Optimizing conservation practices in watersheds: Do community preferences matter?

Adriana D. Piemonti,[1] Meghna Babbar-Sebens,[1] and E. Jane Luzar[2]

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[1] This paper focuses on investigating (a) how landowner tenure and attitudes of farming communities affect the preference of individual conservation practices in agricultural watersheds, (b) how spatial distribution of landowner tenure affects the spatial optimization of conservation practices on a watershed scale, and (c) how the different attitudes and preferences of stakeholders can modify the effectiveness of alternatives obtained via classic optimization approaches that do not include the influence of existing social attitudes in a watershed during the search process. Results show that for Eagle Creek Watershed in central Indiana, USA, the most optimal alternatives (i.e., highest benefits for minimum economic costs) are for a scenario when the watershed consists of landowners who operate as farmers on their own land. When a different land-tenure scenario was used for the watershed (e.g., share renters and cash renters), the optimized alternatives had similar nitrate reduction benefits and sediment reduction benefits, but at higher economic costs. Our experiments also demonstrated that social attitudes can lead to alteration of optimized alternatives found via typical optimization approaches. For example, when certain practices were rejected by landowner operators whose attitudes toward practices were driven by economic profits, removal of these practices from the optimized alternatives led to a setback of nitrates reduction by 2–50%, peak flow reductions by 11–98 %, and sediments reduction by 20–77%. In conclusion, this study reveals the potential loss in optimality of optimized alternatives possible, when socioeconomic data on farmer preferences and land tenure are not incorporated within watershed optimization investigations.

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1. Introduction

1.1. Motivation

[2] Land alterations due to large-scale agriculture and urban developments have had adversarial impacts on the ability of watershed landscapes to intercept, slow, and store surface runoff. This has led to recurring incidences of increased flooding and/or droughts, worsening water quality, and loss of biodiversity worldwide [*Peterjohn and Correl*, 1984; *Bronstert et al.*, 2002; *Kim et al.*, 2002; *Zedler*, 2003]. For example, in the United States, 60% of historically existing wetlands have been drained to establish agriculture [*Zedler*, 2003]. In midwestern states, the loss of wetlands has been even most significant, and as high as 87% in Indiana [*Dahl*, 1990].

[3] In order to overcome the effects of land alterations, the use of ecological flood mitigation schemes via conservation practices, such as riparian forest and wetlands have been proposed by multiple researchers [e.g., *Hey et al.*, 2004; *Mitsch and Day*, 2006; D. Lemke and S. Richmond, 2009, Iowa drainage and wetlands landscape systems initiative, Farm Foundation Report]. These conservation practices also improve water quality, preserve the native flora, and create habitats for the fauna [*Peterjohn and Correl*, 1984; *D'Arcy and Frost*, 2001; *Bekele and Nicklow*, 2005]. Recently, there has also been an increased interest in the restoration of degraded upland and downstream storage capacities of watershed landscapes via networks of distributed conservation practices that behave like water storage systems [*Hey et al.*, 2009]. *Hey et al.* [2009] proposed that storage systems consisting of a combination of larger-scale structural projects (such as levees, overflow and backflow structures) and restoration of the bottomlands could retain approximately 75% of all the water above the minor flood stage. The design of these storage systems is, however, extremely challenging and complex when sites and practices have to be selected on the basis of not only physical, biological, and chemical factors, but also on the basis of the sociological and economic factors coexisting in the watershed. A preliminary analysis of just the physical factors, such as soil type, land use, and topography, can yield of suitable potential sites for restoring or creating conservation practice [*Babbar-Sebens et al.*, 2013]. Watersheds are, however, also tightly coupled with

[1]School of Civil and Construction Engineering, Oregon State University, Corvallis, Oregon, USA.
[2]School of Public and Environmental Affairs, Indiana University-Purdue University Indianapolis, Indianapolis, Indiana, USA.

Corresponding author: A. D. Piemonti, School of Civil and Construction Engineering, Oregon State University, Corvallis, OR 97331, USA. (piemonta@engr.orst.edu)

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socioeconomic drivers, such as land tenure type, farmer attitudes and preferences, land productivity, crop prices, municipality regulations, conservation programs, beliefs, and existing social norms. These drivers, though difficult to identify and obtain data for, can be spatially and temporally distributed within the watershed system. This distribution could affect the spatial optimization of decisions undertaken by the community and the final adoption/rejection of conservation practices across the watershed landscape.

[4] In the field of watershed planning and management, multiple studies and approaches have been investigated for finding ideal alternatives to the complex spatial design problems in watersheds using optimization techniques and algorithms. For example, approaches for optimization of spatial distribution of conservation practices and best management practices in agricultural landscape have been investigated by multiple studies, such as *Newbold* [2002, 2005], *Kaini et al*. [2007], *Artita et al*. [2008], *Cutter et al*. [2008], *Maringanti et al*. [2009], and *Tilak et al*. [2011a]. However, the inclusion of sociological factors in the design of optimized combinations of conservation practices in the watershed has been mostly absent in these studies and approaches.

[5] Studies such as those by *Kaini et al*. [2007] and *Tilak et al*. [2011a] have investigated approaches for optimizing spatial distribution of ponds and wetlands in a watershed, based on physical factors. Both teams of authors used a combination of different evolutionary algorithms and the Soil and Water Assessment Tool (SWAT), a hydrologic model from the United States Department of Agriculture (USDA) [*Arnold et al*., 2001, 2005], to find the best possible combination of wetlands in different subbasins (SBs) of watersheds in the Midwestern region. Kaini et al.'s study was based on the goal of minimizing the maximum daily peak flow, while constraining the maximum areas of ponds within an upper limit. They used a single-objective genetic algorithm (GA) to modify pond sizes in SBs across the watershed. They found that the optimal solution of distribution of ponds in their watershed site (Silver Creek watershed in Illinois) could lead to a reduction of maximum daily flows by 16.8%. Although their work demonstrates a useful watershed-scale approach to designing storage systems such as retention ponds, they did not incorporate any influence of socioeconomic criteria on the design of these detention ponds.

[6] Similar to *Kaini et al*. [2007], *Tilak et al*. [2011a] explored the design of structural water storage practices across the watershed landscape. *Tilak et al*. [2011a], however, investigated and compared two types of search/optimization algorithm; Non-Sorting Genetic Algorithm (NSGA-II) [*Deb et al*., 2002] and a Decentralized Pursuit Learning Algorithm (DPLA) [*Tilak et al*., 2011b] for the spatial design of a distributed system of wetlands in a watershed. Their optimization formulation was based on two conflicting watershed-scale objectives: minimize the total area used by wetlands in the watershed, and minimize the difference (using a mean square error type of metric) between stream hydrographs at outlets of SBs when all wetlands of maximum areas are implemented and stream hydrographs at the outlets of SBs when only a subset of wetlands proposed by the optimization algorithm are implemented. The results showed that, for the entire watershed, NSGA-II has a better performance than DPLA in finding solutions with better overall flow benefits for a specific total wetland area. The optimization was based on a binary decision variable scheme, for either installing or not installing a wetland in any SB. When a specific SB had wetlands, the maximum area of wetlands possible in that SB was used to estimate the performance of the wetland. This study also, similar to *Kaini et al*. [2007], used physical factors to determine the suitability of SBs for wetlands, even though they discussed the importance and need for inclusion of socioeconomic criteria in the optimization algorithms for further evaluation of the wetlands designs from the perspective of the landowners.

[7] Other researchers have tried to include economic criteria to represent landowner preferences for each conservation practice within the optimization. For example, *Newbold* [2005] proposed a landscape design model coupled with a hydrologic simulation model within an optimization framework for prioritizing potential wetlands restoration sites in Central Valley, California. The main objective of the study was to design the spatial distribution of wetlands that achieve maximum reduction of nitrogen from nonpoint sources for minimum restoration economic costs. Newbold's final results emphasize the importance of targeted site selection for the improvement of water quality. His work also shows that the reduction in restoration costs depends on the proximity of restoration sites to other existing water bodies and also demonstrated that incorporated only one benefit can yield limited reductions for the restoration. However, even though *Newbold* [2005] included economic drivers as part of the cost-benefit analysis, he did not consider the effect of landowner tenure and other social factors on the development of the economic function and the overall prioritization of restoration sites.

[8] Similarly, other researchers, such as *Bekele and Nicklow* [2005], *Artita et al*. [2008], and *Maringanti et al*. [2009], have incorporated economic objectives and criteria along with environmental benefits as part of the optimization of conservation practices. For example, *Bekele and Nicklow* [2005] studied the effect of different agricultural land uses (i.e., no tillage for row crops) that provide ecosystem services such as sediments, phosphorus and nitrogen reductions in the watershed. They used a combination of a strength Pareto evolutionary algorithm 2 (SPEA2) and the SWAT hydrologic model to identify the best scenarios of land use changes in the watershed. The objectives used in their study were sediments reduction, phosphorus reduction, nitrogen reduction, and the annual gross margin. The annual gross margin was calculated using a generic function based on the combination of land uses and tillage practices in the watershed over a period of time. This generic function also incorporated physical variables such as water quality, hydrology and hydraulics, and variables such as crops yields and average market prices of crops. However, the authors did not provide a descriptive equation for the generic function, thereby, making it difficult to get insights into how the various variables were used in the calculation of the overall socioeconomic function. Their results showed the importance of a trade-off curve between multiple objectives, where the best selection can be made based on a general assessment of all multiple objectives, instead of just one objective at a time. However, their study did not

include landowner social conditions and preferences, such as ownership of the land, environmental attitudes, and practice preferences when locations are selected for restoration practices.

