP cropland field modeling.

Data from 923 cropland fields, which includes the 771 fields in the Chesapeake Bay region, with at least some additional fields in each of the Chesapeake Bay states. In both cases, data was grouped by the amount, timing, and method (including tillage) of P application; conservation practices applied; and site conditions, including CEAP modeling results.

General

With the exception of the application data input already described, the majority of the P Indices were populated matching field characteristics to categories in the various tech note tables and entering the indicated numeric value on the spreadsheet. The operation would be repeated for each of the more than 900 fields. Values such as average annual RUSLE2 and wind erosion and average annual P losses from all sources were taken directly from the results of the CEAP modeling for that field, and reflect an average annual value.

The above effort resulted in a unique P Index value for each of the 922 fields. Since each state chose different rating criteria, it was meaningless to compare the six P Indices to each other.

The average runoff, soil attached, and subsurface P losses as modeled in CEAP using the APEX model were added together and listed for each of the fields. The correlation function in EXCEL was used to correlate each field P Index with the total P loss as modeled in CEAP. For most states, P Index values were closely related to predicted P loss (Table E; from Moffitt et al., 2012).

Table E. Correlation coefficients comparing CEAP modeled Total P loss and P Index values for cropland fields in the Chesapeake Bay states and Texas.

P Index	Correlation CEAP Total P with P Index	Chesapeake Bay states							TX	
		DE	MD	NY	PA	VA	WV		East	West
Delaware	0.84	0.46	0.82	0.83	0.83	0.83	0.90			
Maryland	0.84	0.49	0.82	0.84	O.84	0.83	0.91			
New York	0.72	0.65	0.81	0.63	0.89	0.85	0.94			
Pennsylvania	0.77	0.77	0.78	0.72	0.76	0.79	0.92			
Virginia	0.81	0.65	0.56	0.81	0.86	0.88	0.90			
West Virginia	0.39	0..08	0.28	0.66	0.29	0.42	-0.20			
Texas									0.69	0.74

APPENDIX 4

APLE Model Description

APLE is a Microsoft Excel spreadsheet model that runs on an annual time step. The model simulates sediment bound and dissolved P loss in surface runoff. It does not consider subsurface loss of P through leaching to groundwater or artificial drainage networks. It is intended to simulate edge-of-field P loss for uniform fields of several hectares in size, or smaller. **APLE** does not simulate P loss through grassed waterways or buffers that may occur beyond the field edge. The model considers different kinds of animal manure (beef, dairy, poultry, swine), applied either by machine or by grazing beef or dairy cattle, but considers only highly soluble commercial fertilizers such as superphosphate, triple superphosphate, or mono- and di-ammonium phosphate.

APLE is intended to be user-friendly and does not require extensive input data to operate. All data are input directly into the spreadsheet (See **APLE** User's Manual). User-input data include:

- Soil property data, including depth of the top two soil layers, Mehlich-3 STP, soil clay content, and soil organic matter content
- The area of the field (ha)
- The annual rain, runoff, and erosion amounts
- The total annual crop P uptake
- When grazing animals are present, the total number of animal days in the field, including beef cattle and calves, dairy lactating and dry cows, and dairy heifers and calves.
- For manure applications, the manure amount applied, manure %solids, manure total P_20_5 content, % of manure total P that is water extractable P, the % of manure that is incorporated, and the depth of incorporation.
- For fertilizer applications, the mass of fertilizer P applied, the % of fertilizer that is incorporated, and the depth of incorporation.

Dissolved P runoff from manure and fertilizer

APLE estimates annual dissolved P loss from surface manure and fertilizer based on the daily time-step models of Vadas et al. (2004; 2008; 2007). In **APLE**, manure is applied in either a solid form or a liquid form, as specified by the user. Fertilizer is assumed to be applied in a solid form. Based on limited data of Vadas (2006), **APLE** assumes that for any manure with solids content less than 15%, 60% of applied manure P infiltrates into soil immediately at application and becomes unavailable for direct loss in runoff. **APLE** also assumes that the solids from these liquid manures remaining on the soil surface after the initial infiltration cover only 50% of the field area. If tillage occurs, **APLE** incorporates any applied manure or fertilizer according to user-specified depths of incorporation and percentages of P applied that are incorporated. **APLE** estimates annual dissolved P loss directly from any manure or fertilizer remaining on the soil surface.

