PAY-FOR-PERFORMANCE CONSERVATION USING SWAT HIGHLIGHTS NEED FOR FIELD-LEVEL AGRICULTURAL CONSERVATION

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ABSTRACT. *Pay-for-performance (PFP) is a relatively new approach to agricultural conservation that attaches an incentive payment to quantified reductions in nutrient runoff from a participating farm. Similar to a payment for ecosystem services approach, PFP lends itself to providing incentives for the most beneficial practices at the field level. To date, PFP conservation in the U.S. has only been applied in small pilot programs. Because monitoring conservation performance for each field enrolled in a program would be cost-prohibitive, field-level modeling can provide cost-effective estimates of anticipated improvements in nutrient runoff. We developed a PFP system that uses a unique application of one of the leading agricultural models, the USDA's Soil and Water Assessment Tool, to evaluate the nutrient load reductions of potential farm practice changes based on field-level agronomic and management data. The initial phase of the project focused on simulating individual fields in the River Raisin watershed in southeastern Michigan. Here we present development of the modeling approach and results from the pilot year, 2015-2016. These results stress that (1) there is variability in practice effectiveness both within and between farms, and thus there is not one "best practice" for all farms, (2) conservation decisions are made most effectively at the scale of the farm field rather than the sub-watershed or watershed level, and (3) detailed, field-level management information is needed to accurately model and manage on-farm nutrient loadings.*

Keywords. *Agricultural conservation, Pay-for-performance, Phosphorus, River Raisin, SWAT, Western basin of Lake Erie.*

The western basin of Lake Erie (WBLE) is currently experiencing a resurgence of harmful algal blooms (HABs) and low oxygen conditions (hypoxia), driven primarily by increases in phosphorus (P) loads to the lake (Obenour et al., 2014; Scavia et al., 2014, 2016; Rucinski et al., 2016). To reduce the occurrence and severity of HABs and hypoxia, the U.S. and Canada set a lake-wide P load target of a 40% reduction from 2008 levels. Given that the drainage area of the WBLE is approximately 70% agricultural, and that an estimated 89% of total phosphorus (TP) and 71% of dissolved reactive phosphorus (DRP) loads come from nonpoint sources (Maccoux et al., 2016), it is necessary to develop solutions to reduce agricultural nonpoint source P losses.

Many agricultural conservation programs in the U.S., such as the Environmental Quality Incentives Program (EQIP), focus on implementing conservation practices and may not have the ability or funding to track or maximize the associated environmental benefits (Claassen et al., 2008; Sharpley et al., 2015). Additionally, programs like EQIP rely primarily on voluntary participation, which makes it difficult to target conservation to areas that need it most (Talberth et al., 2015; Wardropper et al., 2015). To address some of these concerns within current U.S. approaches to agricultural conservation, there is a growing movement to implement pay-for-performance (PFP) conservation programs (Winsten and Hunter, 2011; Fales et al., 2016; Kerr et al., 2016; Palm-Forster et al., 2016). In this approach, the farmers still participate voluntarily, but payments are made for the environmental benefits provided by implementing conservation practices, as opposed to paying for the practices themselves. This ensures that all farms work toward a quantifiable goal, allows for flexibility in the practices that farmers choose, and helps get the most effective practices in the places of greatest need. The PFP approach is similar to the payments for ecosystem services framework, implemented around the globe, that aims to create a market for benefits provided by the environment (Schomers and Matzdorf, 2013).

Theoretical modeling approaches to evaluating opportunities in PFP agricultural conservation have indicated, from an economics perspective, the potential improvements for

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agricultural conservation that focuses on payments for benefits or outcomes, rather than payments for practices or inputs (Talberth et al., 2015; Drechsler, 2017). In addition to theoretical modeling, some studies have piloted PFP programs in the U.S. (Winsten, 2009; Douglas-Mankin et al., 2013; Fales et al., 2016). However, one difficulty in implementing a PFP program, and a potential reason why they are not used more widely, is the cost and complexity of quantifying performance. Measuring field-scale nutrient losses, for example, can be quite costly, and a number of years may be needed to demonstrate practice effectiveness due to weather variability (Santhi et al., 2014). Therefore, PFP programs can more efficiently apply indices (Winsten, 2009) or models (Douglas-Mankin et al., 2013; Fales et al., 2016) to quantify the potential conservation performance for a given system. To our knowledge, this project is the first implementation of the Soil and Water Assessment Tool (SWAT) to assess agricultural conservation practice performance at the field scale for a P-based PFP program. While not specifically calling the program PFP, Douglas-Mankin et al. (2013) described a program for "paying for sediment" reductions that was implemented in Black Kettle Creek watershed in Kansas, and it represents the most similar approach to our work with respect to modeling in a PFP system. Their work demonstrated the potential for PFP to achieve water quality improvements in a cost-effective and flexible manner. We build on this work with a P-based PFP system using SWAT and use the findings to highlight the importance of field-based conservation. The overall goal is to present our initial experiences in modeling farm-scale P load reductions with SWAT and to provide insights into the practical application of this method for quantifying the performance of a PFP conservation program.

METHODS

STUDY AREA

The agriculturally dominated River Raisin watershed (RRW; ~2737 km^2; HUC 04100002) is located in southeastern Michigan and drains into the WBLE. It is ~54% cropland (primarily corn, soybeans, and winter wheat) and ~18% grassland and pasture (fig. 1). Apart from the Detroit River, the RRW is Michigan's largest contributor of sediment and nutrients to the WBLE (Maccoux et al., 2016), contributing an annual average of 173 metric tons of TP from 2003 to 2013 and 37 metric tons of DRP from 2009 to 2013 into Lake Erie (Maccoux et al., 2016). While the soils are not as poorly drained as those in the neighboring Maumee River watershed, there is still a high rate of subsurface drainage (also called tile drainage), especially in the southeast portion that is more dominated by heavy clay soils. The northwest section is characterized by hilly slopes and woody wetlands, while the southeast is relatively flat and agricultural.

The RRW was designated as a Great Lakes "area of concern" based on beneficial use impairments from contaminated sediments associated with loss of fish and wildlife habitat (USEPA, 2016). The river also has Clean Water Act 303d-listed impaired sections, including stretches designated as impaired due to excess nitrates.

PAY-FOR-PERFORMANCE MODELING FRAMEWORK

The SWAT model was developed as part of a larger PFP effort that included (1) farmer surveys (see the Supplemental Information at https://hdl.handle.net/2286/R.A.191651) about field-level management and practices that they were interested in applying to reduce P loss from their farmland to waterways, (2) modeling baseline P losses and estimating the anticipated benefits of implementing new practices for individual fields using SWAT, (3) calculating the total cost to farmers for implementing these new practices and comparing these costs to the payments that farmers would receive for the amount of P reduced, (4) signing contracts indicating payments and costs to the farmers, (5) verifying implementation of the new practices, and (6) using SWAT to determine the average P loss reduction from all participating farms based on their selected practices. This article focuses on the development and application of the SWAT model within this larger framework.

SWAT MODEL DEVELOPMENT

SWAT is a process-based, hydrologic and water quality model developed by the USDA (Arnold et al., 1998, 2012) that is commonly applied to simulate the water quality impacts of agricultural conservation and land management (Gassman et al., 2014). The model uses landscape data (soils, elevation, land use, and land management) and associated process equations to mathematically represent watershed dynamics. The model runs at a daily scale, driven by weather data (temperature, precipitation, solar radiation, relative humidity, and wind speed), and provides hydrologic and water quality outputs at multiple spatial and temporal scales.