[9] On the other hand, *Maringanti et al*. [2009] tried to incorporate some aspects of landowner preferences in their optimization approach that used a combination of NSGA-II and the SWAT hydrologic model to optimize multiple best management practices in a watershed. They incorporated landowner preferences by using the records from stakeholders and county agents to identify most popular and commonly adopted BMPs in their watershed sites and then use those BMPs (i.e., nutrient management, buffers, conservation till, and no-till) within the optimization approach. However, their approach did not investigate the effect of underlying distributions of attitudes and preferences of stakeholders in the selection of these BMPs. One may argue that obtaining socioeconomic data on attitudes and preferences of individual stakeholders toward practices, along with the spatial distribution of decision makers in a watershed is extremely challenging, if not impossible. Hence, many watershed plans are developed based on averaged data on farmer preferences of practices (such as in the approach of *Maringanti et al*. [2009]), obtained from a socioeconomic survey conducted at a particular point in time in the watershed. An underlying assumption is made in such approaches that a survey provides some aggregated view of stakeholder preferences that are sufficient to identify which practices will be adopted by the community. In reality, at the time of implementation, many farmers may not adopt specific conservation practices based on their emerging attitudes, biases, and preferences (which might not have been captured by the survey), socioeconomic barriers, and based on where they live or work [*Söderqvist*, 2003; *Valentin et al*., 2004; *Reimer et al*., 2010]. This can lead to deterioration of the effectiveness of original optimized watershed plan/design by transforming it to a suboptimal modified design, and thereby, defeating the original purpose and effort of spatially optimizing conservation practices in a large watershed.

[10] The most commonly held assumption that economic factors are the only drivers that influence adoption of a specific conservation practice is also not always valid. For example, *Söderqvist* [2003] found that factors such as environmental attitudes and future planning of the land can strongly influence a landowner's attitude and decision to adopt a practice, even when initial investment does not allow a favorable profit. Attitudes and behavior of agricultural stakeholders have also been studied by several other economists [*Lynne et al*., 1988; *Weaver*, 1996; *Luzar and Cosse*, 1998; *Luzar and Diagne*, 1999; *Soule et al*., 2000; *Söderqvis*t, 2003; *Oliver*, 2008; *Ahnström et al*., 2009; *Reimer et al*. 2010].

[11] *Lynne et al*. [1988] suggest that *Feather*'s [1982a, 1982b] work on the idea of a psychological environment where a stakeholder conducts personal negotiations is valid for agricultural stakeholders too. A farmer will negotiate between the positive evaluations (e.g., advantages of conservation practices) and negative evaluations (e.g., economic costs), in order to decide his/her final action in adopting or not adopting a specific conservation practice. This negotiation usually involves a weighing of importance or prioritizations of the various estimations in the individual's psychological environment. *Lynne et al*. [1988] also adapted *Lemon*'s [1973] socioeconomic decision model to a farmer's decision model. Based on this, the actual conservation behavior is influenced by three main factors; first, a social situational factor, that would include income, costs of practices, and farm features; second, the attitude of the farmers toward the conservation practice; and third, social norm or the perception of others in the community.

[12] In the agricultural economics field, researchers such as *Luzar and Cosse* [1998], *Luzar and Diagne* [1999], *Soule et al*. [2000], *Söderqvist* [2003], *Oliver* [2008], *Ahnström et al*. [2009], and *Reimer et al*. [2010] have tried to improve the understanding of preferences for conservation practices and their adoption. Features such as crop and land prices, surveys, risk perception, incentives, regulations, and demographic characteristics have been suggested by these authors to evaluate the socioeconomic drivers (i.e., land tenure, environmental attitudes, regulations, beliefs and available conservation programs), preferences of landowner operators, and their likelihood of adoption.

1.2. Objectives

[13] Successful implementation of watershed management plans requires a successful adoption of conservation practices by landowner operators if the cumulative benefits of a distribution of practices are to be attained at a watershed level.

[14] Three are the main objectives of this study: (a) how landowner tenure and attitudes of farming communities affect the preference of individual conservation practices in agricultural watersheds, (b) how spatial distribution of landowner tenure affects the spatial optimization of conservation practices on a watershed scale, and (c) how underlying land tenures and farmer attitudes can modify the effectiveness of alternatives obtained via classic optimization approaches that do not include existing social attitudes in typical optimization approaches (such as those undertaken by *Newbold* [2002, 2005], *Kaini et al*. [2007], *Artita et al*. [2008], *Cutter et al*. [2008], *Maringanti et al*. [2009], and *Tilak et al*. [2011a]). The following sections describe the methodology comprised of the case study, the hydrologic and water quality model, the optimization formulation, and the different experiments performed. Results of the various experiments are then presented and discussed, followed by a section on concluding remarks.

2. Methodology

2.1. Eagle Creek Watershed Case Study

[15] Eagle Creek Watershed (ECW) is a HUC-11 watershed (05120201120) located in central Indiana, about 16 km northwest of Indianapolis, Indiana. It is part of the Upper White River Watershed (Figure 1). Its drainage area is approximately 419.26 km^2. It drains into the Eagle Creek Reservoir (ECR), one of the major recreational and water drinking supplies for Indianapolis. The reservoir was developed as a flood control method of the seasonal inundated northwest area of Indianapolis and Speedway. This reservoir has been impaired mainly by sediments, pesticides, herbicides, and fertilizers from the agricultural land in the

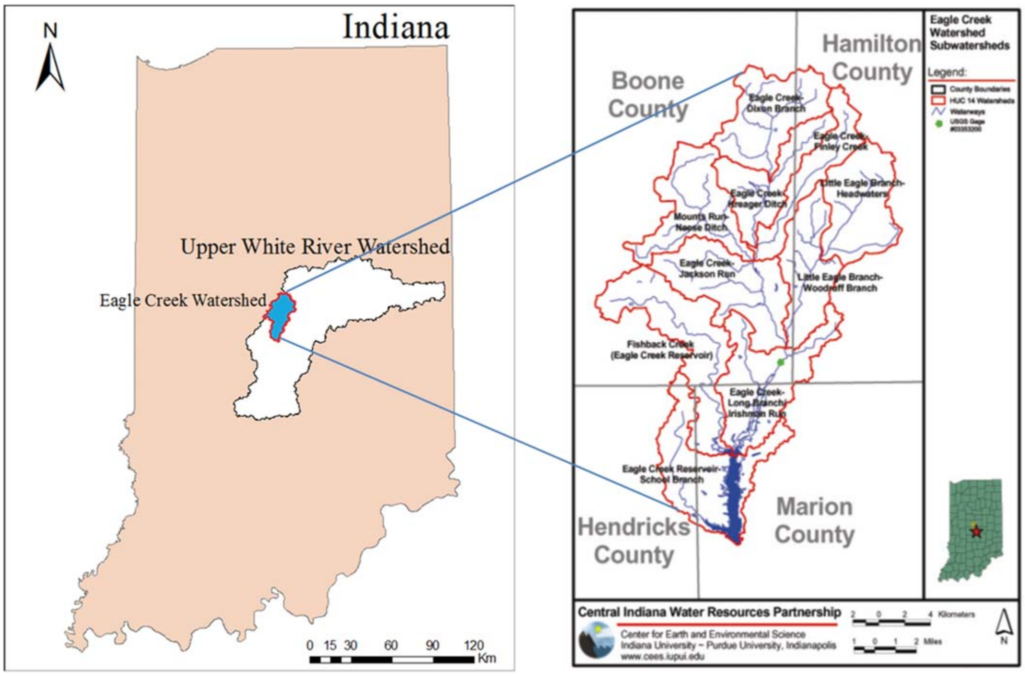

Figure 1. Location of Eagle Creek Watershed in the Upper White River Watershed.

upstream areas [*Tedesco et al*., 2005]. Agricultural pollutants are transported by tile drains, ditches, and streams.

[16] The eight named tributaries that join Eagle Creek above the reservoir include Dixon Branch, Finley Creek, Kreager Ditch, Mounts Run, Jackson Run, Woodruff Branch, Little Eagle Branch, and Long Branch (Figure 1). There are also two tributaries that contribute to the reservoir: School Branch and Fishback Creek. The watershed topography is relatively flat to undulating, with some dissection near Eagle Creek reservoir.

