CONSERVATION INNOVATION GRANTS

Semi-annual and Final Progress Report

Grantee Name: NC State University	
Project Title: Refine and Regionalize Southern Phosphorous Assessment Tools Based on Validation and State Priorities	
Agreement Number: 69-3A75-12-182	
Project Director: Deanna Osmond	
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Period Covered by Report: 05/01/2016-9/30/2016	
Project End Date: 09/30/2016	

A) Summarize the work performed during the project period covered by this report:

- Modeling for all projects and state P Index runs was completed. Information was compiled.
- Four papers were submitted to a special edition of JEQ. Abstracts for these manuscripts are provided below.
- Three presentations were presented at the International Soil and Water Conservation conference during two sessions entirely focused on results from the southern CIG-P.
- The southern group participated in writing the unifying document for this work that will be provided by the P Index Integration CIG lead by Andrew Sharpley.

DATA BASES

- This work was accomplished early so that the remaining work could be completed.

MODELING

- Monthly conference calls were held among the modelers throughout the project.
- Work from University of Georgia, Mississippi State University, ARS-Kentucky, and NC State University provided comparisons of TBET, APEX, APLE and southern P Indices that will be published in a special edition of JEQ. Abstracts to this information are provided below.
- Information provided by Oklahoma State University for TBET and NC State University for Drainmod are provided as reports.

Georgia (TBET)

Evaluation of a Quantitative Phosphorus Transport Model for Potential Improvement of Southern Phosphorus Indices

Thomas A. Forsberg, David E. Radcliffe, Carl H. Bolster, Aaron Mittelstet, Daniel E. Storm, and Deanna Osmond

Abstract

Due to a shortage of available phosphorus (P) loss data sets, simulated data from a quantitative P transport model could be used to evaluate a P Index. However, the model would need to accurately predict the P loss data sets from field experiments that are available. The objective of this study was to compare predictions from the Texas Best Management Evaluation Tool (TBET) against measured P loss data to determine whether the model could be used to improve P Indices in the Southern Region. Field-scale measured P loss data from study sites in Arkansas, Georgia, and North Carolina were used to assess the accuracy of TBET for predicting field-scale loss of P. We found that event-based predictions using an uncalibrated model were generally poor. Calibration improved runoff predictions and produced scatter plot regression lines that had slopes near one and intercepts near zero. However, TBET predictions of runoff met the performance criteria (NSE ≥ 0.3, PBIAS ≤ 35%, and MAE ≤ 10 mm) in only one out of six comparisons: NC during calibration. Sediment predictions were imprecise and dissolved P predictions under-estimated measured losses. Total P predictions using the calibrated model were a matter of getting the right answer for the wrong reasons in Arkansas and Georgia: over-predicting sediment loss and under-predicting dissolved P loss resulted in reasonably good predictions of total P loss. We conclude that TBET cannot be used to improve southern P Indices, but a curve number approach could be incorporated into P Indices to improve runoff predictions.

Mississippi (APEX)

Evaluation of the APEX model to simulate runoff quality from agricultural fields in the southern region of the US

J.J. Ramirez-Avila, D. Osmond, D. Radcliffe, C. Bolster, S.L. Ortega-Achury, A. Forsberg, A. Sharpley[5] J.L. Oldham[6]

Abstract

The phosphorus (P) Index (PI) is the risk assessment tool approved in the NRCS 590 standard used to target critical source areas and practices to reduce P losses. A revision of the 590 standard, suggested using the Agricultural Policy/Environmental eXtender (APEX) model to assess the risk of nitrogen and P loss. We compared uncalibrated and calibrated APEX model predictions against measured water quality data from row crop fields in North Carolina and Mississippi, and pasture fields in Arkansas and Georgia. Model performance was evaluated using the Nash-Sutcliffe efficiency (NSE) and percent bias (PBIAS) with critical values of NSE ≥ 0.30 and absolute value of PBIAS < 0.35, 0.6, 0.7, and 0.7 for runoff, sediment, dissolved P (DP) and total P (TP). Comparisons were made on an event basis and using long-term 25-yr simulations. Overall, both the uncalibrated and calibrated APEX models predicted runoff that met the performance criteria for both the event-based and long-term predictions at most sites. However, neither the uncalibrated nor the calibrated model could simulate sediment, DP, or TP losses. APEX tended to underpredict P losses from fields where manure was surface applied and this may have been due to the lack of a surface manure pool for P that was separate from the soil

surface layer pool. The APEX model's capability to predict P losses is limited and consequently, so is the potential for using APEX to refine or replace P Indices in the southern region.

APLE

Comparing an annual and daily time step model for predicting field-scale P loss

Carl H. Bolster*, Adam Forsberg, Aaron Mittelstet, David E. Radcliffe, Daniel Storm, John Ramirez-Avila, and Deanna Osmond

Abstract

A diverse set of mathematical models are available for predicting phosphorus (P) losses from agricultural fields, ranging from simple empirically-based annual time step models to more complex process-based daily time-step models. In this study, we compare field-scale P loss predictions between the Annual P Loss Estimator (APLE), an empirically-based annual time-step model, and the Texas Best management practice Evaluation Tool (TBET), a process-based daily time step model based on the Soil and Water Assessment Tool (SWAT). We first compared predictions of field-scale P loss from both models using field and land management data collected from 11 research sites throughout the Southern US. We then compared predictions of P loss from both models with measured P loss data from these sites. We observed a strong and statistically significant ($p < 0.001$) correlation in both dissolved (DP; $\rho=0.92$) and particulate (PP; $\rho=0.87$) P loss between the two models; though APLE generally predicted, on average, 44% greater DP loss whereas TBET predicted, on average, 105% greater PP loss for the conditions simulated in our study. When we compared model predictions with measured P loss data, neither model consistently outperformed the other indicating that more complex models do not necessarily produce better predictions of field-scale P loss. Our results also highlight limitations with both models and the need for continued efforts to improve the accuracy of these two models.

PHOSPHORUS INDEX

Southern P Indices, Water Quality Data, and Modeling (APEX, APLE, and TBET) Results: A Comparison

Osmond, D., C. Bolster, A. Sharpley, M. Cabrera, S. Feagley, A. Forsberg, C. Mitchell, R. Mylavarapu, J. L. Oldham, D. E. Radcliffe, J. J. Ramirez-Avila, D.E. Storm**,** F. Walker, and H. Zhang

Abstract

Phosphorus (P) Indices in the southern United States frequently produce different recommendations for similar conditions. We compared risk ratings from 12 southern states (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, and Texas) using data collected from benchmark sites in the South (Arkansas, Georgia, Mississippi, North Carolina, Oklahoma, and Texas). Phosphorus-Index ratings were developed using both measured erosion losses from each benchmark site and RUSLE2 predictions; mostly, there was no difference in P-Index outcome. The derived loss ratings were then compared to measured P loads at the benchmark sites by using equivalent USDA-NRCS P-Index ratings and three water quality models (Annual P Loss Estimator, APLE; Agricultural Policy/Environmental eXtender, APEX; and, Texas Best management practice Evaluation Tool, TBET). Phosphorus Indices were finally compared against each other using USDA-NRCS loss ratings Model estimate correspondence with USDA-NRCS loss ratings was 61% (APEX),

48% (APLE), and 52% (TBET) and overall P index correspondence was 55%. Additive P Indices (Alabama and Texas) had the lowest USDA-NRCS loss rating correspondence (31%), while the multiplicative (Arkansas, Florida, Louisiana, Mississippi, South Carolina, and Tennessee) and component (Georgia, Kentucky, and North Carolina) Indices had similar USDA-NRCS loss rating correspondence, 60% and 64%, respectively. A Kendall modified Tau analysis suggested that correlations between measured and calculated P-loss ratings were similar or better for most P Indices than the models.

Oklahoma, Texas and Mississippi (TBET)

Dan Storm, Oklahoma State University

Texas Best Management Evaluation Tool

The Texas Best management practice Evaluation Tool (TBET) (White et al., 2012) is based on a specially modified version of Soil and Water Assessment Tool (SWAT) 2009 (Arnold et al., 1998) a product of more than 35 years of model development by the United States Department of Agriculture Agricultural Research Service. The field-scale model is a vastly simplified Graphical User Interface, which utilizes numerous updates and local climate, soils, topography and management databases supporting the application throughout the south central United States. Required data for TBET simulations include crop system and management practices, soil type, field area, distance to stream and soil test phosphorus.