A baseline SWAT model was developed for the entire RRW using medium-resolution streams from the National Hydrography Dataset (NHD), 30 m digital elevation model (DEM) from the U.S. Geological Survey, land use data from the 2006 National Land Cover Dataset (Fry et al., 2011), soil data from the Soil Survey Geographic Database (USDA-NRCS, 2016a), and weather data from the Great Lakes Environmental Research Laboratory. A 4,000 ha stream threshold was used to delineate sub-basins that were approximately the size of 12-digit hydrologic unit codes. Hydrologic response units (HRUs) were defined using a 0% land use threshold, 10% soil threshold, and a single slope class. Using a single slope class means that the HRUs were not defined by their slope; however, the average slope derived from the DEM was used in calculations. Point sources were added to each sub-basin based on the U.S. Environmental Protection Agency's Discharge Monitoring Report. Wetlands and reservoirs were added to each sub-basin based on the NHD waterbody dataset.

Agricultural land crop rotations were determined based on overlaying six years (2007-2012) of the National Agricultural Statistics Service (NASS) cropland data layers (CDL). The most common rotations identified using this approach were corn and soybean and combinations of corn, soybean, and winter wheat. Rotations were applied across the watershed to ensure that the percentages of corn, soybean, and wheat matched well with the 2012 CDL and to maintain the appropriate amount of cropland with wheat in

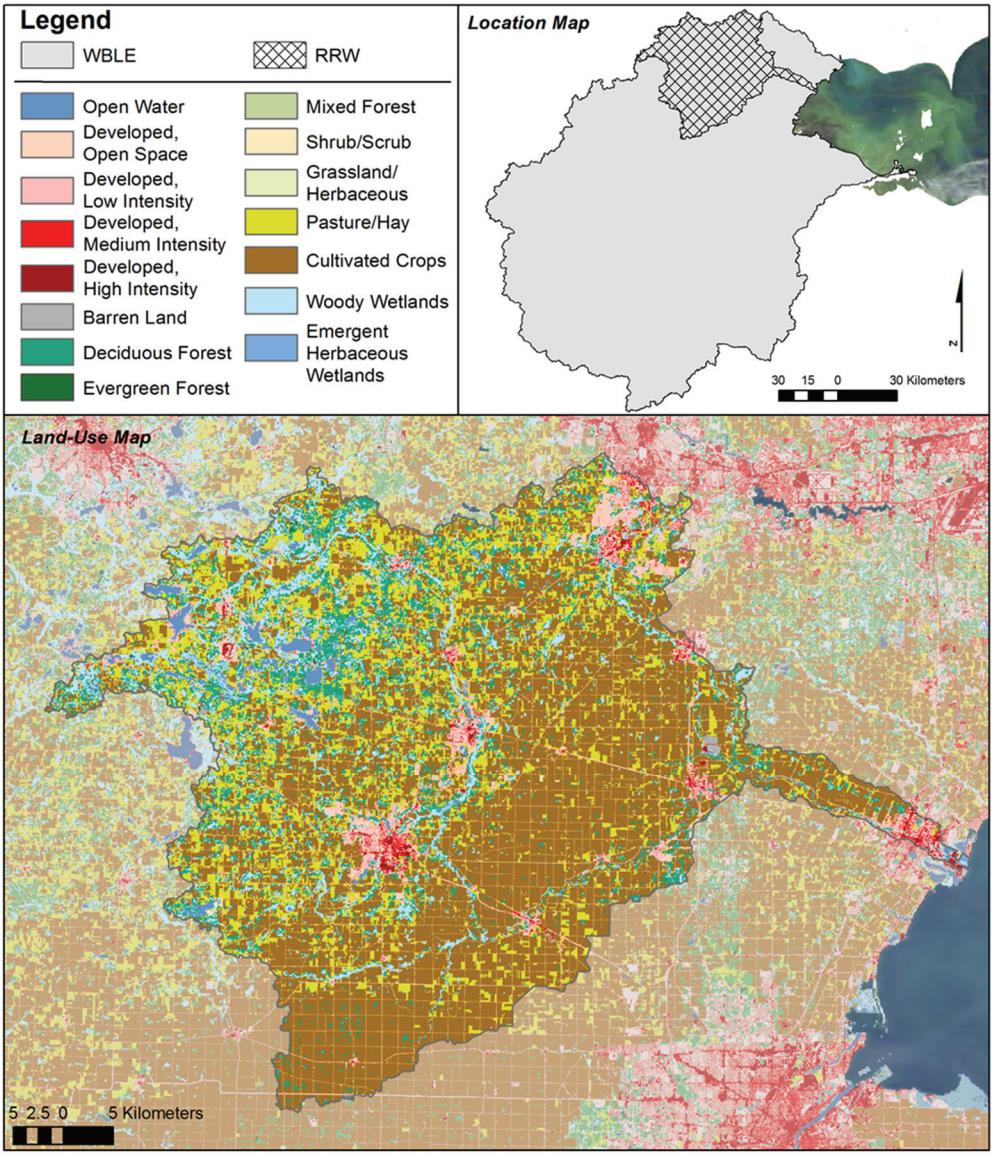


Figure 1. Location of the River Raisin watershed (RRW) draining to the western basin of Lake Erie (WBLE) and land use from the 2006 National Land Cover Dataset. The location map also shows the algae in the WBLE on 2 August 2015 (true-color image retrieved from NASA Worldview, courtesy of the NASA EOSDIS Land Processes Center, Sioux Falls, South Dakota).

its rotation. The total amount of fertilizer applied was based on county-level fertilizer sales (Ruddy et al., 2006), while manure application rates were developed based on methods from Ruddy et al. (2006) using numbers of animals for each county from the 2007 NASS census. A mass balance approach was used to ensure that the total amount of inorganic and organic nutrients in the watershed was applied within crop rotations and was allocated to crops based on agronomic need using the Tri-State Standard (Vitosh et al., 1995). Manure-based nutrients were also allocated based on proximity to a confined animal feeding operation by assuming that fields within five miles of these large operations are more likely to receive manure applications. This is a reasonable assumption because all of the confined animal feeding operations in the region are swine and dairy, which most likely produce liquid manure that is difficult and not cost-effective to transfer more than a few miles (Nowak et al., 2002). The total amount of nutrients applied matched well with published estimates of nutrient inputs for this period (Han et al., 2012). Tillage operations were estimated based on the 2006 National Crop Residue Management survey from the Conservation Technology Information Center (http://www.ctic.purdue.edu). Tile drains were assumed to be present on row cropland with very poorly, poorly, and somewhat poorly drained soils using the most recently developed tile drainage routine in SWAT, based on DRAINMOD equations (activated by setting SWAT's parameter ITDRN to 1). Other existing practices, such as filter strips and cover crops, were not included because these data were not accessible. More details on the SWAT model setup, including crop management files, are provided in the Supplemental Information.