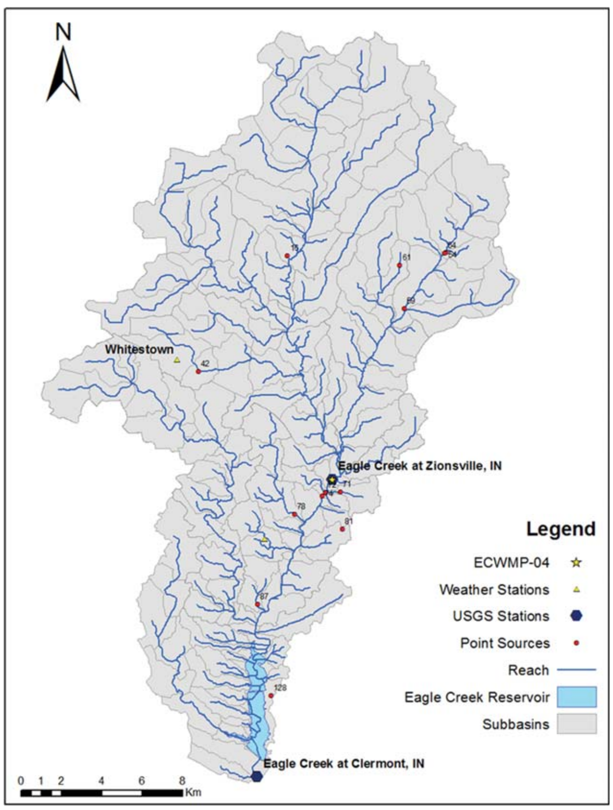

Figure 2. Distribution of 130 modeled subbasins and their outlets, point sources, weather stations, reservoir and water quality monitoring station in Eagle Creek Watershed.

[17] The watershed is located across four different counties: Marion, Hamilton, Hendricks and Boone (Figure 1)—and was divided into 130 SBs (average area of 327.41 ha) and 130 reaches for the modeling purposes (Figure 2). Agriculture is the dominant land use in the north area of the watershed (approximately 60%), with predominantly corn and soybean based crops [*Census of Agriculture*, 2007]. Urban development has occurred mostly in the southeast region of the watershed, due to growth in the Indianapolis population (U.S. Department of Agriculture's (USDA) crop data layers database). According to USA.com reports, Indianapolis growth population rate since 2000 is 4.93 (http://www.usa.com/indianapolis-in.htm)

[18] The dominant soils association in the area consists of the Crosby-Treaty-Miami association in the headwaters (USDA's Soil Survey Geographic Data Base). These soils are generally deep, poorly drained, and nearly level to gently sloping soils formed in a thin silty layer overlying glacial till, whereas downstream areas are dominated by Miami-Crosby-Treaty association, generally deep well drained to somewhat poorly drained, and nearly level to moderately steep soils formed in a thin silty layer and the underlying glacial till. The Eagle Creek valley has a minor soils association that consists of Sawmill-Lawson-Genesee. In the northwestern boundary, two minor associations exist: Fincastle-Brookston-Miamian association and Mahalasville-Starks-Camden association. The minor soils also vary in their drainage characteristics based on the composition.

[19] The climate in this area is predominantly temperate continental and humid [*Clark*, 1980; *Newman*, 1997], with

Table 1. Typical Values in Central Indiana for Tile Parameters Used in the SWAT Model for Eagle Creek Watershed

Parameter	Files	Value
DEIMP (depth to impermeable layer)	.hru,.bsn	2500 mm
DDRAIN (depth to tile drains)	.mgt	1000 mm
TDRAIN (time to drain soil to field capacity)	.mgt	24 h
GDRAIN (drain tile lag time)	.mgt	96 h

an average annual temperature of approximately 11°C. The average annual precipitation varies from 97 to 102 cm, with late spring being the wettest seasonal period and February being the driest. Most of this average annual precipitation occurs during the 5–6 months of frost-free growing season.

[20] All four counties have experienced a decrease in the total land assigned to farms over the last few years, with the ranges of farmland loss varying from 27% in Marion County to 1% in Boone. All four counties have farmland owners with similar race, age, principal operator's gender, and principal crop. The agriculture community population consists mainly of Caucasian males in their mid-fifties. The community mostly produces corn and soybeans row crops (C. L. Dobbins et al., 2002–2012, Purdue Crop Cost and Return Guide, http://www.agecon.purdue. edu/extension/pubs/index.asp). Since within-county data with detailed information on the distribution of the demographics is not available, this study assumes that many of these features at the county scale are also valid for the farmlands within the watershed.

2.2. Hydrologic and Water Quality Model

[21] The hydrology and water quality were simulated using the Soil and Water Assessment Tool 2005 (SWAT 2005) model; developed by Dr. Jeff Arnold for the USDA Agricultural Research Service [*Arnold et al*., 1998; *Neitsch et al*., 2005]. This is a physically based, time model that can also be operated from ArcGIS interface (via ArcSWAT). SWAT model was developed to simulate and predict impact of management practices at subbasin (SB) and watershed scales. The spatial factors such as topography, land use, soil type, and climate are necessary inputs for the development of the model.

[22] For this study, the Eagle Creek Watershed, SWAT model was built on a daily time step for a short time period of five years (i.e., 2004–2008). A predefined watershed with 130 SBs and stream network based on the topographic maps published by United States Geological Survey (USGS) was used in the model.

[23] For each SB, the program calculated the SB outlet on the stream network based on the digital elevation model (10 m DEM) and predefined boundaries. Once outlets were fixed, the point sources (National Pollutant Discharge Elimination System (NPDES) located in SBs: 16, 42, 54, 59, 61, 71, 72, 74, 81, 87, and 128) and the reservoir (located in SB 128) were added (Figure 2).

[24] The land use (USDA crop data layer, 2008) and soil type (USDA SSURGO) maps were then added to the model. These two maps were then combined with the land slope map (classified into three classes of 0–1%, 1–2%, and >2%) to further divide the SBs into hydrologic response units (HRUs). The HRUs are disconnected, unique combinations of land use, soil type, and slope, in the SWAT model, and are used as a basic spatial unit for the mass balance in the watershed processes. Finally, a 10% threshold was applied for land use, soil class, and slope class in order to eliminate all land use, soil class, and slope class combinations with less than 10% of SB area coverage.

[25] Daily climate data for precipitation and temperature were obtained from the National Oceanic and Atmospheric Administration (NOAA) stations at Whitestown, IN (Station ID GHCND: USC00129557, latitude 39.996°, longitude −86.354°) and Indianapolis Eagle Creek, IN (Station ID GHCND: USC00124249, latitude 39.920°, longitude −86.313°).

[26] Daily flow measurements at the USGS station at Clermont (03353460) were used to represent dam releases. This station was used because complete recordings of daily flow measurements at the USGS station 03353451 just below the reservoir were not available. Based on the close proximity of the two stations (Clermont station is only 1.13 km downstream of USGS station 03353451) and similarity in their runoff area, the assumption of using Clermont station to represent dam releases was considered appropriate. In addition, Clermont station 03353460 receives runoff from only 1.4% additional SB land area compared to the USGS station 03353451 below the reservoir.

[27] Various model input parameters were modified using specific values for the Eagle Creek Watershed. Model parameter values for tile drains are listed in Table 1 based on typical values found for tile drains in Central Indiana. For estimating the runoff routing, the curve number method was chosen. While the Muskingum routing method was chosen for channel routing. Table 2 shows a typical operation schedule for 1 year used for HRUs with corn and soybeans land use. This schedule was repeated over the entire 5 year period for the relevant HRUs.

Table 2. Operation Schedule Used for Corn and Soybeans Land Use

	Operation	Type	Amount (kg/ha)	Heat Units	Heat Units to Maturity
Corn	Pesticide application	Atrazine	1.12	0.1	
	Plant/begin growing season	Corn		0.15	1308.35
	Fertilizer application	Elemental Nitrogen	170	0.16	
	Tillage operation	GFPO[a]		1.2	
	Harvest and kill operation			1.2	
Soybeans	Pesticide application	Atrazine	1.12	0.1	
	Plant/begin growing season	SoyBean		0.15	1308.35
	Tillage operation	GFPO[a]		1.2	
	Harvest and kill operation			1.2	

[a]Generic fall plowing operation.