Field Simulations

TBET simulations were conducted for 10 fields in the states of Oklahoma, Texas and Mississippi (Table 1). A summary of the observed and TBET simulated runoff, erosion, dissolved and total phosphorus and select input variables are given in Table 1. A series of calibrated and un-calibrated TBET simulations are given in Figures 1 through 4.

Combined Field Simulations

TBET simulations were conducted on 54 sites from Oklahoma and Texas Sites (White et al., 2012) (Figures 5 to 8). Validation simulations were grouped by land cover to investigate the effect of land cover. The combined simulations containing all land covers on under predicted runoff. The conventional tillage field performed better compared to the reduced and no- tillage field, with similar results for the grazed and hayed pastures. For sediment, the combined, conventional and reduced tillage validations were similar, and no-till and ungrazed pasture were over predicted.

The total and dissolved phosphorus validations for the combined simulations were acceptable. For total phosphorus, the conventional tillage fields were acceptable, but the reduced tillage fields were under predicted and the pasture, no-till and native grass were over predicted. Similar results were found for dissolved phosphorus, with the conventional, reduced and no tillage simulations under predicted and the pastures over predicted. Native grass simulations were inconclusive. In summary, improvements are need in the TBET dissolved phosphorus routines.

Future Work

As a follow up on this research, detailed daily validation of TBET separated by land use/land cover and Level I and III ecoregions will be conducted and published. The study will include 11 fields across Oklahoma, Texas, Arkansas, Mississippi, Georgia and North Carolina (Figure 9).

References

Arnold, J.G., R. Srinivasan, R.S. Muttiah and J.R. Williams. 1998. Large area hydrologic model development and assessment part 1: Model development. J. Am. Water Res. Assoc., 34(1):73-89.

White, M.J., R.D. Harmel, and R.L. Haney. 2012. Development and Validation of the Texas Best Management Practice Evaluation Tool (TBET). Journal of Soil and Water Conservation, 67(6):525-535.

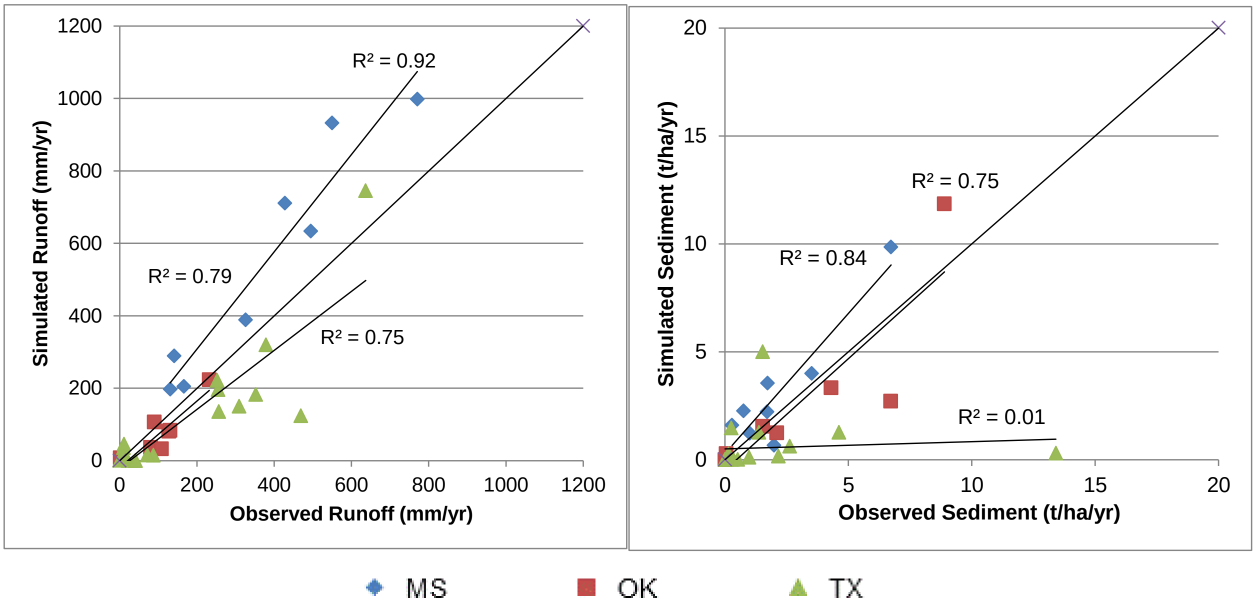


Figure 1. Observed vs un-calibrated TBET predicted runoff and sediment yield by state.

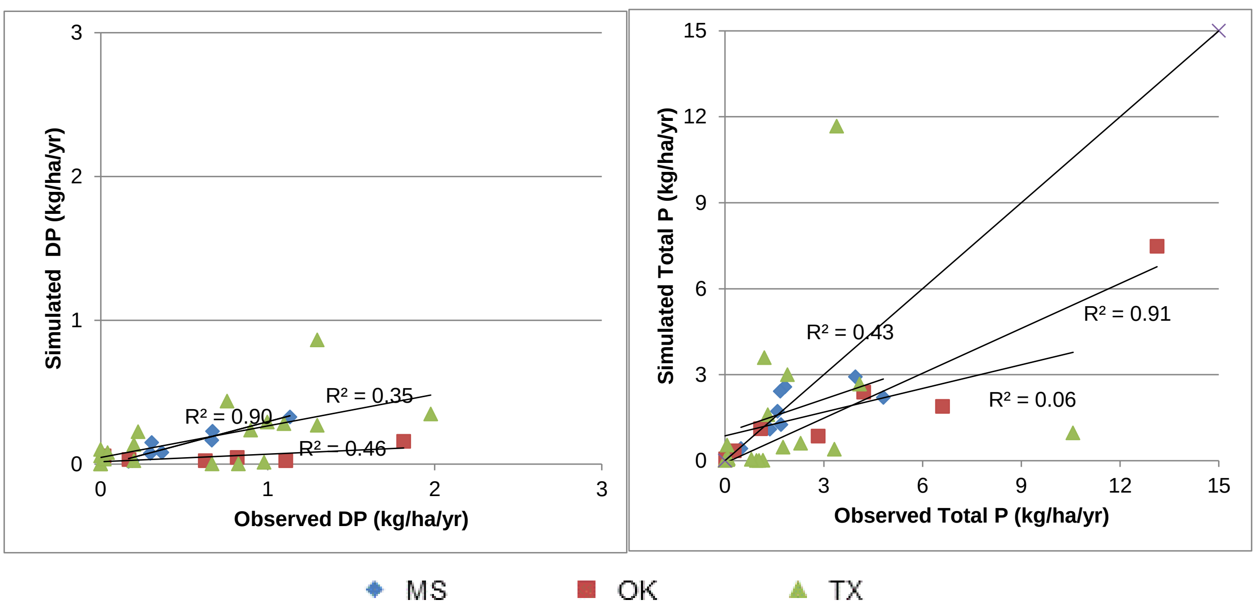
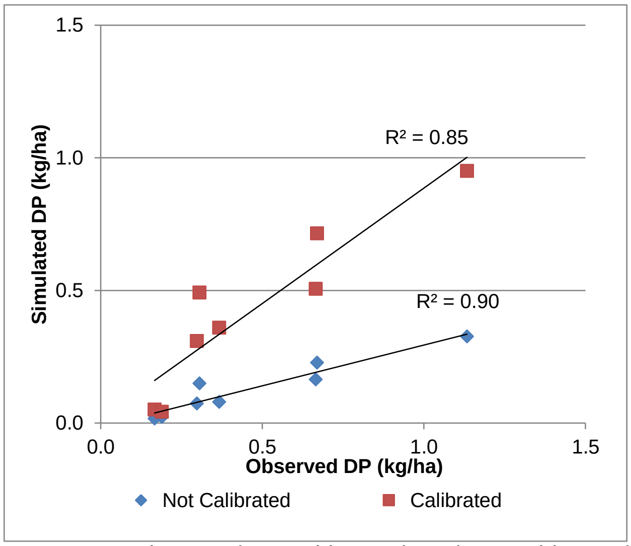
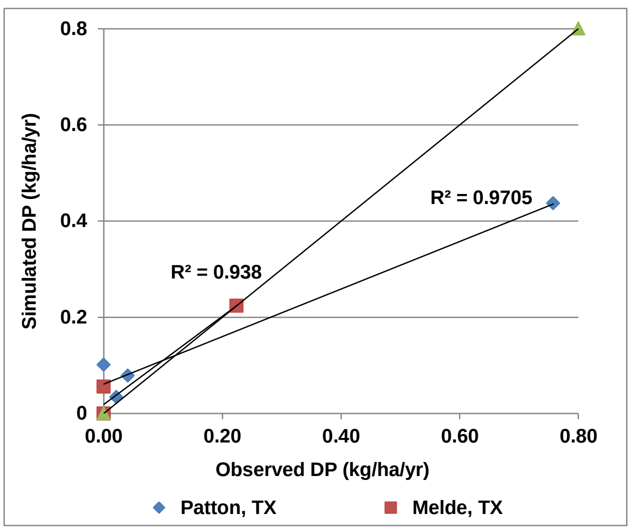


Figure 2. Observed vs un-calibrated TBET predicted dissolved phosphorus (DP) and total phosphorus (TP) by state.