We applied a modified version of SWAT 2012, Revision 635, that corrects for an error in the source code that pre-

vented the correct routing of soluble P through tile drains. More details on this change are provided by Kalcic et al. (2016) and Muenich et al. (2016). We used manual calibration on the most sensitive parameters identified using SWAT-CUP (Abbaspour, 2015) for the period 2001-2005, with validation from 2006 to 2010, ensuring good prediction of streamflow, sediment, TP, DRP, total nitrogen (TN), and nitrate near the outlet of the river to Lake Erie over the ten-year time period. Manual calibration was performed by changing one or multiple parameters at a time, based on a sensitivity analysis and modeler expert knowledge, until three different objective functions, i.e., coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS), reached reasonable levels for streamflow, TP, DRP, TN, and sediment at the gauging station near the watershed outlet and to ensure that field-level outputs (amount of tile flow, amount of nitrogen and P through tiles, and crop yields) were within established ranges. Publicly available observed daily data for all constituents near the outlet of the River Raisin were available from the National Center for Water Quality Research (https://www.heidelberg.edu/academics/research-and-centers/national-center-for-water-quality-research), enabling a robust comparison for all parameters. Daily climate data from the Global Historical Climatology Network (Menne et al., 2012) were lagged by one day to improve calibration performance by accounting for the difference in timing between the 24 h periods considered for climate and in-stream measurements (Kalcic et al., 2016).

Implementing Farmer-Informed SWAT Model at the Field Level

Applying Field-Level Information in the SWAT Framework

Using the surveys filled out by either participating farmers or conservationists (see the Supplemental Information), baseline SWAT management files were created for each field within a farm, and the farm's fields were digitized manually based on farmer-provided maps. Management information included details such as crop rotation, planting and harvesting dates, fertilizer (amount, type, and timing), tillage type and timing, tile drains, and existing conservation practices. For each unique set of field management operations on the farm, all HRU files in the watershed model were changed to match that specific management, and the SWAT model was run. Because we focused exclusively on field-level outputs, and the code used to change management files and run the model was computationally efficient, changing all farm fields simultaneously streamlined the process.

Ten farms were included in this pilot study, all within one tributary of the River Raisin that was identified as a target for conservation in a past watershed management plan. Four of the ten farms had at least some portion of their fields drained by subsurface tile drains. Two of the farms practiced continuous no-till, and on average the farms applied about 28 lb acre^{-1} of P. The farm P applications were higher than the values reported for the region (USDA-NRCS, 2016b), which is not surprising because the intention of the program was to reach farmers who could make the greatest impact with respect to reducing P on their fields. Three of the farms were already using some kind of winter cover crop on some of their fields, and only one of the farms applied manure. More details on the management of each farm are provided in the Supplemental Information.

After simulating a farmer's baseline for each field, we tested all scenarios that the farmer was interested in implementing. Table 1 provides a list of practices and variations of those practices implemented across the participating farms. While most of these are generally considered conservation practices, not all farmers were interested in implementing every practice or combination of practices, and not all practices implemented by farmer preference resulted in improvements from the baseline.

Extracting SWAT Output at the Field Level

While SWAT is not often applied at the field scale, its base unit of calculation (the HRU) essentially provides field-scale outputs, and previous studies have shown its usefulness at the field scale (Daggupati et al., 2011; Douglas-Mankin et al., 2013; Kalcic et al., 2015; Teshager et al. 2016). HRUs are areas with the same soils, slope, and land use within a sub-basin and are lumped together for calculations. Therefore, to extract field-based output, we overlaid field boundaries on top of HRU boundaries and calculated an area-weighted output within the field boundary based on the underlying HRUs. Because we applied a soil lumping threshold of 10%, we had "holes" in our HRU shapefile, indicating that the soil type in that area accounted for less than 10% of the soil (by area) in the sub-basin; therefore, this land area was lumped in with another HRU. This presented a problem when trying to extract data based on field boundaries, so these areas were "filled in" by reversing the lumping process in SWAT. Details on this approach are provided in the Supplemental Information. The model was run for all baseline and scenario conditions for ten years (2001-2010) to dampen interannual variability and to estimate an annual average improvement in nutrient loading (kg ha^{-1}) per field. While final payments were to be based on TP reductions, payments were not made if a selected practice increased DRP.

Table 1. Single practices implemented in scenarios run across fields and farms as well as variations in the implementations. Some practices were run in combination with each other while many were implemented individually.

Practice	Abbreviation	Details and Variations on Practice
Cover crops	CC	Addition of winter cover crop. Species added varied (cereal rye, oats, clover, radish).
Filter strip	FS	Installation of filter strip. Width of implementation varied from 10 to 60 ft.
P application rate change	P RATE	P fertilizer amounts reduced. Reduction varied from 10% to 30%.
P application timing change	P TIME	Changed from spring to fall or fall to spring.
P application method change	P APP	Changed from broadcast to subsurface application or vice versa.
No-till	NT	Changed from current tillage type to no-till.
Tillage change	TILL	Changed from one tillage type to another (neither option was no-till).
Rotation change	ROT	Changed the crop rotation.

Results

Watershed-Scale SWAT Model Calibration and Validation

After model calibration, the model met commonly accepted criteria for performance (Moriasi et al., 2007) based on monthly statistics for streamflow, TP, and DRP during the calibration and validation periods, as well as the entire PFP modeling period (table 2 and fig. 2). For final parameter values, calibration and validation plots, and evaluation statistics for nitrogen and sediment, see the Supplemental Information.

In addition to reasonable matching to observed water quality at the outlet, we examined relevant field-level model outputs. Average annual simulated crop yields for corn (9.6 t ha^{-1}), soybean (1.8 t ha^{-1}), and wheat (4.6 t ha^{-1}) were similar to NASS-reported estimates for the region during the modeling period (2001-2010), i.e., 8.4 t ha^{-1} for corn, 2.5 t ha^{-1} for soybeans, and 4.3 t ha^{-1} for wheat. In addition, we ensured that the flow and nutrients coming through the tile drains were in an appropriate range. In the calibrated model, 24% of the watershed's contribution to streamflow came through the tiles, carrying with it 70% of the nitrate and 30% of the DRP exported from the entire watershed. Given the fact that the RRW is likely not as heavily tiled as some other Midwestern agricultural watersheds, these values fall within reasonable, observed ranges (King et al., 2015; Smith et al., 2015; Williams et al., 2015).

Using the calibrated and validated watershed-scale model, we compared field-scale and farm-scale P losses in three ways: (1) comparing baseline losses determined from the calibrated watershed-scale model to baseline losses from the farmer-informed model for each field on the ten pilot farms, (2) evaluating the variability in baseline P losses within and between farms with the farmer-informed model, and (3) evaluating the effectiveness of conservation practices across fields and farms with the farmer-informed model.

Field-Level Comparisons

Calibrated Watershed Model versus Farmer-Informed Baseline P Losses

We compared results for 2001-2010 from the SWAT model, calibrated in a standard way across the full RRW, with the farmer-informed model for the specific fields within the ten farms submitted to the PFP program. In doing so, we evaluated how well a watershed-scale model calibrated near the outlet of the watershed can provide field-scale information in the absence of field-level management data. For some farms, our calibrated watershed-scale model compared well with the farmer-informed baselines (fig. 3), while for many others it did not.

The simulated annual average P losses from agricultural

Table 2. Monthly calibration and validation statistics and combined PFP period statistics.