Table 3. Flow Calibration Parameters, Allow Ranges, and Final Calibrated Values

Parameter	Description	File	Parameter Range	Calibrated Value
ALPHA_BF	Base flow alpha factor (days)	.gw	0–1	0.048
CH_K2	Effective hydraulic conductivity in main channel (mm/h)	.rte	0–150	10
CH_N2	Manning's n value for main channel	.rte	0–1	0.01
CN_FROZ	Frozen soil adjustment on infiltration/runoff	.bsn	0 or 1	1 (Active)
CN2	Initial SCS runoff curve number for moisture condition II	.mgt	Specific to land use	For land use: AGRR, CORN, SOYB: $0.8075 \times CN2_{default}$ For land use: HAY: $1.045 \times CN2_{default}$ Other land use: $0.95 \times CN2_{default}$
ESCO	Soil evaporation compensation factor	.hru, .bsn	0–1	0.95
GW_DELAY	Groundwater delay time (days)	.gw	0–50	31
GW_REVAP	Groundwater "revap" coefficient/ transfer of water from the shallow aquifer to unsaturated zone	.gw	0.02–0.2	0.02
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mmH_2O)	.gw	0–5000	0
HRU_SLP	Average slope steepness (m/m)	.hru	Specific to HRU	$2 \times HRU\_SLP_{default}$
LAT_TTIME	Lateral flow travel time (days)	.hru		4
SLSUBBSN	Average slope length (m)	.hru	10–150	$2 \times SLSUBBSN_{default}$
SMFMN	Melt factor for snow on December 21 (mmH_2O/°C day)	.bsn	0–10	1.4
SMFMX	Melt factor for snow ok June 21 (mmH_2O/°C day)	.bsn	0–10	6.9
SOL_AWC	Available water capacity of the soil layer (mmH_2O/mm soil)	.sol	0–1	$1.5 \times SOL\_AWC_{default}$
SURLAG	Surface runoff lag coefficient	.bsn	0–10	6

[28] For flow calibration, daily data from 2005 to 2008 (2004 year was let as a warming period for the model) of the USGS gage stations Zionsville gage station and Clermont gage station were compared with the outflows of SBs 70 and 128, respectively. To estimate the efficiency of the model calibration, Nash-Sutcliffe efficiency (E_{NS}) [*Nash and Sutcliffe*, 1970], given by equation (1), was used.

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n} (O_i - M_i)^2}{\sum_{i=1}^{n} (O_i - O_{avg})^2} \tag{1}$$

where O_i is the observed data in day i, M_i is the model data in day i, and O_{avg} is the average value of the observed data. Pearson's product-moment correlation coefficient (R^2) [*Legates and McCabe*, 1999], given by equation (2), was also used to estimate the model performance.

$$R^2 = \frac{\left(\sum_{i=1}^{n} (M_i - M_{avg})(O_i - O_{avg})\right)^2}{\left[\sum_{i=1}^{n} (M_i - M_{avg})^2\right] * \left[\sum_{i=1}^{n} (O_i - O_{avg})^2\right]} \tag{2}$$

where M_{avg} is the model data average. For both efficiency estimations equations, a value close to 1 indicated superior model performance. Table 3 presents the parameters that were adjusted in order to improve the efficiency of the model for prediction of stream flows.

[29] Water quality observed data collected by the Center of Environmental and Earth Sciences (CEES) of IUPUI (Station ID: ECWMP-04, latitude 39.946°, longitude −86.260°) was used for water quality calibration (Figure 2). Since only monthly data from March 2007 to December 2008 were available for sediments and nitrates, we decided to expand the calibration data set for sediments and nitrates by using LOADEST [*Runkel et al.*, 2004], and then compare the interpolated daily data with the SWAT model daily predictions [*White and Chaubey*, 2005]. Table 4 shows the variables that were modified for the sediments and nitrates.

2.3. Conservation Practices

[30] Conservation practices were modeled based on the approaches used by *Bracmort et al.* [2006] and *Arabi et al.* [2007]. These studies give a detailed procedure to successfully model different conservation practices in a watershed using the SWAT model. Based on the functions and hydrologic processes related to each practice, a set of seven different practices commonly used and promoted by USDA Natural Resources Conservation Service (NRCS) in the area were selected for this work. Detail technical information regarding the practices can be found in the Field Office Technical Guide (*FOTG*, http://efotg.sc.egov.usda.gov/efotg_locator.aspx). This is an electronic county level document developed by NRCS for counties nationwide, as a database on costs, laws, maps, flood profiles, management plans, typical installation, and various technical features needed to promote and implement conservation practices. The seven modeled practices include

[31] 1. Strip cropping: This practice increases the surface roughness, reduces surface runoff and reduces sheet and rill erosion [*Arabi et al.*, 2007]. Modifications of the curve number (CN), Practice factor in the Universal Soil Loss Equation (USLE_P), and Manning's roughness coefficient (OV_N) are required to model this practice.

Table 4. Water Quality Calibration Parameters, Ranges of Parameter Values, and Final Calibrated Values

Parameter	Description	File	Parameter Range	Calibrated Value
Sediments				
SPCON	Linear parameter to calculate the maximum amount of sediment reentrained during channel	.bsn	0.0001–0.1	0.001
SPEXP	Exponential parameter to calculate sediment reentrained in channel sediment routing	.bsn	0.0–2.0	0.65
PRF	Peak rate adjustment factor for sediment routing in the main channel	.bsn	0.0–2.0	0.01
CH_COV	Channel cover factor	.rte	0.001–1.0	0.12
CH_EROD	Channel erodibility factor	.rte	0.05–0.08	0.08
ADJ_PKR	Peak rate adjustment factor for sediment routing in the sub basin (Tributary channels)	.bsn		0.01
Nitrates				
NPERCO	Nitrate percolation coefficient	.bsn	0.0–1.0	0.7
SDNCO	Denitrification threshold water content	.bsn		0.8
CDN	Denitrification exponential rate coefficient	.bsn	0.0–3.0	0.7
RSDCO	Residue decomposition coefficient	.bsn	0.02–0.2	0.2
IPND2	Ending month of mid-year nutrient settling "season"	.pnd	0–12	12
RCN	Concentration of nitrogen in rainfall (mg N/L)	.bsn	0.0–15.0	3
RS4	Rate coefficient for organic N settling in the reach at 20°C (day^{-1})	.swq	0.001–0.1	0.001
RS3	Benthic source rate for NH_4-N in the reach at 20°C (mg NH_4-N/(m^2 day))	.swq	0–1	1
N_UPDIS	Nitrogen uptake distribution parameter	.bsn		15
SOL_NO3	Initial NO3 concentration in the soil layer (mg N/Kg soil or ppm)	.chm	0.0–100.0	100
AI1	Fraction of algal biomass that is nitrogen (mg N/mg alg)	.wwq	0.07–0.09	0.071
RHOQ	Algal respiration rate at 20°C/day	.wwq	0.05–0.5	0.5
NSETLW1	Nitrogen settling rate in wetlands for months IPND1 through IPND2 (m/year)	.pnd	0.0–20.0	0.8
NSETLW2	Nitrogen settling rate in wetlands for months other than IPND1-IPND2 (m/year)	.pnd	0.0–20.0	0.8

[32] 2. Crop rotation: According to the NRCS, this practice improves soil quality, creating a balance of nutrients in the soil, conserves water, reduces soil erosion, and decreases plant pest infestations. SWAT simulates crop rotation through the operation schedule inputs in .mgt files. The most common crop rotation use in Indiana is based on corn-soybeans.

[33] 3. Cover crops: According to NRCS, this practice helps in improving soil moisture content, minimizing soil compaction, preventing erosion, and increasing soil organic matter. This practice is generally implemented at the time when land is not being used for production (winter/spring). SWAT model allows scheduling of more than one cover crop per year, once in the fall and once in spring.

[34] 4. Filter strips: This practice reduces suspended solids and associated contaminants in the runoff. It is generally implemented on the edges of channel segments. The variable simulating this conservation practice is the filter width (FILTERW). *Arabi et al*. [2007] varied this variable from 0 to 5 m to simulate the effect of filter strips.

[35] 5. Grassed waterways: This practice reduces gully erosion, reduces flow velocity, and increases sediment settlement [*Arabi et al*., 2007]. SBs with first-order streams were modeled for this practice, and the variable channel cover factor (CH_COV) was modified to simulate the effect of grassed waterways.

[36] 6. No-till: This practice increases the amount of organic matter and moisture in the soil, and also decreases erosion. Conservation tillage practices usually need long-term implementation (over a period of 10 years) before any considerable effect on the quality of soil is observed. However, we still included this practice in order to simulate any short-term effects or benefits on the diverse soil conditions in the watershed. This tillage practice was simulated by including a tillage operation in the operation schedule of the SWAT model, and by replacing the generic fall tillage with a no-till operation.

[37] 7. Wetlands: Wetlands reduce sediments in runoff, reduce peak flows in streams, reduce nutrients loads in runoff, and also provide habitat for wildlife. Wetlands are simulated in SWAT as water bodies at outlets of SBs, with a maximum of one wetland at every outlet. The SWAT variables wet fraction (WET_FR) and maximum wetland area (WET_MXSA) were modified for each SB during the design process by varying the values of these variables between 0.0 and maximum value identified for every SB in the study by *Babbar-Sebens et al*. [2013]. In their research, a GIS (Geographic Information Systems) methodology was first used to identify 2953 wetland sites in Eagle Creek watershed for improving runoff and water quality benefits. Existence of such large number of alternatives can lead to challenges in identification of most optimal design of alternatives, when search space could be as large as 2^{2953} (in the case when one practice is either installed or not installed at a site). Additionally, since SWAT only simulates one wetland per SB, *Babbar-Sebens et al*. [2013] aggregated the areas of all the 2953 potential wetlands into one large wetland per SB, across all SBs (with respective WET_MXSA and WET_FR values). This resulted in 108 possible aggregated wetlands at the outlets of their respective SBs. A design depth of 0.5 m was used to estimate wetland volumes and a seepage hydraulic conductivity of 50 mm/h was used based on existing hydraulic conductivities of hydric soils in the watershed.