	NSE	R^2
Pre-Calibration		
Total P	**0.36**	**0.43**
Dissolved P	**-0.73**	**0.90**
Post-Calibration		
Total P	**0.43**	**0.44**
Dissolved P	**0.83**	**0.85**

Figure 3. Observed vs calibrated and un-calibrated TBET predicted dissolved phosphorus (DP) using a default and calibrated PHOSKD of 175 and 50, respectively, for Mississippi fields.



Patton, TX
- **Rangeland & Grazing**
- **Beef Manure**
- **No calibration needed**

Melde, TX
- **Sorghum & Oats**
- **Conventional Tillage**
- **Commercial N, Beef Manure**
- **No calibration needed**

Riesel, TX
- **Corn-Corn-Wheat**
- **Reduced Tillage**
- **Commercial N & Layer Manure**
- **DP calibration needed**

Goose Branch, TX
- **Coastal Bermuda Hay**
- **Com. N & Beef Manure**
- **Runoff issue**

Figure 4. Observed vs un-calibrated TBET predicted dissolved phosphorus (DP) for two Texas fields.

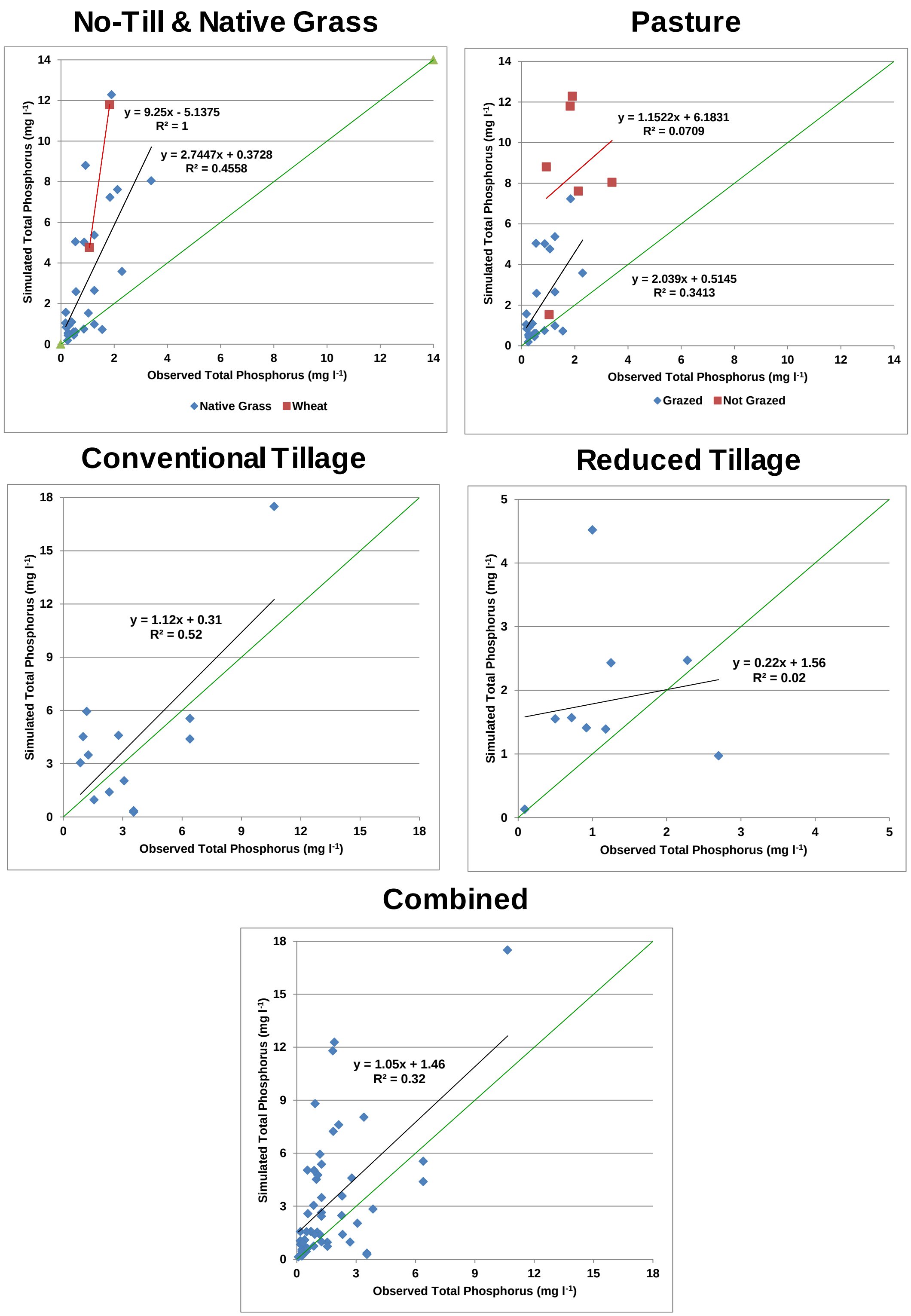


Figure 5. Observed vs un-calibrated TBET predicted runoff for 54 sites in Oklahoma and Texas combined and by land cover.