	Streamflow (cms)			TP (kg)			DRP (kg)		
	NSE	R^2	PBIAS (%)	NSE	R^2	PBIAS (%)	NSE	R^2	PBIAS (%)
Calibration (2001-2005)	0.75	0.8	-7.57	0.59	0.6	-7.83	0.51	0.52	9.5
Validation (2006-2010)	0.82	0.85	-7.75	0.47	0.66	16.15	0.51	0.53	-4.77
PFP period (2001-2010)	0.81	0.83	-7.75	0.5	0.59	5.25	0.54	0.54	5.53

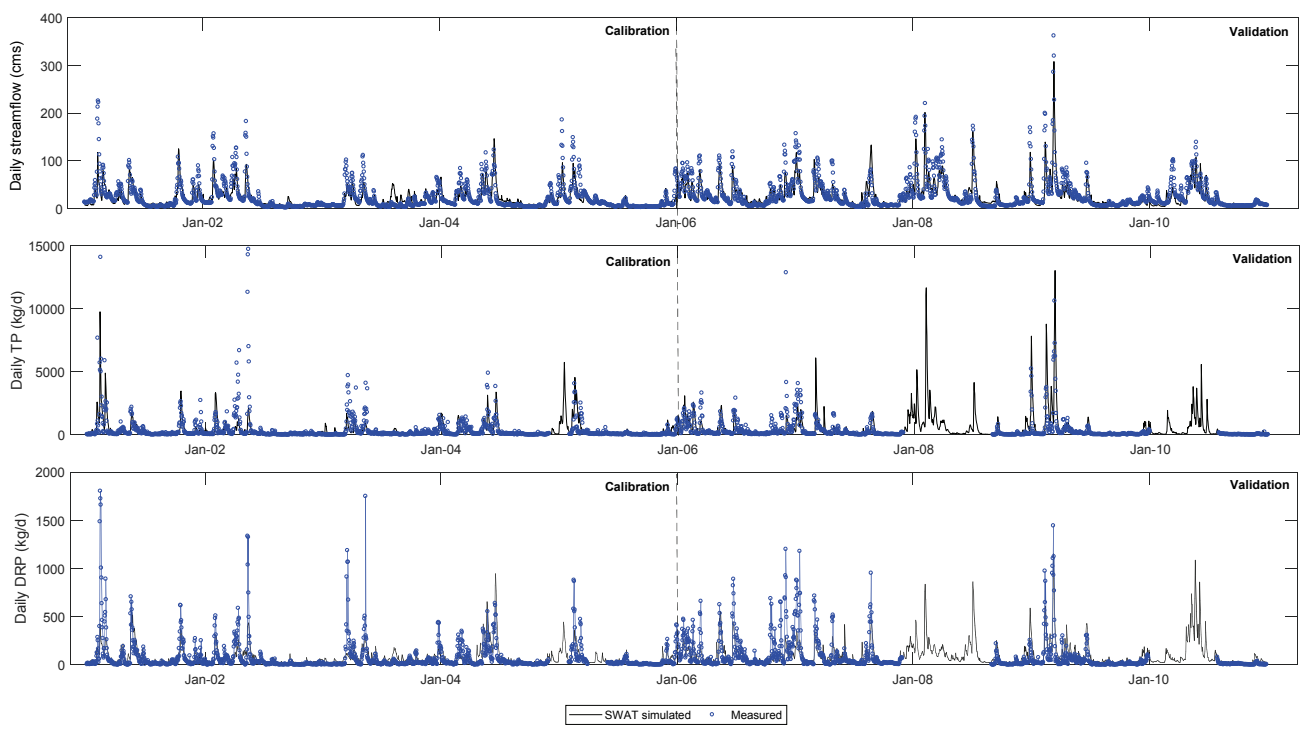
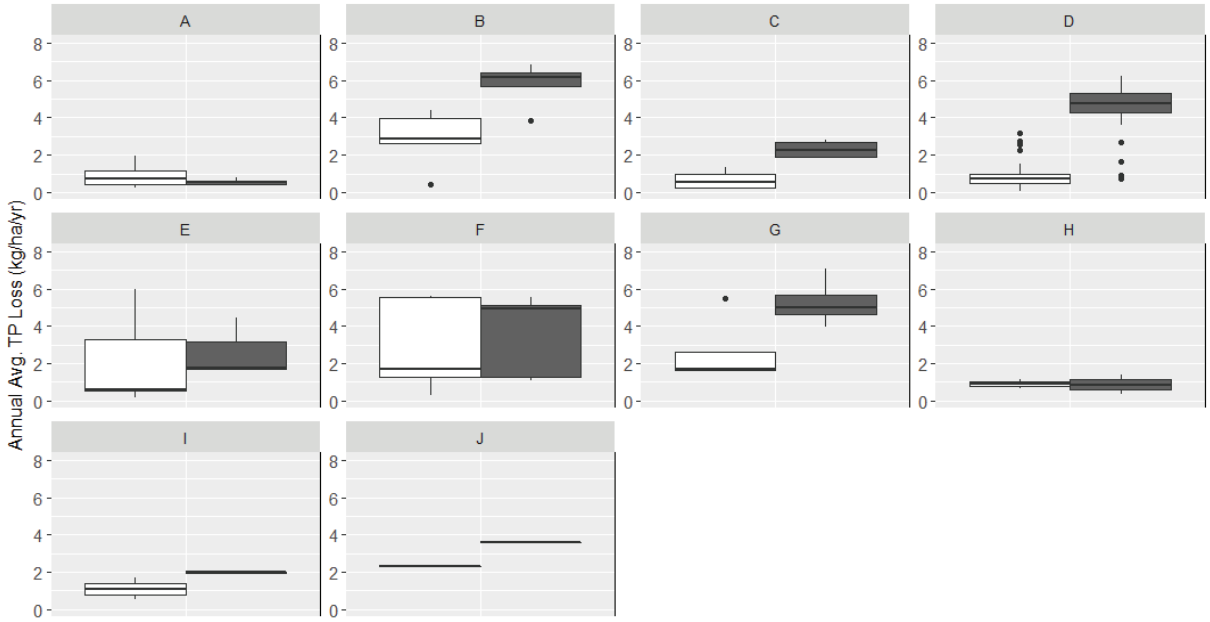
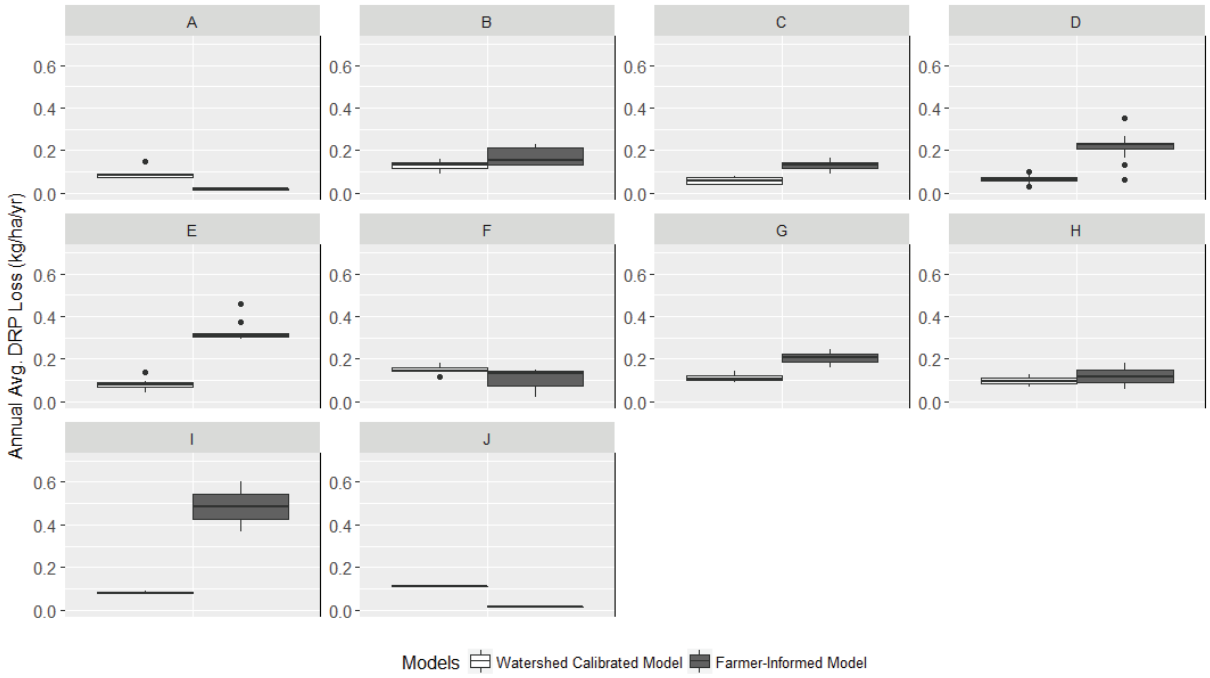