[38] Table 5 shows the necessary changes for each of the variables in a particular conservation practice.

Table 5. Changes Made on the SWAT Model to Simulate Conservation Practices

Practice	SWAT Variable Modified	File	Range	Installation		
Strip cropping	CN	.mgt	−3 units	HRU level, where the LULC		
	USLE_P	.mgt	0.3	belongs to corn or soybeans		
Conservation crop rotation	Operation schedule	.mgt	Example of corn-soybean for 2 years.			
			This operation is change at a HRU level for corn and soybeans			
			Year	HU[a]	Operation	Kg/ha
			1	0.1	Pesticide application	1.12
			1	0.12	Plant corn	
			1	0.3	Fertilizer application	200.00
			1	1.5	Harvest and killing	
			1	0.997	Generic fall tillage	
			2	0.1	Pesticide application	1.2
			2	0.15	Plant soybean	
			2	1.2	Harvest and killing	
			2	0.6	Generic fall tillage	
Cover crops	Operation schedule	.mgt	Example of corn-winter wheat in one year.			
			This operation is change at a HRU level for corn and soybeans			
			Year	HU[a]	Operation	Kg/ha
			1	0.28	Harvest and killing	
			1	0.1	Pesticide application	1.12
			1	0.12	Plant corn	
			1	0.3	Fertilizer application	200.00
			1	1.5	Harvest and killing	
			1	0.997	Generic fall tillage	
			1	0.998	Plant winter wheat	
Filter strips	FILTERW	.mgt	0–5 m	A typical installation requires a 19 ha field and a 37 m length		
Grassed waterways	CH_COV	.rte	0.001	Streams order 1		
No till	Operation schedule	.mgt	Example of corn in 1 year.			
			This operation is change at a HRU level for Corn and Soybeans			
			Year	HU[a]	Operation	Kg/ha
			1	0.1	Pesticide application	1.12
			1	0.12	Plant corn	
			1	0.3	Fertilizer application	200.00
			1	1.5	Harvest and killing	
			1	0.997	No till	
Wetlands	WET_FR	.pnd	0-max wet fraction	All SB. Effects simulated at the outlet		
	WET_NSA		0-max wetland area			

[a]HU represents the heat units.

2.4. Optimization Formulation

[39] Although significant community benefits can be attained from implementation of conservation practices [*Ribaudo et al*., 1994; *Aust et al*., 1996; *Yadav and Wall*, 1998; *Coiner et al*., 2001; *Bryan and Kandulu*, 2009], a spatial design of practices designed to achieve maximum benefits for the watershed at lowest cost have to be ultimately accepted and adopted by all private stakeholders and landowner operators responsible for the actual implementation of the proposed practices on their land. Therefore, it is relevant to assess not only public benefits but also private incentives that would encourage the participation of these landowner operators and stakeholders in conservation programs. Several factors beyond just economic revenue and costs are considered by decision makers when the sustainable management of their land is being addressed. *Valentin et al*. [2004] tested an empirical relation between adoption of conservation practices and farm profitability, developing the idea of a tight relation between economic costs in productions and decision of adoption. However, according to *Ahnström et al*. [2009], some of the decisions for farm stewardship are rooted in long term concerns in health of farms and soil. *Soule et al*. [2000] and *Lambert et al*. [2006] report that participation in conservation programs will also depend on farm size, commodity mix (assortment of different crop types produced), and land tenure. In order to represent the various driving factors reported by these socioeconomic studies, four different criteria were developed and used as objective functions in a multiobjective optimization process. The functions include (1) a costs-revenue economic function based on land tenure, incentive programs, and net profit because of increased yields, (2) a peak flow reduction function, (3) a sediments reduction function, and (4) a nitrates reduction function. These functions represent the multiple stakeholder interests that can play a key role in adoption of conservation practices and the resultant effect on farm operations. The objective functions were included within a multiobjective optimization algorithm called Nondominated Sorting Genetic Algorithm II (NSGA-II) developed by *Deb et al*. [2002]. The NSGA-II was run with a maximum population size of 100 individuals and maximum number of generation

Table 6. Variables Considered in the Cost-Benefit Function Development by Land Tenure

Land Tenure	CI	OM	Rin	SP	PI	Rent	Fraction
Landowner	X	X	X	X	X		
Cash renter	X	X	X			X	
Share renter	X	X	X[a]	X	X		50-50

[a]For share renters, case rent from the incentive programs is not considered as a share factor.

equal to 75 in order to solve the optimization problem within the bounds of the computational framework available. Additionally typical values of 0.9 and 0.05 were chosen for NSGA2 uniform crossover and mutation rates, respectively.

2.4.1. Cost-Revenue Function

[40] Authors such as *Weaver* [1996], *Coiner et al.* [2001], *Arabi et al.* [2006], *Bryan and Kandulu* [2009], *Liu et al*. [2011], etc., used net of economic costs to either estimate the probability of adoption for a practice [*Weaver*, 1996], evaluate implementation of practices [*Liu et al*., 2011], optimize designs based on maximization of benefits [*Coiner et al*., 2001], as design constrainer [*Arabi et al*., 2006], or in the evaluation of practice's cost-effectiveness [*Bryan and Kandulu*, 2009]. In this study, the objective function was developed considering the economic effects of the conservation practice over a period of 5 years (model time period 2004–2008). It represents net present values of economic costs and revenues that the conservation practice will accrue for the landowner investing in this practice (similar to the returns to the land developed by *Coiner et al.* [2001] and *Liu et al.* [2011]). Note that in this study, we assessed economic benefits for only a short-term time period to assess immediate benefits that the landowner operators could reap from their short-term decisions.

[41] Based on what land tenure is actually involved in crop production on the landowner's land within the SB, a relevant economic cost-revenue function for conservation practices was calculated for that landowner. Three types of land tenures for farm operations were considered—landowner operators who farm their own land, cash renters who pay a fixed amount for renting the land, and share renters who share costs and benefits with the landowner for crop production.

[42] Table 6 shows a scheme of the factors considered in the net cost-revenue function if the SB has a specific dominant land tenure type involved in crop production. *CI* is the cost of implementation for each conservation practice, *OM* is the operation and maintenance cost, *Rin* is the rent receive from the conservation program for those land areas that are taken out of production to support a conservation practice, *SP* is the savings in productions (i.e., economic costs of production not spent when an area of land is taken out of production), *PI* represents the net economic profit received by the landowner because of increased productivity, *Rent* is the amount of rent that a renter pays to the landowner when the land is cash rented, and *Fraction* is the part of the total economic costs and economic revenue shared between a landowner and share renter during crop production.

[43] A cash flow was developed for each case and for all the 5 years in the simulation period 2004–2008. The net present value in January of 2004 of all net economic costs (NPV_m) for the entire watershed was then calculated to represent the economic costs-revenue objective function. This is given by

$$Minimize\left\{\sum_{i=1}^{\#\ of\ SB} NPV_{i,m}\right\} \tag{3}$$

where $NPV_{i,\ m}$ (or Net Present Value of Economic Costs $_{i,\ m}$ in dollars) is calculated using one of the following three equations based on which land tenure *m* dominates the *i*th SB. The "landowner operators" function (i.e., when $m=1$ for the case in which the landowner farms his/her own entire land in the specific SB) is presented by

$$NPV_{i,m=1} = \sum_{j=1}^{BMP} CI_j * A_{i,j} + \sum_{n=2}^{years}\sum_{j=1}^{BMP} \left\{\left[\left(OM_j - Rin_j\right) * A_{i,j}\right] - PI_n - SP_n\right\} * PWF_n \tag{4}$$

where *i* is the SB where the BMP (or, conservation practice) is installed, *BMP* is the total number of conservation practices, CI_j is the cost of implementation in dollars per acre for each conservation practice, $A_{i,j}$ is the area in acres of the conservation practice *j* per SB *i*, *years* is the total number of years used to estimate the costs (i.e., 5), OM_j is the operation and maintenance cost in dollars per acre per each conservation practice *j*, Rin_j is the rent received by the conservation program in dollars per acre for those lands that are taken out of production for the conservation practice *j*, SP_n is the savings in costs of crop productions in dollars of taking land out of production in year *n*, PI_n represents the net profits, in dollars, obtained from increased productivity in year *n*, and *PWF* is the single payment present worth per year given by

$$PWF_n = \frac{1}{(1+int)^n} \tag{5}$$

where *int* is the estimated interest rate

[44] PI_n and SP_n are calculated based on the yield production and BMP adopted, given by the following equations (6) and (7).

$$PI_n = \left\{\sum_{k=1}^{HRU\_crops_i} \left(Ynew_{n,k} - Ybase_{n,k}\right) * HRU\_area_k\right\} * Crop\_price_k \tag{6}$$

where HRU_crops_i is the number of hydrologic responds units that have a row crop (corn or soybean) as land use, $Ynew_{n,k}$ is the yield in bushels/acre when a conservation practice is install in the HRU *k* on year *n*, $Ybase_{n,k}$ is the yield in bushels/acre for the baseline model in the same HRU *k* and year *n*, HRU_area_k is the area in acres of the hydrologic respond unit, and $Crop\_price_k$ is a fixed price for the crop in HRU *k* in dollars.