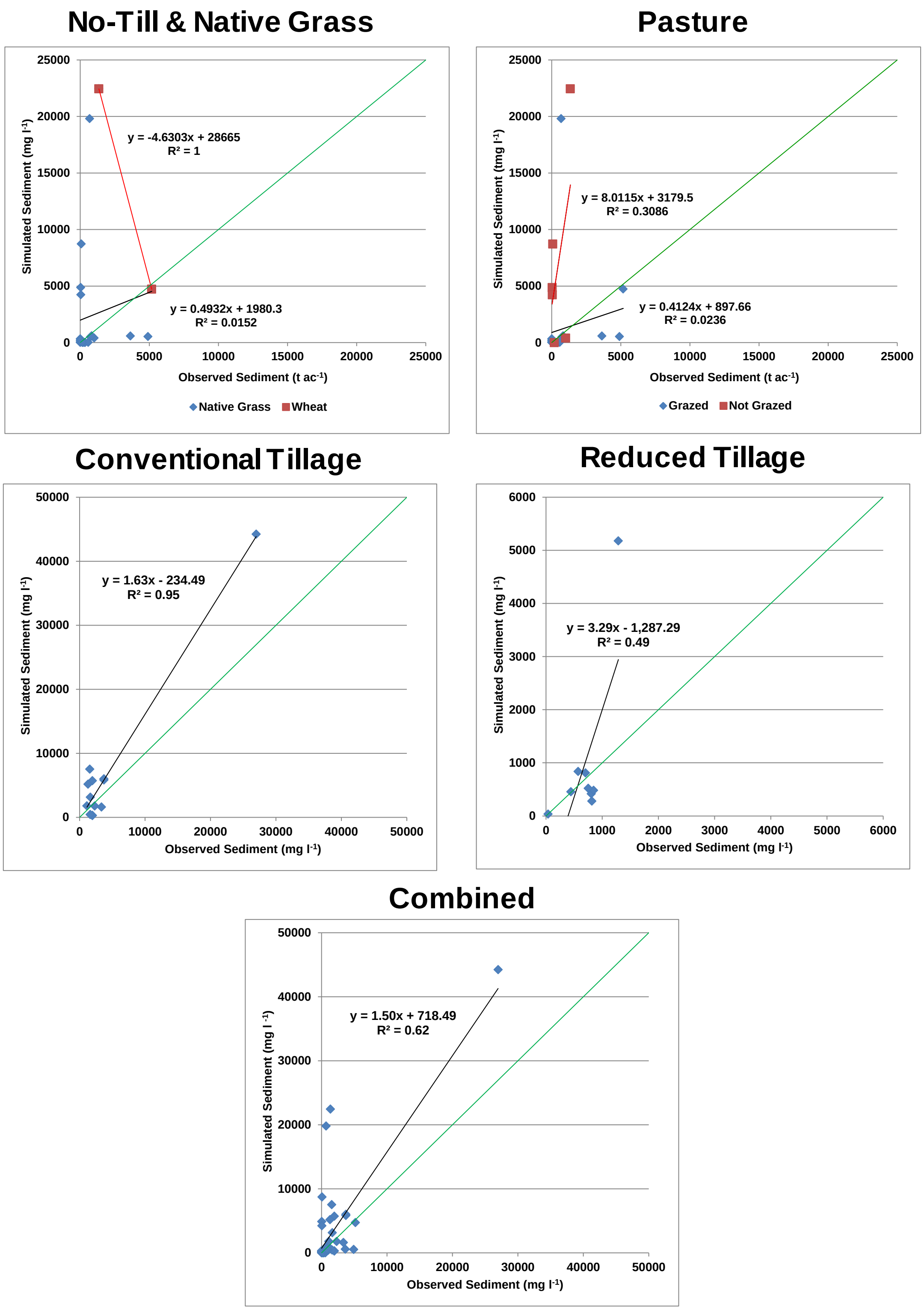


Figure 6. Observed vs un-calibrated TBET predicted sediment yield for 54 sites in Oklahoma and Texas combined and by land cover.

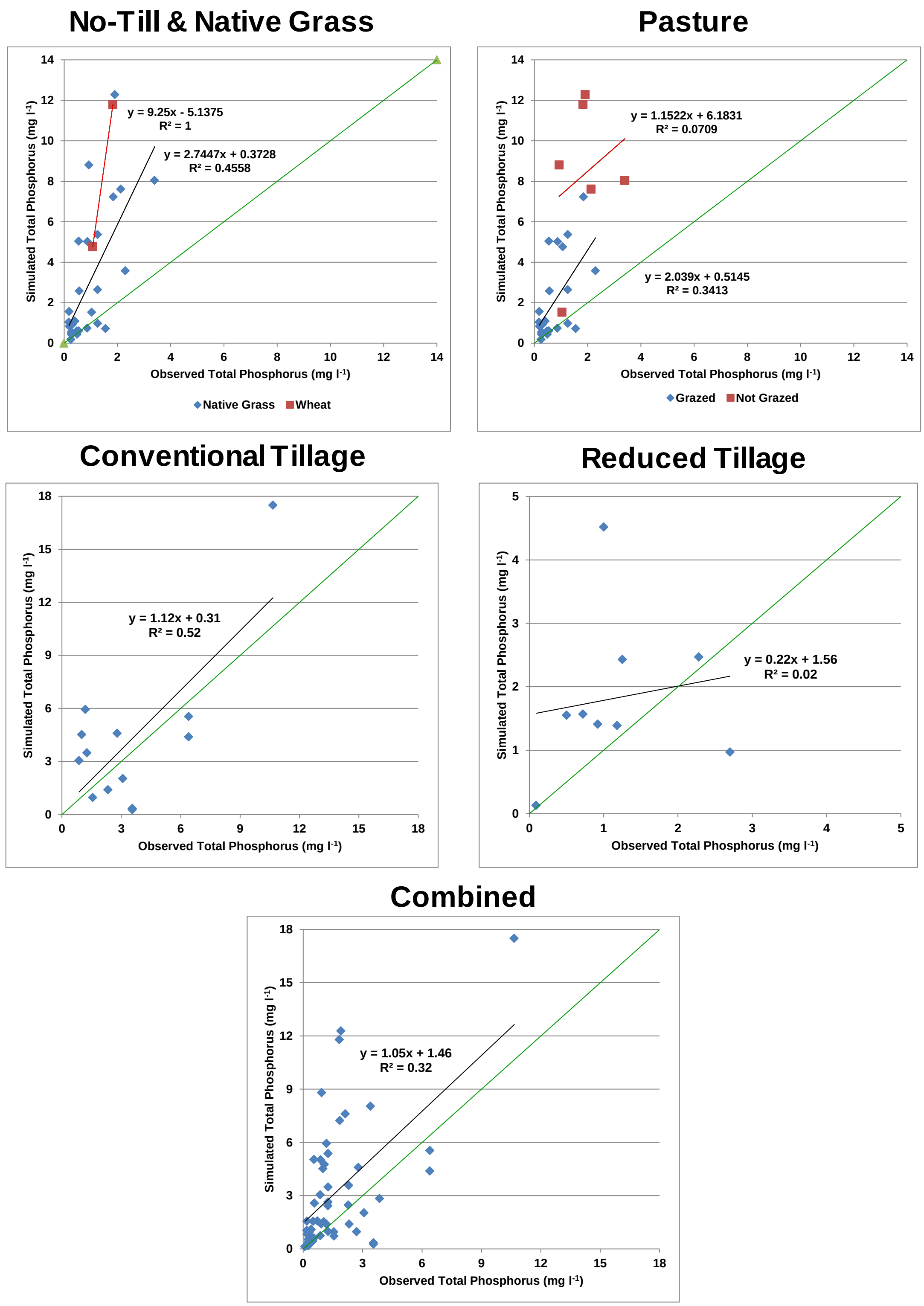


Figure 7. Observed vs un-calibrated TBET predicted total phosphorus for 54 sites in Oklahoma and Texas combined and by land cover.