Figure 2. Time series plots showing the SWAT simulated daily streamflow (cms) and TP and DRP loads (kg d^{-1}) compared to measured data for the calibration (2001-2005) and validation (2006-2010) periods.



(a) TP losses



(b) DRP losses

Figure 3. Comparisons of farm-level (a) TP losses and (b) DRP losses between the baseline, watershed-scale calibrated model (white boxes), and farmer-informed model (gray boxes). Annual average across 2001-2010 was simulated across all fields within a given farm (A to J).

HRUs in the watershed-scale model ranged between 0.49 and 10.7 kg ha^{-1} for TP and between 0.008 and 0.30 kg ha^{-1} for DRP across the entire watershed. For both TP and DRP, the range varied when evaluating field-level data that were informed with actual management information (results from the farmer-informed model; fig. 3). In many cases, the TP and DRP losses when using actual farmer management information were higher than when using the watershed-scale model. This is likely because watershed-scale models typically do not have this kind of detailed management data, so practices tend to be averaged and are not likely representative of the full range of practices. This is further evidenced by some farms that had lower estimated P losses when using actual management data. This suggests that not all farm fields within a sub-basin identified as a critical source area based on modeling or monitoring data are necessarily high contributors where conservation dollars would be optimally spent. Conversely, fields that are not within a critical source area sub-basin may actually have very high losses and could therefore be missed by sub-basin-scale targeting.

Variability in Baseline P Losses within and between Farms

Variability across fields and farms for the farmer-informed baseline model was substantial (figs. 4 and 5). Annual average P losses across all fields and farms ranged from 0.32 to 7.0 kg ha^{-1} for TP and from 0.013 to 0.60 kg ha^{-1} for DRP. It is clear (figs. 4 and 5) that while some fields within a farm have similar losses per acre (e.g., farm A), many farms had variable losses across fields within their farms (e.g., farm E). These results support the idea that conservation should be at the field level rather than the farm level. Programs targeting specific farms only, or using a "representative" field to estimate farm losses, could miss the most effective opportunities to reduce nutrient losses.

Effectiveness and Variation of Conservation Practices

We also compared the effectiveness of different conservation practices or combinations of practices across farms and fields using the farmer-informed model (fig. 6). While cover crops and filter strips were consistently beneficial for reducing TP, they had a variable impact on DRP. Subsurface applications of P reduced DRP losses by a greater percentage than TP losses because this practice reduces the concentration of soluble P in the top soil layer that interacts with surface runoff. In evaluating practice effectiveness across farms, we found that there was no one best practice that should be implemented for both TP and DRP, nor one best practice that should be implemented across all farms.

Looking more closely within each farm (fig. 7) there may be multiple options that reduce phosphorus, given each farmer's interest. In addition, understanding each farm's current practices, plus the physical attributes of the fields, can help in understanding why some practices were more effective than others. For example, farm H had fields without tiles, making practices that intercept or prevent P in surface runoff (e.g., filter strips, cover crops) quite effective. Farm F