$$SP_n = \sum_{k=1}^{HRU\_crops_i} \left(FS_i * Sprice_{n,k}\right) + \left(Wetland_i * AvSprice_{n,k}\right) \tag{7}$$

where FS_i is the filter strip conservation practice that was built following the recommended standards of NRCS of a 36.88 m length for each field of 0.19 km^2 and with width variation from 0 to 5 depending on the optimization tool. $Sprice_{n,k}$ is the savings, in dollars, of productions during year n at HRU k. This saving in production was calculated using a quadratic regression obtain from the average prices in production available in the last 10 years based on Purdue Agriculture Extension reports for Indiana ([*Dobbins et al*., 2002–2012a], Purdue Crop Cost and Return Guide, http://www. agecon.purdue.edu/extension/pubs/index.asp). This regression is shown in equations (8) and (9) for corn and soybean, respectively:

$$Sprice_{n,k} = \left[-0.0072 * \left(Y\ base_{n,k}\right)^2 + 3.036 * \left(Y\ base_{n,k}\right) + 20.296\right] \tag{8}$$

for all the HRU k with land use corn, having a coefficient of determination calculated by excel of $R^2 = 1$ and

$$Sprice_{n,k} = \left[-0.005 * \left(Y\ base_{n,k}\right)^2 + 1.5274 * \left(Y\ base_{n,k}\right) + 91.134\right] \tag{9}$$

for all the HRU k with land use soybean, also with a coefficient of determination of $R^2 = 1$.

[45] $Wetland_i$ is the wetland area, in acres, of SB i and $AvSprice_{n,k}$ is the average of $Sprice_{n,k}$, in dollars/acres, of the entire SB, depending on the land use, calculated using

$$AvSprice_{n,k} = \frac{\sum_{k=1}^{HRU\_crops_i}\left(Sprice_{n,k} * HRU\_area_k\right)}{\sum_{k=1}^{HRU\_crops_i} HRU\_area_k} \tag{10}$$

[46] The net increased productivity (PIn) and the savings in crop productions (SPn) used yield in their calculations, then as we consider the first year as the model warming up period, $PI_1 = SP_1 = 0$.

[47] Equation (11) shows the net economic cost-revenue function when a landowner rents his/her land to a cash renter (i.e., when $m = 2$ for the case in which SB i is dominated by landowners who rent out their land to cash renters).

$$NPV_{i,m=2} = \sum_{j=1}^{BMP} CI_j + \sum_{n=2}^{years}\sum_{j=1}^{BMP}\left\{\left[\left(OM_j - Rin_j\right) * A_{i,j}\right] - RR_n\right\} * PWF_n \tag{11}$$

where RR_n is the rent of the land, in dollars, also calculated based on the yield production of the particular year. This rent was also calculated through a quadratic regression (of $R^2 = 1$) built using the average of the last 10 years in rent data prices (C. L. Dobbins and K. Cook, 2002–2012, Purdue Agricultural Economics Report, Purdue Agricultural Economics Extension, http://www.agecon.purdue.edu/extension/pubs/paer/archive.asp) and is shown in

$$RR_n = \sum_{k=1}^{HRU\_crops_i}\left[0.002 * \left(Y\ base_{n,k}\right)^2 + 0.4078 * \left(Y\ base_{n,k}\right) + 41.459\right] \tag{12}$$

[48] Again, the first year is considered as a warming period for the model and then all the variables dependents on yield are deliberated omitted, then $RR_1 = 0$.

[49] When SB i is dominated by landowners who rent out their land to share renters (i.e., $m = 3$), the net economic costs incurred by these share-renter operators over the period 2004–2008 would be described by

$$NPV_{i,m=3} = \sum_{j=1}^{BMP} CI_j * f + \sum_{n=2}^{years}\sum_{j=1}^{BMP} \left\{\left[\left(OM_j * f - Rin_j\right) * A_{i,j}\right] - \left(PI_n - SP_n\right) * f\right\} * PWF_n \tag{13}$$

where f represents the fraction of costs and revenues shared between the landowner and the share renter. In this case the fraction was selected as 0.5 for each partner based on the North Central Farm Management Extension Committee's 2011 report for crop share rental agreements (http://www.aglease101.org/DocLib/docs/NCFMEC-02.pdf), and also since conservation programs give rent directly to landowner operators so the incentives from rent were not considered as "shared" economic revenues.

[50] Land tenure varies from farm to farm (i.e., at farm scale). However, since the optimization is being performed at SB scale, it was assumed that every SB would have a representative land tenure (which, in practice, could be designated as the representative tenure of the SB that covers the maximum area in the SB) for crop production. In real life, land tenure also changes almost every year. However, since the study considers a short time period, we made a simplifying assumption and assumed a land-tenure scenario in which land tenure remained constant for the entire simulation period.

2.4.2. Peak Flow Reduction Function

[51] The peak flow reduction was calculated based on the maximum difference between the peak flows of the calibrated baseline model without any new conservation practices and peak flows of the model that includes conservation practices proposed by an alternative found via the optimization algorithm. Equation (14) presents the equation for this objective function. The main goal of this function is to maximize the maximum peak flow reduction in the watershed across all SBs, or in other words, minimize the negative of the maximum peak flow reduction.

$$PFR = \min\left[-\max_{i,t}\left(peakflow_{i,t,baseline} - peakflow_{i,t,alternative}\right)\right] \tag{14}$$

where PFR is the peak flow reduction, i is the SB, t is the day in modeled time period 2005–2008, $peakflow_{i,\ t,\ baseline}$ is the baseline peak flow when no new conservation practice exists in the watershed in the SB i at time t, and $peakflow_{i,\ t,\ alternative}$ is the modeled peak flow when the alternative consisting of a specific combination of conservation practices exists in the watershed in SB i, at time t. The peak flow in the equation is defined as

$$peakflow_{i,t,case} = flow_{i,t,case}\ , \tag{15}$$

$$if\ \ flow_{i,t,case} > flow_{i,t-i,case}\ \ and\ \ flow_{i,t,case} > flow_{i,t+1,case}$$

[52] else, $peakflow_{i,\ t,\ case} = 0$. Where, $case$ is either baseline or alternative on SB i at time t.

2.4.3. Sediments Reduction Function

[53] Sediments reduction objective function (*SR*) is calculated as per equation (16). This function represents the loss of fertile soil from landscape, across all SBs upstream of the reservoir and for the time period 2005–2008 (i.e., t = 367–1828 days).The main goal of this function is to minimize the negative of sediment reduction.

$$SR = \min\left\{-\sum_{i=1}^{\#\ of\ SB}\left[\sum_{t=367}^{1828}\left(Sedout_{i,t,baseline} - Sedout_{i,t,alternative}\right)\right]\right\} \tag{16}$$

where i is the SB number, t is the day, $Sedout_{i,t,baseline}$ is the sediment load at the outlet of reaches for the calibrated model without conservation practices, and $Sedout_{i,t,alternative}$ is the sediment load at the outlet of reaches when the optimization alternative with a specific combination of conservation practices are modeled in the watershed model. The main goal of this function is to maximize nitrate reduction or minimize the negative of nitrate reduction

2.4.4. Nitrates Reduction Function

[54] Nitrates reduction objective function (*NR*) is shown in equation (17). This function represents loss in nitrates via runoff, including those originating from the applied fertilizers, across all SBs upstream of the reservoir and for the time period 2005–2008 (i.e., t = 367–1828 days).

$$NR = \min\left\{-\sum_{i=1}^{\#\ of\ SB}\left[\sum_{t=367}^{1828}\left(Nitsout_{i,t,baseline} - Nitsout_{i,t,alternative}\right)\right]\right\} \tag{17}$$

where i is the SB number, t is the day, $Nitsout_{i,\ t,\ baseline}$ is the nitrate load at the outlet of a reach in SB i as predicted by the calibrated model without conservation practices, and $Nitsout_{i,\ t,\ alternative}$ is the sediment load at the outlet of a reach in SB i as predicted by the watershed model when an optimization alternative with a specific combination of conservation practices is included in the model.

2.4.5. Decision Variables

[55] Each of the conservation practices in the 108 agricultural SBs of Eagle Creek Watershed were included in the optimization in the form of a binary or real decision variable. All the practices, with the exception of filter strips and wetlands, were modeled as binary decision variables, x_{ij}, where a value of 1 indicates that the ith practice has being implemented in the jth SB, while a value of 0 indicates that the ith practice has not been implemented in the jth SB.