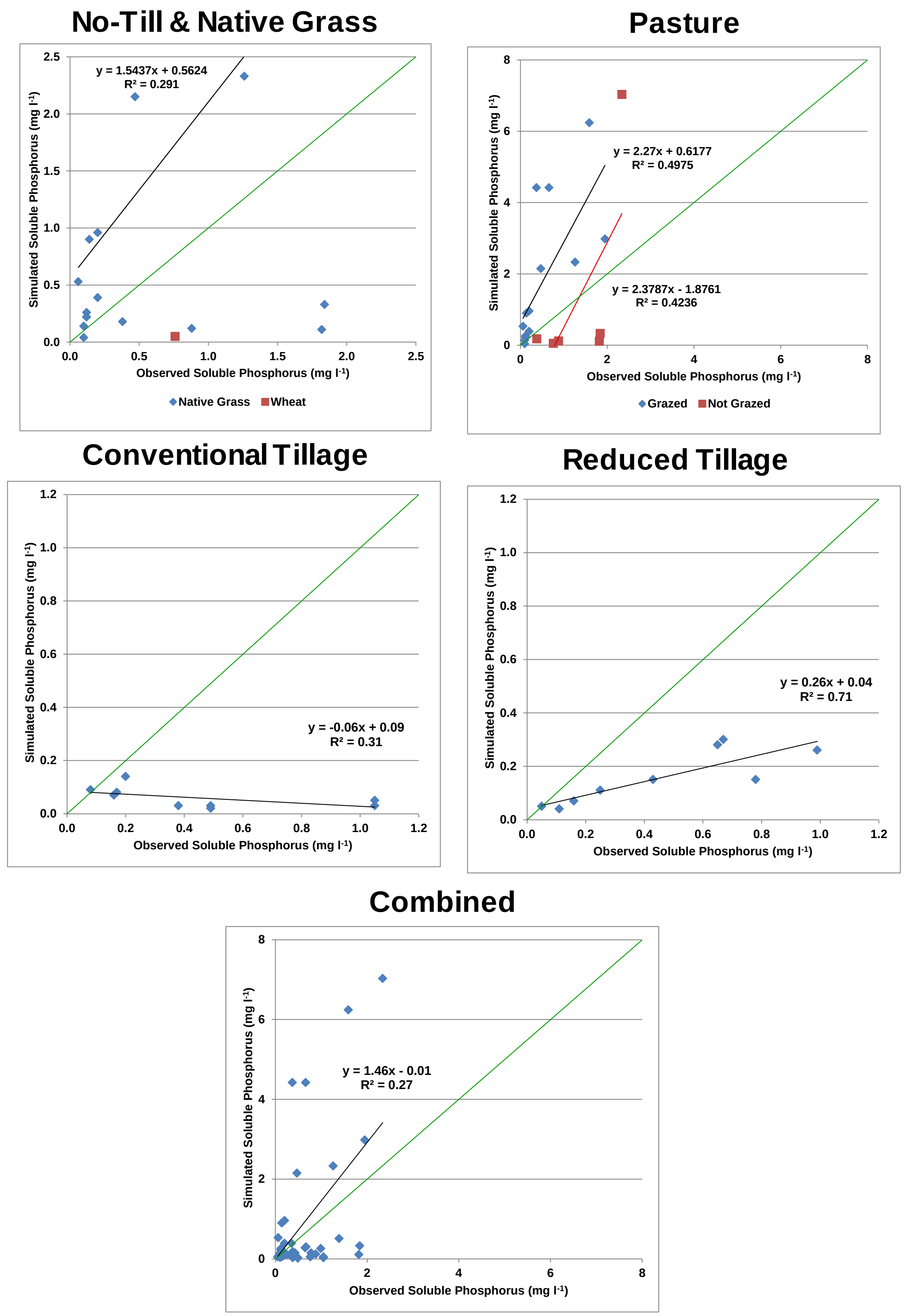


Figure 8. Observed vs un-calibrated TBET predicted total phosphorus for 54 sites in Oklahoma and Texas combined and by land cover.

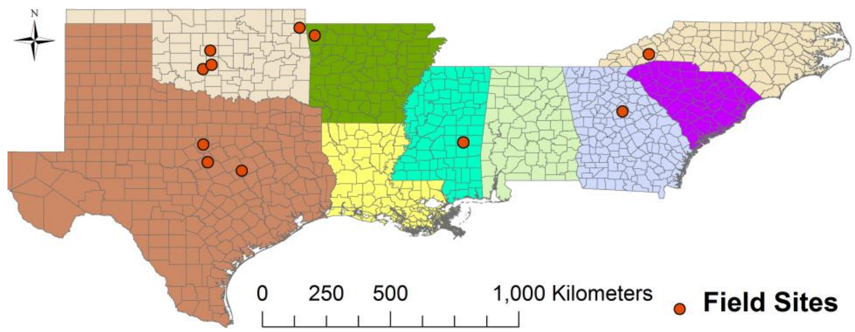


Figure 9. Field locations for future detailed TBET validation study.

Table 1. Summary of observed and TBET simulated runoff, erosion, dissolved phosphorus (DRP) and total phosphorus (TP), and select input variables. Highlighted yellow cells are annual.

State	Field ID	Year	Precipitation	Predicted Runoff	Predicted Erosion	STP M3	Fertilizer P Applied	Surface Manure P2O5	Total Cow Days	Observed		TBET Predicted	
										DRP	TP	DRP	TP
			in	in	t/ac	ppm	lbs P2O5/ac	lbs p2o5/ac		kg/ha	kg/ha	kg/ha	kg/ha
MS	1	1996	46.0	7.76	0.64	49	0			0.17	0.48	0.02	0.42
MS	1	1997	50.3	27.98	0.49	49	0			0.19	1.36	0.02	1.09
MS	1	1998	53.1	39.28	3.99	49	19			0.67	4.81	0.16	2.20
MS	1	1999	39.5	36.71	1.43	49	0			0.37	1.82	0.08	2.57
MS	2	1996	46.0	11.37	0.89	67	0			0.31	1.60	0.15	1.72
MS	2	1997	50.3	8.08	0.26	67	0			0.30	1.70	0.07	1.25
MS	2	1998	53.1	24.95	1.61	67	19			1.13	3.96	0.33	2.92
MS	2	1999	39.5	15.31	0.91	67	0			0.67	1.68	0.23	2.42
OK	ChickashaC3	1973	39.6	8.80	4.80	20	60			1.81	13.13	0.16	7.48
OK	ChickashaC3	1974	29.1	1.50	0.50	20	60			0.63	2.83	0.02	0.85
OK	ChickashaC3	1975	35.9	3.20	1.35	20	60			0.82	4.21	0.04	2.39
OK	ChickashaC3	1976	31.1	3.30	1.10	20	60			1.11	6.61	0.02	1.89
OK	Eucha_5DemoNorth	2006	41.9	0.30	0.00	50	0	27	410	0.02	0.02	0.06	0.06
OK	Cyril	1980	23.7	0.50	0.04	35	25			0.15	1.08	0.01	0.11
OK	Cyril	1981	30.3	0.10	0.06	35	25		183			0.00	0.13
OK	Cyril	1982	29.4	1.20	0.11	35	25		183			0.03	0.29
OK	Cyril	1983	35.3	2.10	2.57	35	25		183			0.09	4.41
OK	Cyril	1985	25.4	0.10	0.01	35	25		183			0.00	0.02
OK	Cyril	1984	39.9	3.70	0.69	35	25		183			0.09	1.41
OK	elreno	1977	26.2	1.30	0.04	15	0	0	183		0.28	0.02	0.11
OK	elreno	1978	24.6	0.30	0.01	15	0	0	183			0.00	0.02
OK	elreno	1979	30.0	2.20	0.06	15	0	0	183			0.04	0.17

OK	elreno	1980	24.6	1.80	0.04	15	0	0	183	0.03	0.12
OK	elreno	1981	33.9	0.60	0.01	15	0	0	183	0.01	0.03
OK	elreno	1982	37.9	9.00	0.23	15	0	0	183	0.16	0.69
OK	elreno	1983	41.9	6.40	0.19	15	0	0	183	0.10	0.55
OK	elreno	1984	29.1	2.60	0.07	15	0	0	183	0.04	0.21
OK	elreno	1985	33.4	5.00	0.13	15	0	0	183	0.10	0.39
OK	elreno	1986	44.0	9.20	0.25	15	0	0	183	0.15	0.74
OK	elreno	1987	40.6	5.30	0.14	15	0	0	183	0.09	0.37
OK	elreno	1988	28.4	3.40	0.07	15	0	0	183	0.07	0.24
OK	elreno	1989	38.7	6.60	0.18	15	0	0	183	0.10	0.53
OK	elreno	1990	35.2	6.40	0.19	15	0	0	183	0.12	0.54
OK	elreno	1991	35.8	3.40	0.11	15	0	0	183	0.06	0.31
OK	elreno	1992	37.3	3.30	0.09	15	0	0	183	0.06	0.21

Table 1 (cont.). Summary of observed and TBET simulated runoff, erosion, dissolved phosphorus (DRP) and total phosphorus (TP), and select input variables. Highlighted yellow cells are annual.

				Predicted									
State	**Field ID**	**Year**	**Precipitation**	**Runoff**	**Erosion**	**STP M3**	**Fertilizer P Applied**	**Surface Manure P2O5**	**Total Cow Days**	**Observed**		**TBET Predicted**	
			in	**in**	**t/ac**	**ppm**	**lbs P2O5/ac**	**lbs p2o5/ac**		**DRP kg/ha**	**TP kg/ha**	**DRP kg/ha**	**TP kg/ha**
TX	Goosebranch	1998	26.5	0.58	0.01	435	0	69	0	1.98	3.33	0.35	0.39
TX	Goosebranch	1999	22.9	0.00	0.00	435	0	69	0	0.98	1.15	0.01	0.01
TX	Goosebranch	2000	27.3	0.00	0.00	435	0	69	0	0.83	0.96	0.00	0.00
TX	Goosebranch	2001	28.7	0.00	0.00	435	0	69	0	0.67	1.03	0.00	0.00
TX	Melde	2005	21.4	1.40	0.10	34	0	40, 51	0	0.00	0.06	0.06	0.54
TX	Melde	2006	18.9	0.16	0.00	34	0	40, 51	0	0.00	0.03	0.00	0.02
TX	Melde	2007	37.9	7.70	0.51	34	0	41, 51	0	0.22	4.10	0.22	2.67
TX	Melde	2008	14.3	0.02	0.00	34	0	40, 51	0	0.00	0.00	0.00	0.00
TX	Patton	2005	21.3	1.80	0.00	10	0	33	13	0.00	0.08	0.10	0.10
TX	Patton	2006	19.7	0.50	0.00	10	0	33	13	0.02	0.09	0.03	0.03
TX	Patton	2007	46.7	12.60	0.04	10	0	33	13	0.76	1.77	0.44	0.47
TX	Patton	2008	19.4	0.40	0.00	10	0	33	13	0.04	0.10	0.08	0.08
TX	Riesel	2001	35.3	7.20	0.13	51	0	30	0	0.24	10.61	0.27	0.85
TX	Riesel	2002	36.8	5.60	0.05	51	0	30	0	0.19	1.90	0.24	0.40
TX	Riesel	2003	44.9	8.00	0.11	51	0	30	0	0.25	1.20	0.29	0.66
TX	Riesel	2004	35.3	6.40	0.06	51	0	30	0	0.24	2.30	0.28	0.52
TX	Riesel	2005	38.7	4.90	0.06	51	0	30	0	0.13	1.30	0.13	0.36