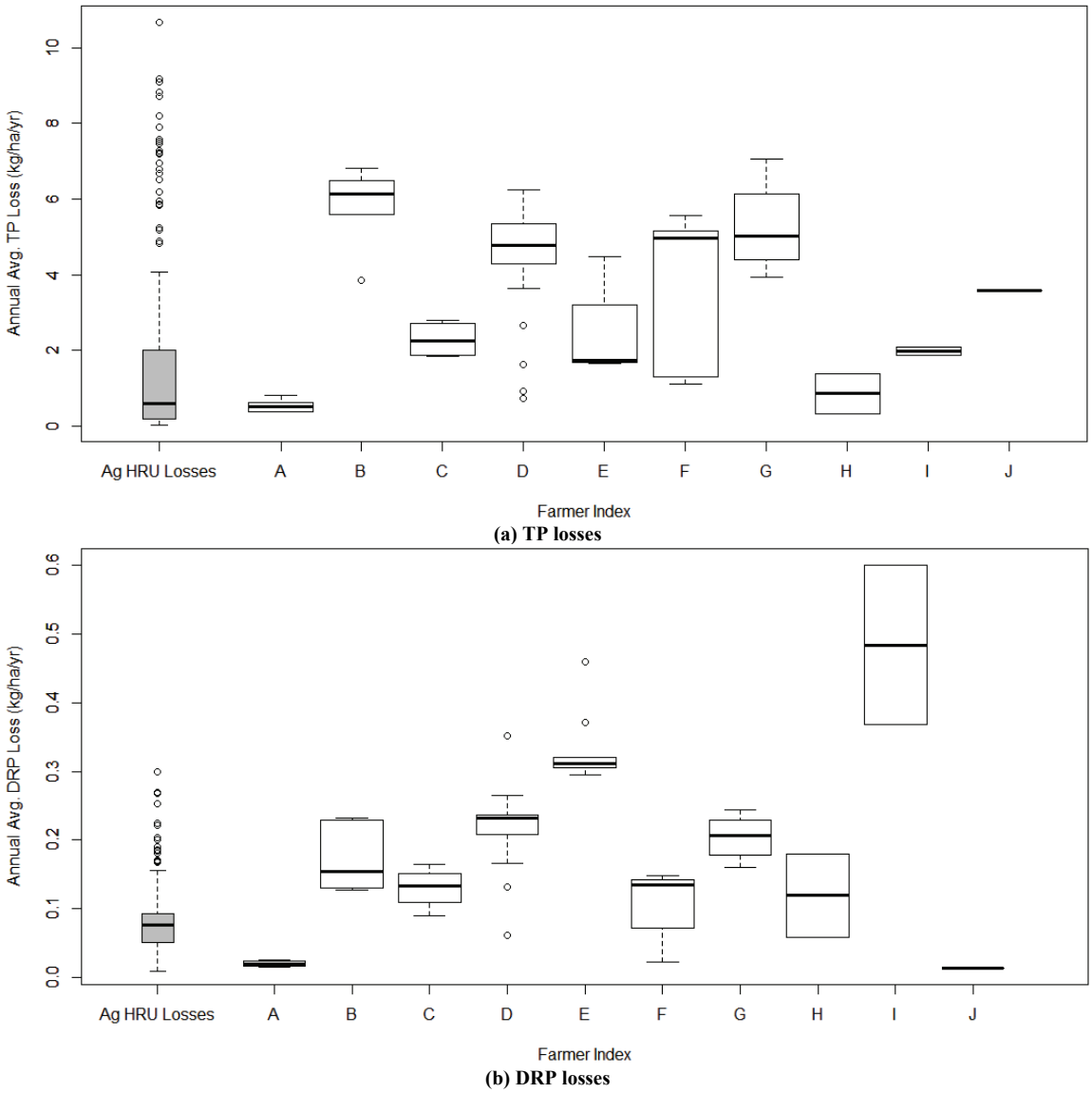
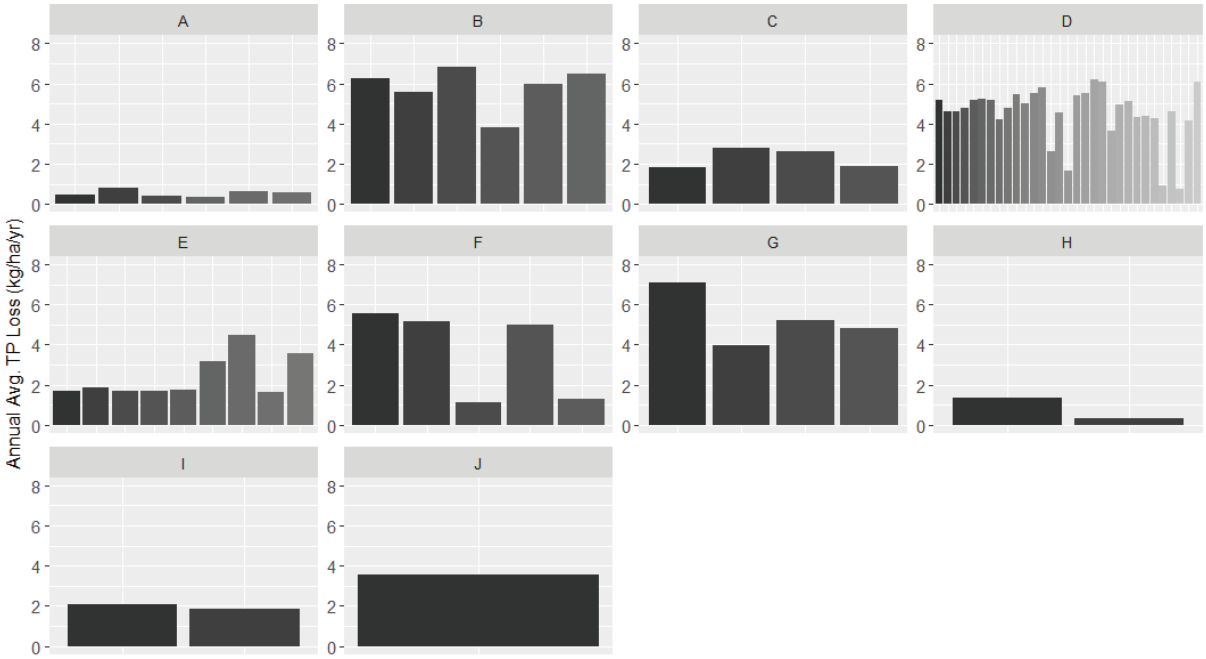
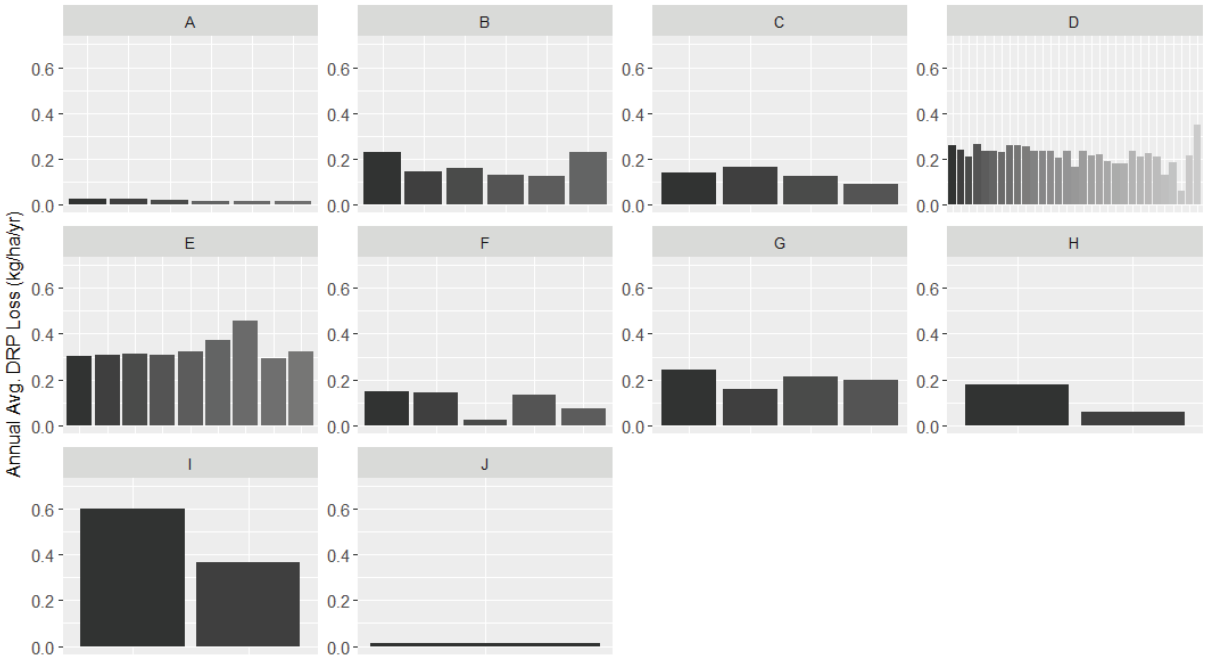


Figure 4. Annual average agricultural HRU losses in the watershed-scale calibrated model (gray box) and farm-level losses (white boxes) for baseline (a) TP and (b) DRP. Annual average across 2001-2010 simulated with farmer-informed SWAT model. Each box represents a specific farm (A to J); the spread of the box represents the variation between fields within the farm.



(a) TP losses



(b) DRP losses

Figure 5. Field-level baseline (a) TP and (b) DRP losses across each field for each farm (A to J). Annual average across 2001-2010 simulated with farmer-informed SWAT model. Each bar within a subplot represents a different field within the farm.