[56] Filter strips were modeled as real number values of the filter width variable y_{ij}, where i is the filter strip practice ID (among all the modeled conservation practices) and j is the SB. The value of this variable was allowed to vary from 0 to 5 m based on USDA-NRCS recommended values. Wetlands were also modeled as real number variables. Two variables, namely maximum wetland area (WET_MXSA$_{ij}$) and fraction of SB area that drains into its wetland (WET_FR$_{ij}$, also called wet fraction), were modeled for the wetland practice (that had a specific ID i) in every SB j. The maximum value of these two variables was determined using the same techniques developed by *Babbar-Sebens et al.* [2013].

2.4.6. Analysis of Attitudes

[57] Socioeconomic literature on attitudes of landowners and farmers and the effect on adoption of conservation practices [*Lynne et al.*, 1988; *Weaver*, 1996; *Luzar and Cosse*, 1998; *Luzar and Diagne*, 1999; *Soule et al.*, 2000; *Söderqvist*, 2003; *Lambert et al.*, 2006; *Ahnström et al.*, 2009] was used to relate specific scenarios of attitudes to the landowners' overall preference of conservation practices. The literature suggests that there can be multiple concerns that determine the overall suitability of a practice for a decision maker. From a theoretical perspective, the correspondence between intention of adoption and the actual implementation of conservation practices could be estimated using attitude measurement techniques [*Ajzen and Fishbein*, 1980]. A ubiquitous rating scale was used to represent landowner operators' attitudes toward the various conservation practices [*Dawes*, 1972]. We proposed a weighting approach to create a "preference score" for each practice. This approach is based on recommended approaches in Psychology literature [e.g., *Ajzen and Fishbein*, 1980; *Ajzen*, 2002; *Martin et al.*, 2008] for assessing decision maker attitudes toward an object or entity of interest. Attitudes of persons are found to be related to their beliefs or intentions that any entity of interest has specific properties and their evaluation of those properties. Such studies have recommended the use of a weighted model for measuring attitude, given by the equation (18) (where A = measurement of a person's attitude toward an entity or object of interest, b_i = strength (ranging between 0 and 1) of the person's belief that the entity or object of interest has certain properties, and e_i is the measurement of the person's evaluation of each property/attribute, and i are all the different properties or attributes):

$$A = \sum b_i e_i \tag{18}$$

[58] In this study, we explored the variation of landowners' attitudes by varying the variable b_i for the various e_i evaluations (estimated by the i objective function values). All objective functions evaluations can also be interpreted as "concerns" of stakeholders that drive their attitudes and preferences for a practice. These evaluations were normalized from 0 to 1, then multiplied by corresponding weights that indicate the strength of the stakeholder's belief in that evaluation (Table 7), and then finally summed together to calculate the "preference score." The "preference score" is an indicator of the stakeholder's attitude toward the practice. In this manner, the objective functions were used as "factors" that determined a landowner's strong attitude or weak attitude toward adopting a specific conservation practice based on whether the preference score was high or low. The preference score for landowner operators whose strong attitudes toward practices are driven by the concerns for economic profits and incentives (which are dependent on the land tenure operating in the watershed), or by flood-related benefits (i.e., peak flow reductions), or by fertilizer loss related benefits (i.e., nitrate reductions), or by soil fertility and conservation related benefits (i.e., sediment reductions) were all estimated using equation (10). Higher weights were chosen for factors, when the strong attitude was driven by the specific factor. For example, in the case of landowner operators with

Table 7. Extreme Weights for Different Attitudes Preferences

Attitude Driven By	Objective Function	Weights
Economic concerns	Cost revenue	High (weight_high = 0.7–0.9)
	Peak flow reduction	Low ([1 − weight_high] × 0.25)
	Sediments reduction	Low ([1 − weight_high] × 0.25)
	Nitrates reduction	Medium ([1 − weight_high] × 0.5)
Flood concerns	Cost revenue	Medium ([1 − weight_high] × 0.5)
	Peak flow reduction	High (weight_high = 0.7–0.9)
	Sediments reduction	Low ([1 − weight_high] × 0.25)
	Nitrates reduction	Low ([1 − weight_high] × 0.25)
Erosion concerns	Cost revenue	Medium ([1 − weight_high] × 0.5)
	Peak flow reduction	Low ([1 − weight_high] × 0.25)
	Sediments reduction	High (weight_high = 0.7-0.9)
	Nitrates reduction	Low ([1 − weight_high] × 0.25)
Fertilizer concerns	Cost revenue	Medium ([1 − weight_high] × 0.5)
	Peak Flow reduction	Low ([1 − weight_high] × 0.25)
	Sediments reduction	Low ([1 − weight_high] × 0.25)
	Nitrates reduction	High (weight_high = 0.7–0.9)

strong attitudes driven by concerns for economic profits, the cost-revenue function was given a high weight, while peak flow reduction and sediments reduction were given low weights. For this particular case, nitrates reduction was given a medium weight, assuming that it is associated with fertilizer loss, which is closely related to high economic costs of fertilizer applications and fertilizer losses (C. L. Dobbins et al., 2002–2012, Purdue Crop Cost and Return Guide, http://www.agecon.purdue.edu/extension/pubs/index.asp).

[59] Note that the selection of the weights was made in such a way that the sum of all the weights would equal to one, irrespective of what the value of high weights (i.e., "weight_high" in Table 7) was chosen within the ranges in Table 7. Hence, all other weights (i.e., weight = medium, and weight = low) for a specific attitude were modified relative to "weight_high". Equation (19) below describes the preference score model:

$$Score_{K,l,m} = -\left(\frac{NPV_{l,m}}{maxNPV_m} * \gamma_{costs,m} - \frac{PFR_l}{maxPFR} * \gamma_{Flood,m} - \frac{SR_l}{maxSR} * \gamma_{seds,m} - \frac{NR_l}{maxNR} * \gamma_{fert,m}\right) \quad (19)$$

where K represent the different objective functions (or factors), l is the conservation practice, and m is the tenure-type operating the watershed. Note, that here, maximum value of $m = number\ of\ land\ tenures$ *(i.e.,* 3*)* $\times number\ of\ attitudes$ *(i.e.,* 4*)*. Variables $maxNPV_m$, $maxPFR$, $maxSR$, $maxNR$ are the maximum values for each objective functions net present value of economic costs (equations (4), (11), or (13) depending on land tenure), peak flow reduction (equation (14)), sediment reduction (equation (16)), and nitrate reduction (equation (17)), respectively, among all the practices. Variables $\gamma_{costs,\ m}$, $\gamma_{Flood,\ m}$, $\gamma_{Seds,\ m}$, and $\gamma_{fert,\ m}$ are the weights assigned to the various factors based on how strongly a factor affected the landowner's attitude toward the conservation practice.

2.4.7. Pareto Front Comparison

[60] There are multiple options in the literature for evaluating and comparing nondominated sets or Pareto fronts obtained from multiobjective optimization studies. *Van Veldhuizen* [1999] present a series of metrics based on error ratio, generational distance, maximum Pareto front error, Hyperarea and ratio, spacing, etc. to measure distance between any two alternatives. In this study, we proposed and calculated an overall distance between any two sets of alternatives, whether the two sets consisted of two different Pareto fronts, or whether one set consisted of a Pareto front and the other set consisted of modified alternatives from the Pareto front in the first set. Hence, in this manner, we were also able to evaluate the effect on optimization results, when practices are removed from the alternatives in the original Pareto front because of stakeholder attitudes and preferences.

[61] This overall distance metric was based on the Euclidean distance inspired by *Deb et al*. [2002] and *Knowles and Corne* [2002]. This metric compared the position between every *i*th alternative in the original Pareto front and all *j* alternatives in the modified Pareto front (i.e., after removing practices for which the stakeholders have low preference), for two objective functions at a time. Note that that maximum value of *i* is equal to maximum value of *j* for both Pareto fronts. In the end, an average of all the distances between alternatives in the two Pareto front was calculated to estimate the overall distance. The method for calculating distance, D, can be written mathematically as showed in equation (20):

$$D(A,\ B) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\sqrt{\left(A_i - A_j\right)^2 + \left(B_i - B_j\right)^2}}{n} \quad (20)$$

where D is the sum of all the distances based on scaled values of objective functions A and B, and n is the total number of alternatives in the Pareto front. The objective functions A and B were rescaled using the linear approach of dividing the difference between the original value of set ($OriginalA_i$) and the minimum value of the set ($minA$) by the difference between the maximum ($maxA$) and minimum ($minA$) value of the set, as shown in equation (21). Maximum values of *D(A,B)* possible is 1.414 (or $\sqrt{2}$).

$$A_i = \frac{OriginalA_i - minA}{maxA - minA} \quad (21)$$

3. Results and Discussion

3.1. Flow Calibration

[62] Daily stream flow predictions from 2005 to 2008 were first calibrated in the SWAT model, yielding a calibrated model with Nash-Sutcliffe efficiency (E_{NS}) of 0.68 and Pearson's product-moment correlation coefficient (R^2) of 0.83 for daily flows at Zionsville USGS gage station (Figure 3a). Similarly, the calibrated model predicted daily flows from 2005 to 2008 at Clermont USGS gage station with $E_{NS} = 0.90$ and $R^2 = 0.95$ (Figure 3b).