TX	Riesel	2006	64.5	29.34	0.36	51	0	30	0	0.77	3.40	0.86	1.85
TX	Riesel	2007	28.8	0.62	0.00	51	0	30	0	0.01	0.80	0.02	0.04

DRAINMOD

Progress Report on the

Development and testing of a version of DRAINMOD for simulating P dynamics in artificially drained high water table soils

By: Mohamed A. Youssef

Date: May 15, 2016

The funds obtained from the multi-institution CIG grant, entitled “Refine and Regionalize Southern Phosphorous Assessment Tools Based on Validation and State Priorities” has been primarily used to support a PhD student to work on this project with the overall goal of developing DRAINMOD-P model, an integrated, process-based field-scale model for simulating P cycling and dynamics in drained agricultural fields. This goal is being achieved by modeling key hydrological and biochemical processes that affect fate and transport of P in drained agricultural fields. Specific objectives of the research project include:

1. Enhancing the hydrology component of DRAINMOD to model water flow and transport in soil macropores.
2. Developing a P component for DRAINMOD to simulate P-cycling and dynamics.
3. Testing the developed model using field measured data from two sites, one in North Carolina and one in Ohio.
4. Applying the model to assess the long term effects of Best Management Practices (BMPs) on P losses from drained croplands.

<u>What has been achieved since the beginning of the project?</u>

1. The graduate student, Manal Askar, has completed two years of course work.
2. The advisory committee has been formed (Chair: Mohamed Youssef; Members: George Chescheir, Dean Hesterberg, Wayne Skaggs)
3. An extensive review of the literature was conducted and different modeling approaches were compared.
4. A conceptual model (Figure 1) of DRAINMOD-P was developed.
5. The code is currently being written in FORTRAN programing language and is expected to be completed by the end of 2016.

DESCRIPTION OF DRAINMOD-P MODEL

Adding a Macropore flow Component to DRAINMOD

The first step for adequately modeling P dynamics and predicting P loss using DRAINMOD is to modify DRAINMOD’s hydrology component to simulate macropore flow and transport. The approach selected for simulating macropore flow will adequately represent the phenomena while keeping the model relatively simple and easy to parameterize. An approach similar to that used in MACRO model (Larsbo et al., 2005) is selected for simulating preferential flow. Macropores and micropores are separate domains in MACRO, each characterized by a degree of saturation, hydraulic conductivity, and flux. MACRO uses a modified Kinematic Wave Equation (KWE) of the one presented by German and Beven (1985) to represent gravitational movement of macropore flow,

$$\frac{\partial \theta_{ma}}{\partial t} = \frac{\partial K_{ma}}{\partial z} \pm \sum S_i \tag{1}$$

where, θ_{ma} and K_{ma} are the macropore water content and hydraulic conductivity, respectively, S_i is a source/sink term, and z is depth. The Kinematic wave equation is similar to Richards equation assuming capillarity is negligible in macropores (i.e. $\frac{\partial \varphi}{\partial z}$ = 0, where φ is the soil water pressure head). Compared to models that use Richards equation for macropore flow, no water retention of the macropore domain is required and less parameters are needed for the KWE (Gerke, 2006). However, the equation accounts for vertical gravity flow only and capillarity is ignored. Therefore, upward flow during ET periods cannot be simulated. MACRO uses a threshold pressure head for defining the boundary between micropores and macropores. Therefore, in addition to total saturated water content (θ_s) and total saturated hydraulic conductivity (K_s), the user must define a breakpoint pressure head (φ_b) which is used to partition total porosity into micro- and macroporosity, where φ_b falls within the range -6 to -10 cm (Jarvis and Larsbo, 2012). Corresponding water content (θ_b) and hydraulic conductivity (K_b) at this point represent the saturated state of the soil matrix (Fig. 1).

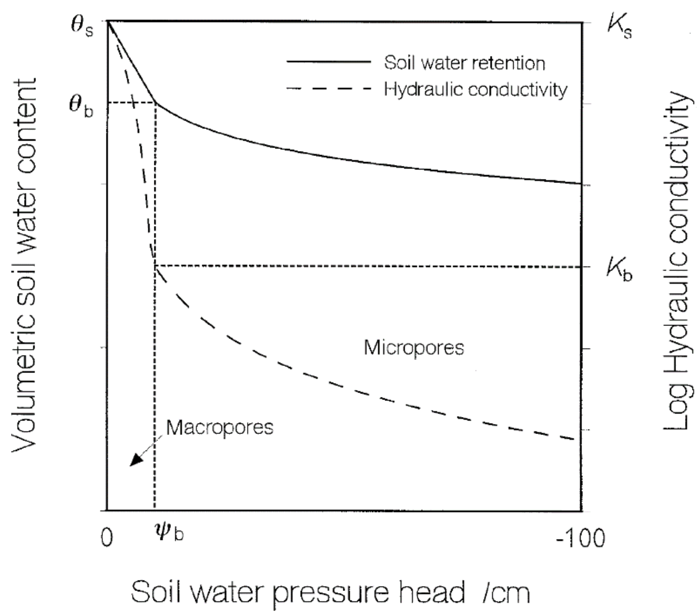


Figure 1 Modified van Genuchten soil water retention function used in MACRO (After Larsbo et al., 2005)

Macropore hydraulic conductivity is expressed as a power function of macropore water content (Larsbo et al., 2005)

$$q_{ma} = K_{ma} = K_{s(ma)}(S_{ma})^{n^*} = (K_s - K_b)\left(\frac{\theta_{ma}}{\theta_{s(ma)}}\right)^{n^*} \tag{2}$$

Where, q_{ma} is water flow in macropores, K_{ma} is the macropore hydraulic conductivity, $K_{s(ma)}$ is the saturated macropore conductivity, S_{ma} is the macropore degree of saturation, $\theta_{s(ma)}$ is the saturated macropore water content (macroporosity) equals θ_s-θ_b, n^* is kinematic exponent reflecting macropore size distribution, connectivity, and tortuosity (usually set to 3), K_s is the total saturated conductivity, K_b is the saturated soil matrix conductivity. An upper flux boundary condition is used such that rainfall rate greater than infiltration capacity is routed to macropores until saturation. Excess rainfall then generates overland flow.

For lateral water flow, MACRO uses a first order equation (Eq. 3) for water transfer from macropores to matrix. Conversely, flow can occur instantaneously from matrix to macropores if matrix water content exceeded field capacity in any computational layer. The exchange is controlled by an 'effective' diffusion pathlength and driven by water content gradient

$$S_w = \left(\frac{G_f D_w \gamma_w}{d^2}\right)(\theta_b - \theta_{mi}) \tag{3}$$

Where, G_f is geometry factor, d is effective diffusion pathlength (accounts for size and shape of aggregates, density and distribution of biotic macropores, and macropores linings), D_w is the effective water diffusivity, θ_b is the saturated water content in soil matrix, θ_{mi} is matrix water content, and γ_w is scaling factor to match approximate and exact solutions.