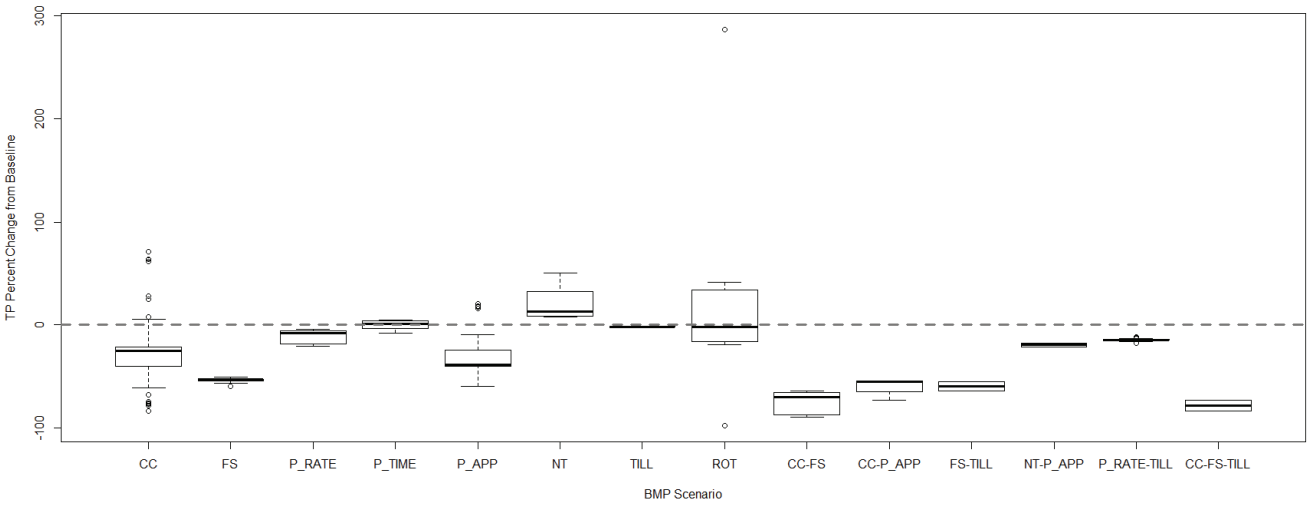
had all fields in continuous no-till, and changing the broadcast P fertilizers to subsurface application prevented P stratification to the top soil layer and greatly reduced the farm's DRP losses. For more details on each farm and the variability across fields, see the Supplemental Information.

Discussion

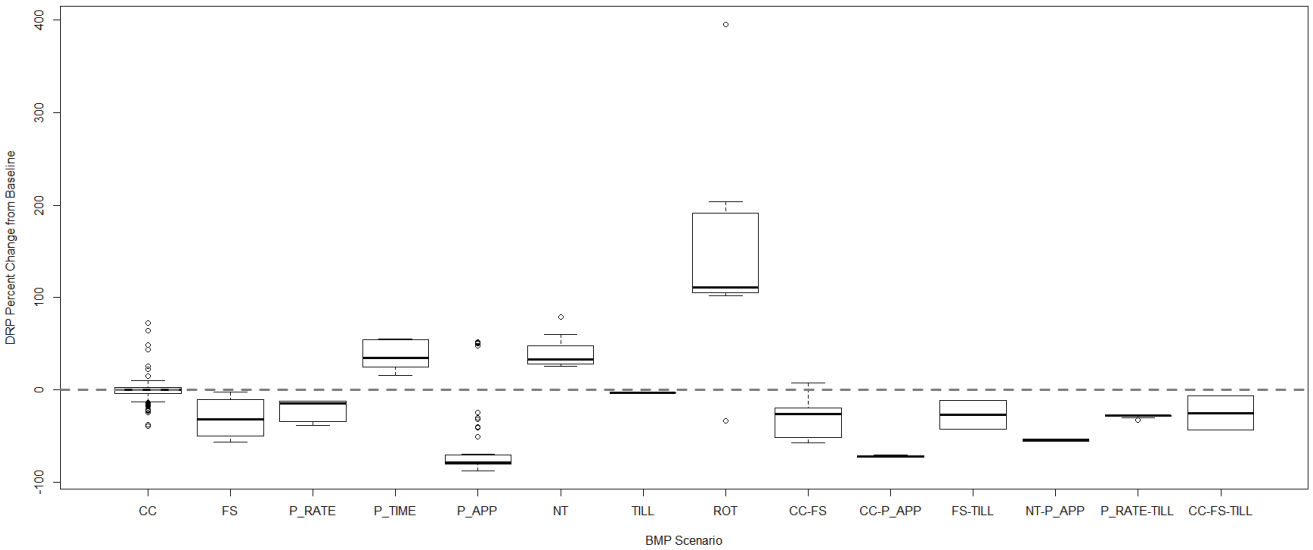
Results from the first ten farms participating in this PFP program demonstrated the need for improved modeling, targeting, and assessment of farms and fields for implementing agricultural conservation. In this section, we highlight these findings and offer some considerations for implementing a PFP conservation program.

Modeling Needs Field-Level Management Data

One of the greatest challenges in modeling agricultural landscapes is access to detailed management data. This kind



(a) TP losses



(b) DRP losses

Figure 6. Percent change in farm baseline and scenario (a) TP and (b) DRP losses for different conservation practices and combinations. Annual average for each field simulated across 2001-2010 with farmer-informed SWAT model. Conservation practices are defined in table 2.

of information is not generally accessible due to USDA confidentiality rules. Therefore, non-government modelers must rely on lower-resolution data (e.g., county-level aggregated data) or expert advice (e.g., from extension educators or farmer advisory groups) to identify "average" or "typical" management operations in a given watershed. While this may be necessary to simulate the watershed in the absence of fine-grained data, our results clearly demonstrate that modelers need access to detailed, field-level management data to get the right practices in the right places. The PFP approach works directly with the farmers to gain access to this information.

The farmers involved in this project were provided with multiple conservation options for each field. While modeling multiple fields and options can be time-consuming, tools are being developed to streamline the modeling effort. In the next phase of this project, an automated PFP system is being developed for the RRW. Automated tools can reduce the need for modelers to process results manually and allow conservation planners to conduct the process independently when they meet with producers.

Targeting is More Effective at Field Scale

The pilot phase of this work focused on farmers within a previously identified hotspot tributary of the RRW that was the location of 80% of the participating farmers' fields. We found that targeting conservation practices to specific fields can be a better way to achieve reductions than sub-basin level targeting based on modeling or monitored results. Some current approaches target conservation funds to priority watersheds or sub-basins. While targeting watersheds is an important step, our results confirm what other studies (Collick et al., 2015; Winchell et al., 2015) have shown, i.e., that field-level variability can be high, even within a hotspot area.