For any manure applied, the model assumes a portion of the manure total P is in a water extractable (Shinners et al.) form. Both the manure total P content and the percent of total P that is WEP are user-specified variables. For the **APLE** model, manure WEP should be measured by shaking fresh manure with de-ionized water at a water to solids extraction ratio of 250:1 for 1 h, filtering extracts through 0.45-um filters, and measuring P in filtrates (Vadas et al., 2004). Manure WEP is commonly estimated at extraction ratios other than 250:1. For example, the Arkansas pasture P Index uses manure WEP to estimate field-scale, annual P loss, but bases WEP values on a 10:1 extraction ratio. However, data generated from other extraction ratios can be converted to a 250:1 equivalent using relationships from Vadas et al. (2005a). The model estimates the amount of dissolved manure P loss in runoff from the manure WEP on the soil surface

The portion of manure P that is not in a WEP form (non-WEP) at application can mineralize during the year and add to the amount of manure WEP on the soil surface. **APLE** assumes that for winter-applied manure, which APLE simulates as the first season of the year, 20% of non-WEP left on the soil surface after infiltration of liquid P, injection, or tillage mineralizes into WEP. This value is 15% for spring-applied manure, 10% for summer-applied manure, and 5% for fall-applied manure. The user specifies the season of application.

The user can also specify how many dairy or beef cattle graze the field during the year. This will add manure and manure P to the field and increase the amount of dissolved manure P loss in runoff. **APLE** assumes daily feces production and fecal total P content for dairy and beef cattle as listed in Table F. Feces WEP at deposition is 55% of total P, and 75% of feces WEP is available the same year for P loss in runoff and 25% is available the following year. **APLE** also assumes that 20% of feces non-WEP on the soil surface mineralizes into WEP the same year.

Table F. Daily feces production and fecal total P content for grazing 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

APLE estimates annual manure or fertilizer dissolved P loss in runoff as:

Manure Runoff P = (Manure WEP)(Annual Runoff/Precipitation)(P Distr. Factor) [1]

Fertilizer Runoff P = (Fertilizer P) (Annual Runoff/Precipitation) (P Distr. Factor) [2]

The P Distribution Factor is an empirical factor between 0.0 and 1.0 that distributes released P between runoff and infiltration and is calculated as:

Manure: P Distribution Factor = (Runoff/Precipitation) 0.225 [3]

Fertilizer: P Distribution Factor = 0.034 exp [(3.4) (Runoff/Precipitation)] [4]

The precipitation represents total rain, snow, and irrigation for an entire year. For fall-applied manure, APLE assumes 75% of manure WEP on the soil surface is available for loss in runoff the same year of application and 25% the following year.

When applying equation [1] and [2] for liquid manure and grazing dung, **APLE** reduces the amount of dissolved P loss in runoff by a factor that accounts for the fact that these manures and dung do not cover the entire soil surface and not all of the annual precipitation interacts with them to leach P. In calculating the reduction factor for grazing dung, **APLE** first assumes that each 250 g of dung (dry weight) covers an area of 659 cm^2 (James et al., 2007) and calculates what percentage of the field area this covers (assuming the field is always 1 ha since P loss calculations are made on a kg/ha basis). **APLE** then calculates the dung reduction factor as:

$$\text{Reduction Factor} = 1.2 \times (250 \times \%\text{ cover}) / [(250 \times \%\text{ cover}) + 73.1)] \qquad [5]$$

where % cover is expressed in a decimal form. For liquid manures, **APLE** assumes % cover is 0.5, and uses equation [6] to determine the P loss reduction factor.

$$\text{Reduction Factor} = 2.2 \times (250 \times \%\text{ cover}) / [(250 \times \%\text{ cover}) + 300.1)] \qquad [6]$$

Equations [5] and [6] are taken from the daily time-step model of Vadas et al. (2007), where they are used to calculate the portion of manure P that is released for a given storm.

Sediment bound and dissolved P runoff from soil

APLE estimates sediment P loss in runoff as:

$$\text{Sediment P Loss} = (\text{Eroded Sediment})(\text{Soil Total P})(\text{P Enrichment Ratio})(10^{-6}) \qquad [7]$$

where:

Sediment P Loss: Annual P loss in runoff associated with eroded sediment (kg ha^{-1})

Eroded Sediment: Annual soil lost in runoff due to erosion (kg ha^{-1})

Soil Total P: Total P content of surface soil (mg kg^{-1})

P Enrichment Ratio: Unitless ratio of total P in eroded sediment to that in the source soil. **APLE** calculates the P Enrichment Ratio based on equations from Menzel et al. (1980) and Sharpley (1980):

$$\ln(\text{P Enrichment Ratio}) = 2.2 - 0.25 \ln(\text{eroded sediment}) \quad [8]$$