Parameters used for soil hydraulic properties can either be measured, obtained from literature, calibrated, or estimated. Parameters that are often uncertain and need calibration include saturated matrix conductivity (K_b), effective diffusion pathlength (d), kinematic exponent (n^*), and saturated macropore water content (macroporosity) ($\theta_{s(ma)}$). For solute transport, the advection-dispersion equation that already exists in DRAINMOD N II model will be used to simulate reactive P transport in both soil matrix and macropores.

Modeling Phosphorus transformations

Most process-based P models represent P cycling with the multi-pool P model described by Jones et al. (1984) and Sharpley et al. (1984). P cycling subroutines of the EPIC model, which uses the same approach, will be modified and added to DRAINMOD. Our aim is to improve the P model by including non-linear P sorption isotherms for predicting dissolved P concentrations. Generally, organic P (OP) and inorganic P (IP) are partitioned into different pools according to the rate at which P flows from each pool.

Inorganic P is divided into three different pools; labile, active, and stable mineral pools (Fig. 1). The labile pool is the readily available P while the stable pool represents the very slowly available P. It should be noted that all pools are defined for each soil layer. Rapid equilibrium (days to weeks) is assumed to exist between the labile pool and active pool (Sharpley et al., 1984). Size of labile P pool and active P pool are assumed to be in equilibrium and can be related using equation (4)

$$P_{labile} = P_{active}\left(\frac{PAI}{1 - PAI}\right) \tag{4}$$

where, PAI is the P availability index defined as the fraction of applied fertilizer (P_f) that remains labile after six-month incubation with several wetting and drying cycles (Jones at al., 1984). PAI can be calculated using the method outlined by Sharpley et al. (1984) by estimating the slope of the linear relation between labile and added fertilizer P as shown in equation (5)

$$PAI = \frac{(P_{labile,f} - P_{labile,i})}{P_f} \tag{5}$$

where $P_{labile,f}$ and $P_{labile,i}$ are the labile P after and prior to fertilization.

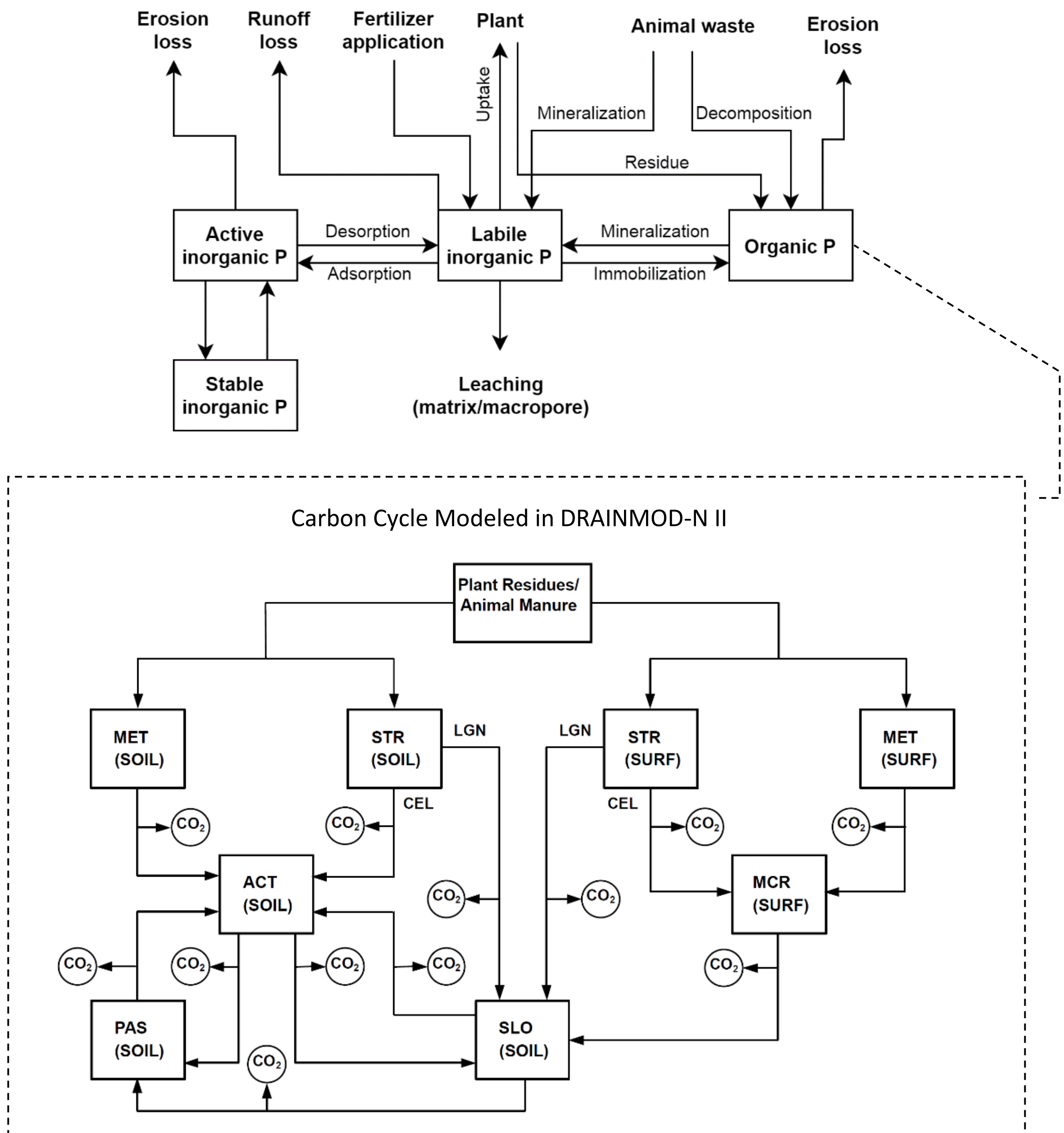


Figure 1. Integrating P pools and flows for the proposed model with current biogeochemical processes simulated in DRAINMOD. The carbon cycle is adapted from (Youssef et al., 2005) where (MET=metabolic pool, STR-structural pool, ACT=active pool, PAS=passive pool, SLO=slow pool, MCR=microbial pool, LGN=lignin, CEL=cellulose, SURF=occurs on surface, SOIL=occurs below surface)

For the interaction between both labile and active inorganic P, either Freundlich or Langmuir equations can be used for simulating nonlinear isotherms. The general form of Freundlich isotherm is

$$Q = K_F C^b \tag{6}$$

where, Q, quantity of P sorbed (mg kg^{-1}), C, P concentration in solution (mg L^{-1}), K_F (mg^{1-b} L^{b} kg^{-1}) and b (unitless), fitting parameter. An alternate approach is the Langmuir equation:

$$Q = Q_{max}[K_L C/(1 + K_L C)] \quad (7)$$

where, Q_{max}, maximum amount of P sorbed (mg kg^{-1}), K_L, constant related to the binding energy of P (L mg^{-1}). However, Langmuir equation has the advantage of specifying a theoretical maximum adsorption, Freundlich equation lean more to fit P isotherms compared to the Langmuir equation (Jonge et al., 2001, Zhao et al., 2007). Fitting coefficients can be calibrated, estimated from literature, or measured in lab.

Slow equilibrium is assumed to exist between the active pool and slow pool (Sharpley et al., 1984). The size of the inorganic stable P pool is initialized to be four times the size of the inorganic active pool as suggested by Sharpley et al. (1984) according to unpublished data. For simplicity, linear isotherm can be used for the slow rate of P movement between active and stable P pools (equation 8)

$$R_{as} = K_{as}(4\, P_{active} - P_{stable}) \quad (8)$$

where, R_{as}, is rate of P movement between active and stable P pools, K_{as}, rate constant. Values of K_{as} for calcareous and noncalcareous soils can be estimated from Cox et al. (1981) study.

Organic P: Some P processes are closely linked to C dynamics in soil organic matter as C supply is essential for these processes to take place. Therefore, interaction between OP and IP forms during organic matter (OM) decomposition will be regulated by the C submodel that already exists in DRAINMOD. In consistence with soil organic matter, OP will be divided into three pools (active, slow, and passive), two above- and below-ground fresh pools (metabolic and structural), and a surface microbial pool (Youssef et al., 2005). The metabolic pool will have easily decomposable materials while structural pool will have more resistance to decomposition materials. Like plant residues, the organic portion of the animal manure added to soil surface will be incorporated to surface structural and metabolic pools, while the inorganic portion will be incorporated to the labile pool. If manure is applied at a specific soil depth, the organic portion will be added to the subsurface pools.