There is No "One Size Fits All" Approach to Agricultural Conservation

There is often a temptation to identify a single practice or combination of practices to implement on a large scale to reduce nutrient pollution and maintain fairness for program

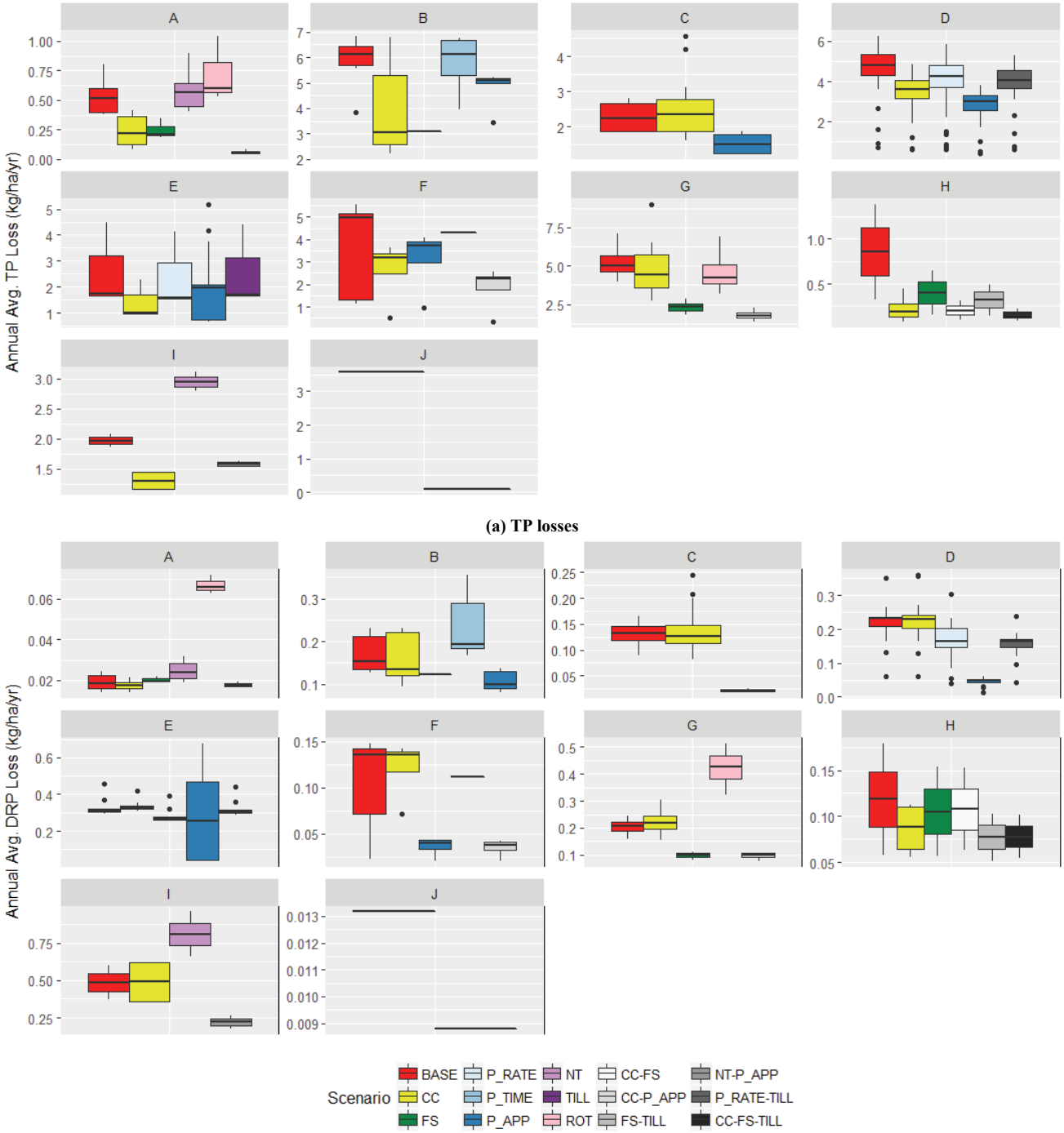


Figure 7. Farm baseline and scenario (a) TP and (b) DRP losses for different conservation practices. Annual average across 2001-2010 simulated with farmer-informed SWAT model. Practices are defined in table 2. The scale for each farm is different to better view the practices.

participants. For example, a Minnesota law (2015 Buffer Law; MBWSR, 2017) requires buffers around all public water and drainage systems by 2018. While buffers are highly effective at trapping sediment and certain nutrients in overland flow, subsurface tile drains typically bypass buffers and empty directly into ditches and streams. In addition, fields with good drainage or low slopes may have little overland flow in a typical year, with nutrient losses instead migrating off the field in subsurface flow. In these cases, buffers would not be very effective. While buffers provide benefits beyond nutrient reduction (e.g., habitat provision, aesthetics, stream stabilization; Lovell and Sullivan, 2006), Scavia et al. (2017) demonstrated that achieving the 40% load reduction targets for the Lake Erie watershed will be challenging and will require unprecedented levels of funding and implementation of conservation practices. Therefore, it is critical to find the most effective practices or sets of practices at the field level at the least cost to farmers and taxpayers. The PFP approach certainly affords the opportunity to target these practices where they are needed by paying for the water quality bene-

fit, while simultaneously maintaining farmer independence by allowing farmers to self-select into the program and choose their preferred practices.

On the ten farms that we assessed, not every practice was modeled for every field or farm (e.g., farmers selected specific practices that they were interested in), and not every practice was implemented the same way on every farm (e.g., cover crops were sometimes different species, or filter strips were different widths). Nevertheless, it is evident that conservation practices designed to reduce P cannot take a "one size fits all" approach. Each field on a farm should be assessed for its physical vulnerabilities to P loss in combination with existing management actions.

Future Work

These results are from the first ten farms that signed up during our pilot phase. In addition to improving our knowledge of agricultural conservation needs, this study demonstrated the difficulties in achieving field-level targeting of conservation practices at a large scale. One of the greatest difficulties is incorporating detailed, field-level data into models. This can be time-consuming, especially when there are many fields, if fields are managed in different ways across the farm, or if fields are managed differently over time. Our future work will include automating this process through an online interface on the Great Lakes Watershed Management System (http://www.iwr.msu.edu/glwms). This automation will save time for modelers and for conservationists or farmers when inputting data.

Another consideration for this type of program is that a farmer may not be interested in every practice capable of water quality benefit. While allowing farmers more autonomy ensures flexibility from their perspective, it could also prevent the most effective practices from getting to the fields of greatest need if the farmers fail to enroll, or if they select practices with minimal water quality benefit. Finally, this implementation of PFP focused specifically on field-level losses. Future work will attempt to evaluate the impact of these identified changes at the watershed scale. This is important because not all P that leaves a field will make it to the watershed outlet, or do so within the same period. Some P may be stored in streambanks, in reservoirs, or taken up by algae and plants along the way.

Conclusions

We presented the modeling component of a PFP conservation program in the RRW in southeastern Michigan. This area of Michigan contributes to the WBLE, which has been experiencing a resurgence of HABs and hypoxia in recent years due primarily to excess P loading from nonpoint sources. Innovative practices, programs, and policies will be required to address nonpoint-source pollution, in particular to achieve the 40% load reduction target required by the Great Lakes Water Quality Agreement. Our findings reiterate the need for modelers to access field-level management data in order to make informed decisions about watershed critical source areas. We found that even within a sub-basin hotspot area, not all fields or farms had the same high P losses; in fact, some field contributions were quite low. This highlights the need for field-level agricultural conservation decisions. Additionally, we showed the potential for an agricultural conservation framework that is more flexible in terms of farmer choice, and more effective by paying only for the achievement of reductions. Finally, our results confirm that there was not one "best" practice that could be implemented everywhere to reduce P. Overall, we demonstrated how a PFP approach can be implemented using a commonly applied watershed model driven by detailed field-level management data.

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