Soil total P in Eq. [7] is estimated as described in the soil P processes section of this document. **APLE** estimates dissolved inorganic P loss in runoff (kg ha^{-1}) from soil using the equation of Vadas et al. (2005b):

$$\text{Dissolved Soil Runoff P} = (\text{Soil Labile P})\,(0.005)\,(\text{Annual Runoff})\,(10^{-6}) \quad [9]$$

where Annual Runoff is in L ha^{-1}. Soil Labile P (mg kg^{-1}) is estimated as described in the soil processes section. The 0.005 value is an extraction coefficient that estimates dissolved P in runoff (mg L^{-1}) from soil Labile P.

Soil P processes

Number of Soil Layers

APLE is intended to simulate processes in only the topsoil, but can simulate two layers in the topsoil. This is intended to estimate P stratification (i.e., significantly different P concentrations in different soil layers) in soils with no or limited tillage. This would be important for pastures or no-till soils where more P might accumulate in the top 1 inch of soil than deeper in the topsoil. The depth of the two soil layers is specified by the user at the beginning of a simulation.

Soil Phosphorus Pools and Exchanges

APLE does all soil P process calculations in the units of kg ha^{-1}. Soil P routines for each topsoil layer in **APLE** are based on the model of Jones et al. (1984) and simulate three inorganic P pools (Labile, Active, and Stable) and one Organic P pool. Labile P represents easily desorbable P immediately available for plant uptake or transfer to runoff, and is defined as P extracted by anion exchange resin (Sharpley et al., 1984). Labile P is initialized based on user-specified concentrations of Mehlich-3 STP (ppm), with **APLE** assuming that Labile P is one half the value of Mehlich-3 P (Vadas and White, 2010). Active P represents more stable P that is not easily desorbable, but in equilibrium with Labile P. Active P is initialized from Labile P and a P sorption coefficient, or P availability Index, (PSP) as:

$$\text{Active P} = (\text{Labile P})\ (1 - \text{PSP}) / \text{PSP} \qquad [10]$$

The PSP represents how much of any inorganic P added to soil remains Labile P upon reaching relative equilibrium. A PSP of 0.4 means 40% of added P remains Labile P and 60% becomes Active P. Experimentally, PSP values are determined by measuring Labile P in a soil, adding inorganic P to the soil, incubating the soil for six months, and again measuring Labile P. The percentage of added P that remains Labile is the PSP (Sharpley et al., 1984). In **APLE**, PSP is estimated from user-defined soil properties of clay content (%) and organic matter content (%) as (Vadas and White, 2010):

$$\text{PSP} = -0.053*\ln\ (\%\ \text{clay}) + 0.001*(\text{Labile P}) - 0.029*(\%\ \text{Organic C}) + 0.42 \qquad [11]$$

The organic carbon (C) content is assumed to be 58% of user-defined organic matter content (%). The PSP is given lower and upper limits of 0.05 and 0.90.

Soil Stable P is assumed to be four times the size of Active soil P. Soil Organic P is initialized from user-defined soil organic C amounts and by assuming that the C:Nitrogen (N) ratio of soil organic substances is 14:1 and the N:P ratio is 8:1. This method for estimating Humic P results in similar estimates as equations for estimating soil organic P from Sharpley et al. (1984). **APLE** maintains this ratio of organic P to organic C ratio as organic P fluctuates from either addition in manure or in mineralization (see two following paragraphs). **APLE** estimates soil total P (which is used for sediment P loss in runoff in Eq. [5]) as the sum of the Labile, Active, Stable, and Organic P pools.

When P is added to soil in manure or fertilizer, **APLE** first distributes the added P to the appropriate soil layer based on user-defined tillage practices, depths, and degree of soil mixing by the tillage operation. **APLE** assumes that 5% of added manure P becomes Organic P. This 5% represents a final amount of manure P that would remain organic after all annual mineralization processes are complete. The remaining 95% of added manure P and all added fertilizer P are added to the soil inorganic P pools. APLE distributes added inorganic P between the Labile, Active, and Stable pools based on the equilibrium relationships established by the daily time-step model of Jones et al. (1984). In that model, all added P is initially added to the Labile P pool, which disturbs the equilibrium between the two pools as described in Eq. [8]. The P is thus slowly added to the Active P pool at a rate of 0.1 per day. Moving P from Labile P to Active P in turn disturbs the equilibrium between Active P and Stable P, and P is moved from Active to Stable P. Based on this model of Jones et al., APLE calculates what fraction of added inorganic ultimately ends up in the Stable P pool as:

$$\text{Fraction Added P to Stable P} = (-0.187 \times \text{PSP}) + 0.189 \qquad [12]$$

The remainder of added inorganic P is distributed between Labile and Active P based on the PSP value, which determines the relative size of the pools at equilibrium.