The active organic pool represent fast decomposition rate matter with short turnover time, while the slow organic pool includes more biological resistance to decomposition matter with intermediate turnover time (Fig. 2). Passive pool will represent physically protected matter with the longest turn over time. Each pool is characterized by a certain rate of decomposition and C:N:P ratio (Youssef et al., 2005). Mineralization and immobilization of P will depend on the associated C:P ratio of the decomposing C source. In other words, mineralized organic C (OC) in the SOM will have a corresponding mineralized OP regulated by the C:P ratio. Mineralized or desorbed P will be added to the labile P pool, while, immobilized or adsorbed P will be subtracted from the labile P pool (Fig. 2).

As previously mentioned, simulating particulate P transport is a complex process, particularly in the subsurface, and usually ignored by P models as it requires a representation of the colloids detachment and transport in soil and their interaction with contaminants. MACRO (Jarvis et al., 1999) and ICECREAM (Larsson et al., 2007) are of the few models capable of modeling colloid and particle subsurface transport and both use similar approaches. Approaches similar to the ones used in MACRO for simulating particle mobilization and transport are being considered when developing DRAINMOD-P. Particles detachment rate is described as a function of rainfall kinetic energy and readily available dispersible particles (Equation 9)

$$D = K_d\, E\, R\, M_s \quad (9)$$

where, D, rate of detachment (g m^{-2} h^{-1}), K_d, soil detachability coefficient (g J^{-1}), E, kinetic energy (J m^{-2} mm^{-1}), R, rainfall rate (mm h^{-1}), M_s, available dispersible particles (g g^{-1} soil). Soil particle replenishment rate is calculated using

$$P = K_r \left(1 - \frac{M_s}{M_{max}}\right) \tag{10}$$

where, P, particle replenishment rate (g m^{-2} h^{-1}), K_r, replenishment rate coefficient (g m^{-2} h^{-1}), M_{max}, maximum available particles (g g^{-1} soil). Available particles at the surface can be computed using a the following mass balance equation

$$\frac{dA_s}{dt} = P - D \tag{11}$$

where

$$A_s = M_s\, \gamma z_i \tag{12}$$

where, A_s, available particles at surface (g m^{-2}), γ, soil dry bulk density (g m^{-3}), z_i, soil depth affected by detachment (m). The model mainly focuses on colloids transport via macropores and assumes most colloids are trapped and filtered by micropores except in coarse sands and gravels (Jarvis et al., 1999). However, for simplicity we will assume PP travelling through soil matrix is trapped and neglected. P concentrations in water infiltrating macropores and micropores are assumed to be identical. For representing concentration of both DP and PP routed into macropores, the approach used in ICECREAM (Larsson et al., 2007) can be used which assumes an instant and complete mixing of rainfall and water stored in a shallow surface layer

$$C_{DP,ma} = \frac{P_{labile,x_d}}{R + (x_d(\theta_{top} + \gamma_{top} K_{dw})} \tag{13}$$

where

$$K_{dw} = 100 + 250cc \tag{14}$$

in which, $C_{DP,ma}$, concentration of DP in macropores, x_d, mixing depth (recommended 1mm), P_{labile,x_d}, labile P stored in x_d, θ_{top}, water content of top layer, γ_{top}, dry bulk density of top layer (g m^{-3}), K_{dw}, sorption distribution coefficient (L Kg^{-1}), cc, clay fraction. The same mixing depth approach is used for calculating PP routed into macropores ($C_{PP,ma}$)

$$C_{PP,ma} = \frac{D}{R + x_d \theta_{top}} \tag{15}$$

The flux of suspended particles reaching subsurface drainage is then reduced to account for particles filtered (entrapped) in macropores using a filter coefficient

$$M_d = q_{ma} C_{PP,ma} e^{(-f z_d)} \tag{16}$$

in which, M_d, flux of suspended particles reaching drains (mm d^{-1}), q_{ma}, water flow through macropores (mm d^{-1}), f, is a filter coefficient (m^{-1}), z_d, depth to tile drains (m). Flux of PP transported (M_d, mm d^{-1}) can be estimated by summing a fraction (f_{M_d}) of all P pool such that

$$f_{M_d} = \frac{M_d}{x_d\, \gamma_{top}} \tag{17}$$

Advection-dispersion equation is to be used to model DP transport in both matrix and macropores, while dispersion of PP in macropores is to be neglected.

In addition to the previous approach, methods used in the EPIC model for simulating erosion and surface loss of P due to surface runoff will be considered as well. EPIC (Williams et al., 1984) uses the modified

USLE equation developed by Wischmeier and Smith (1979) that takes into consideration both runoff and rainfall variables

$$Y = \left(0.646\ EI + 0.45\ Q\ {q_p}^{0.333}\right) K\ Crop\ PE\ S \tag{18}$$

where, Y, sediment yield (t ha^{-1}), EI, rainfall energy factor, Q, runoff volume (mm), q_p, peak runoff rate (mm h^{-1}), K, soil erodibility factor, $Crop$, crop management factor, PE, erosion control practice factor, S, slope length and steepness factor. $Crop$ and S can be computed using equations recommended by Williams et al. (1984). For simulating DP loss in surface runoff, EPIC uses equation (19)

$$YDP = 0.01 \frac{C_{lp,top} Q}{k_d} \tag{19}$$

where, YDP, dissolved P (Kg ha^{-1}) lost in surface runoff (Q, mm), $C_{lp,top}$, labile P concentration in top layer (g t^{-1}), k_d, P concentration in sediment divided by that in water (m^3 t^{-1}) (a value of 175 is used in EPIC). While for simulating PP transport via surface runoff, equation (20) is used

$$YPP = 0.001\ Y\ C_{p,top}\ ER \tag{20}$$

where, YPP, sediment attached P (Kg ha^{-1}) lost in surface runoff, $C_{p,top}$, P concentration in top layer (g t^{-1}), ER, enrichment ratio which is estimated using the sediment concentration.

The recently developed vegetation component of DRAINMOD will be modified to determine plant uptake of P, which will be simulated using a similar procedure of N uptake by Youssef et al. (2005). Plant P uptake will be controlled by the labile pool and availability of labile P in the root zone.

B) Describe significant results, accomplishments, and lessons learned. Compare actual accomplishments to the project goals in your proposal:

This work represents an important contribution to our understanding of agricultural water quality models, not just from the Southern CIG effort but also from the Heartland and Chesapeake efforts. Lessons learned are as follows:

1. Water quality models often are adequate for describing hydrology but not sediment or P losses. Critically, southern P Indices were just as good as the more difficult to use water quality models. USDA-NRCS should not use these models for management decision making.
2. NRCS 590 standard is not interpreted in all states similarly
3. Even though southern P Indices do not produce the same ratings across all states for the same conditions, they are as robust (in some cases more robust) than the difficult and time consuming water quality models.
4. Not unexpectedly, modeling work is very time-consuming and technically challenging, even running models without calibration and validation. Currently modeled losses of P are dissimilar to measured losses, at least for the Georgia, Mississippi, and North Carolina sites.
5. Without resources to develop water quality data states within each state and resources for university faculty and their colleagues (state agency and USDA-NRCS state personnel), there is little expectation for changes in P Indices.
6. Most southern states rarely utilize P Indices. Maybe it's time to set soil test P thresholds to make the process simpler so that soil test P does not continue to build.

C) Describe the work that you anticipate completing in the next six-month period: N/A

D) Provide the following in accordance with the Environmental Quality Incentives Program (EQIP) and CIG grant agreement provisions:

1. A listing of EQIP-eligible producers involved in the project, identified by name and social security number or taxpayer identification number; **None.**

2. The dollar amount of any direct or indirect payment made to each individual producer or entity for any structural, vegetative, or management practices. Both biannual and cumulative payment amounts must be submitted. **$0.0**

3. A self-certification statement indicating that each individual or entity receiving a direct or indirect payment for any structural, vegetative, or management practice through this grant is in compliance with the adjusted gross income (AGI) and highly-erodible lands and wetlands conservation (HEL/WC) compliance provisions of the Farm Bill. **Not applicable.**