When annual P removal from a soil layer is greater than annual P inputs, **APLE** decreases soil P from the three inorganic soil P pools. Based on the model of Vadas et al. (2006), **APLE** uses Eq. [13] to determine the fraction of P that is removed from the Labile P pool:

$$\text{Fraction P Removed from Labile P} = 0.41 \times \text{PSP}^2 + 0.54 \times \text{PSP} + 0.005 \qquad [13]$$

The remaining P decrease is partitioned between the Active and Stable pools based on their relative sizes. For example, if a soil layer loses 10 kg ha^{-1} of P in a year and has a PSP of 0.3, then 2.06 kg ha^{-1} of P is removed from the Labile pool. If Stable P is four times Active P, then 1.59 kg ha^{-1} of P is removed from the Active pool and 6.35 kg ha^{-1} of P is removed from the Stable pool.

APLE estimates soil organic P mineralization if Labile P becomes less than 10 mg kg^{-1} by allowing enough organic P to mineralize to maintain Labile P at 10 mg kg^{-1}. Any organic P mineralized is moved from the Organic P pool to the Labile P pool. Mineralization also occurs if the net decrease in soil P is greater than the total P available in the three inorganic P pools. In this instance, P mineralized is equal to half of the calculated difference. However, this P is not added to the Labile P pool, but is assumed to be removed from the modeled system.

Soil Mixing Between Topsoil Layers

APLE mixes P between the two topsoil layers based on the user-defined degree of soil mixing based on tillage or natural mixing processes, such as mixing by earthworms or freeze-thaw actions. If one soil layer contains more P than the other, the overall effect is to reduce P in one layer and increase it in the other by an amount proportional to the degree of mixing.

Phosphorus Leaching from Topsoil Layers

APLE estimates the fraction of annual precipitation that leaches through the two topsoil layers in L ha^{-1} as:

$$\text{Leachate/Precipitation} = -0.07 \times \ln(\text{Soil Layer Depth}) + 0.6 \qquad [13]$$

where soil layer depth is the depth of the bottom of the soil layer in inches. This equation is based on data from Nelson et al (2005), who measured the amount of water leaching through a sandy soil in North Carolina.

APLE estimates a concentration of dissolved P (mg L^{-1}) in the soil leachate based on a P sorption isotherm, which relates the amount of P sorbed on the soil and the amount dissolved in the soil water. This is similar to the approach taken by Nelson and Parsons (2006) to modify the GLEAMS model to better simulate P leaching in waste-amended soils. In APLE, P sorbed onto the soil (mg kg^{-1}) and dissolved P in soil water (mg L^{-1}) are related as:

$$\text{P Sorbed} = (a) \ln(\text{Dissolved P}) + b \qquad [14]$$

In **APLE**, P sorbed is assumed to be equal to the sum of soil Labile P at the beginning of the year and half of the added manure and fertilizer P that are estimated to remain Labile P by the end of the year. **APLE** calculates the a and b variables as:

$$a = (173.51)\ (\%\ \text{soil clay}) + 8.48 \qquad [15]$$

$$b = (4.726)\ (a) - 8.97 \qquad [16]$$

Equations [14]-[16] are taken from Vadas (2001). **APLE** sets a maximum dissolved P concentration of 20 mg L^{-1} for soil leachate based on observations of Nelson et al. (2005) and a maximum amount of P (kg ha^{-1}) that can be leached equal to P Sorbed in Eq. [14]. A portion of P that leaches from the first layer is added to the Labile P in the second layer and a portion leaves the modeled system. The portion added to the second layer is determined according to the relative thickness of the two topsoil layers as:

Portion of P into Second Layer = exp [-0.2 x (1st Layer Thickness /2nd Layer Thickness) [17]

Phosphorus that leaches from the second layer leaves the modeled system.

Crop export of P

APLE accounts for soil P export in harvested crops (crop P removal) according to the user-specified annual amount. APLE assumes all P exported by crops comes from the two simulated soil layers and distributes P export based on the relative concentration of P in the two layers. For example, if soil P is 50% greater in the upper soil layer compared to the bottom layer, P export from the first layer is 50% greater than P uptake from the second layer.

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