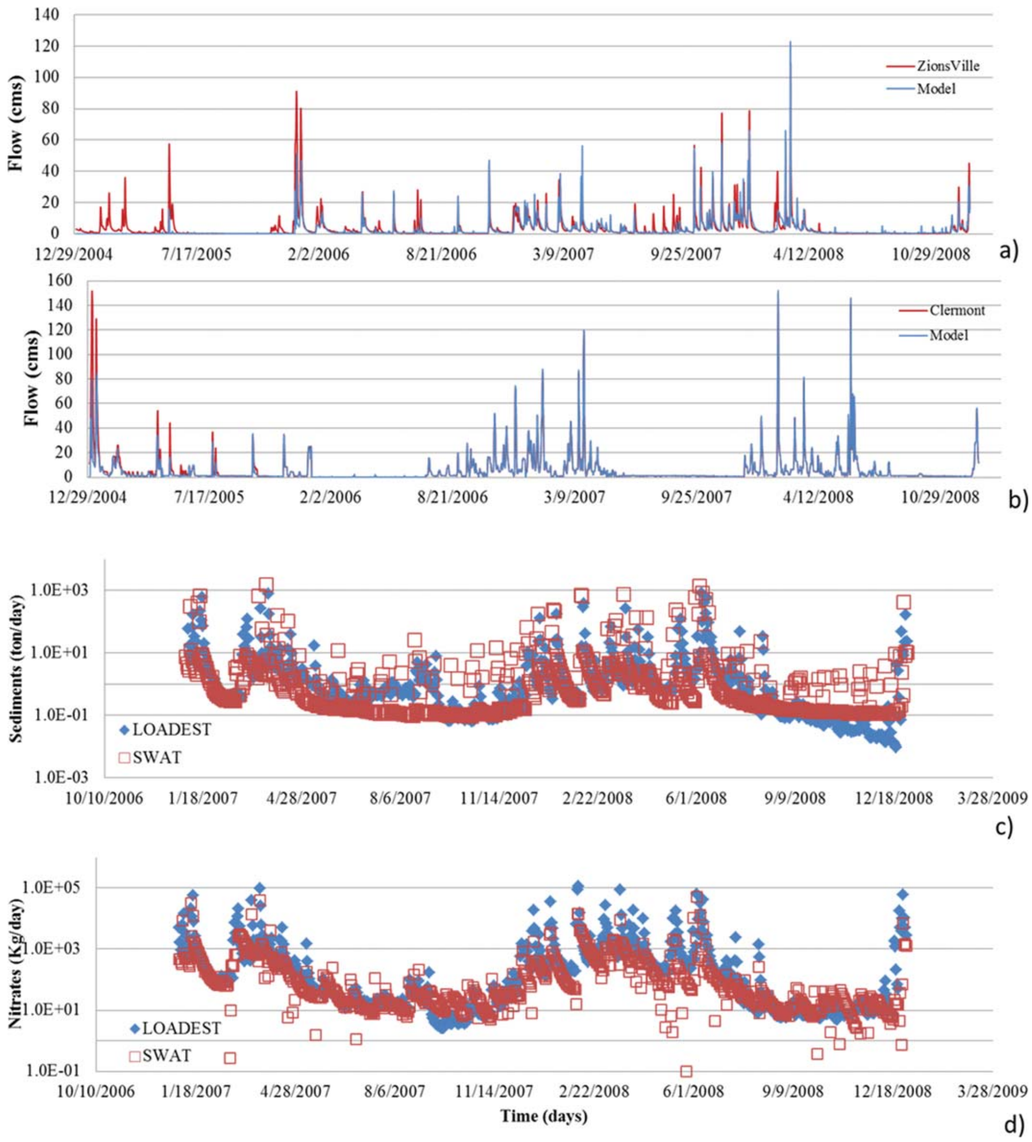

Figure 3. Flow calibration for the Zionsville Gage station (a) and Clermont Gage station (b) in the 2005–2008 modeled years. Water quality calibration for the ECWMP-04 sediments (c) and nitrates (d) in the 2007–2008 modeled years.

[63] These model efficiency values agree with other reported values for stream flow calibration [e.g., *White and Chaubey*, 2005; *Gassman et al.*, 2007], where the model efficiency for flow calibration range from 0.58 to 0.98 for E_{NS} and from 0.63 to 0.97 for R^2. *Gassman et al.* [2007] compiled some reports for hydrologic calibration in SWAT, and reported that most studies focusing on watersheds in Indiana were able to attain a monthly calibration within the range of 0.73 to 0.84 for E_{NS} and a range of 0.86 to 0.92 for R^2. In their report, for daily calibration (also in Indiana) the E_{NS} ranged from −0.23 to 0.28 in most studies. Limitations in observed data and different considerations involved in each watershed were also found to be a source of these discrepancies in reports. Nevertheless, the values reported were considered as valid ranges for expected accuracy of the calibrated SWAT models.

3.2. Water Quality Calibration

[64] As was mentioned in the methodology section, because daily sediment and nitrate observations were not available at the monitoring stations, daily concentrations for sediments and nitrates was estimated from the limited data set using the LOADEST [*Runkel et al.*, 2004; *White and Chaubey*, 2005] software. The LOADEST model of observations at station ECWMP-04 had model efficiency of $E_{NS} = 0.59$ for sediments and 0.73 for nitrates. The estimated daily concentrations were multiplied by daily flow rates to estimate sediment and nitrate loads. Such an approach of using LOADEST to estimate daily water quality observations, when the actual observations are limited, has been used previously by multiple studies [e.g., *White and Chaubey*, 2005; *Cerro et al.*, 2011; *Stenback et al.*, 2011; *Heimann et al.*, 2011]. The estimated daily

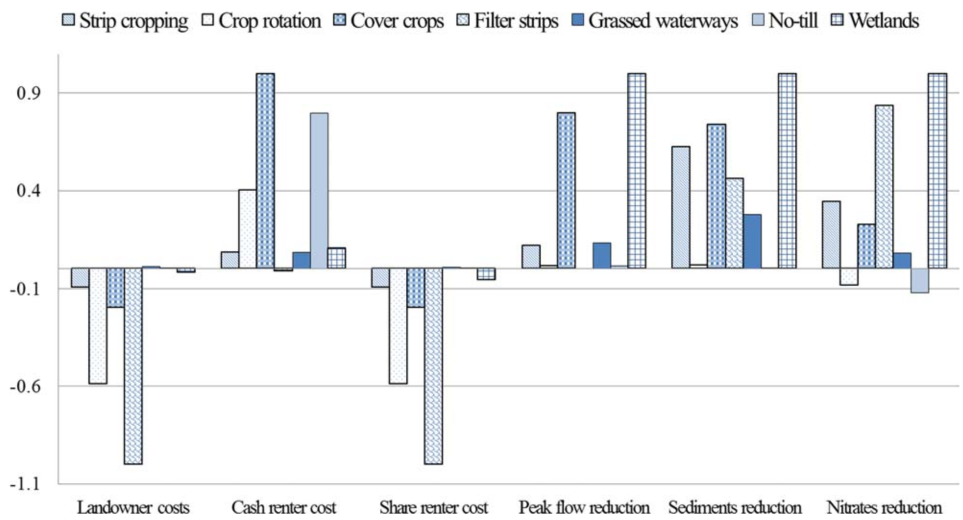

Figure 4. Comparison of practices based on various objective functions/factors/criteria.

observations were then used to calibrate the SWAT model predictions for sediments and nitrates. The results for calibrated sediments, as predicted by the SWAT model and compared with the LOADEST estimations, are shown in Figure 3c. With an $E_{NS} = 0.70$ and $R^2 = 0.90$, the calibration for sediments was considered to be acceptable [*White and Chaubey*, 2005].

[65] The results for calibration of SWAT model's predictions of nitrates are shown in Figure 3d. For this case, $E_{NS} = 0.34$ and $R^2 = 0.71$. Although these values do not represent a high accuracy, we can observe in Figure 3d that this is due to a poor correspondence of the model with the extreme values of the observed data. But the model does a good job with the prediction of nonextreme observations.

3.3. Optimization and Attitudes

[66] Three different experiments were performed to evaluate the effect of attitudes on spatial optimization of conservation practices in the watershed. The results of these three experiments are discussed in the subsections below. The first experiment addressed the first objective and involved a comparative analysis of conservation practices to assess how each of the practices would be preferred based on the attitudes, if the practice was alone implemented at all potential locations in the entire watershed and if the entire watershed was operated by only one of the three land tenures. For each practice and land tenure, we calculated "preference scores" to identify how strong or weak the attitudes of the landowner operators would be toward these practices. The main goals of these experiments were to test the sensitivity of the practices to the individual attitudes (which are themselves dependent on the watershed-scale objective functions) of the landowner operators, who would be the main implementers of these practices.

[67] The second set of experiments addressed the second objective, and involved optimization and comparison of "optimal" or "nondominated" set of alternatives of conservation practices, when the entire watershed has the same land tenure type or a varying distribution of land tenure type. The main goal of these experiments was to investigate how economic drivers that are specific to land tenure would change the design of the optimal solutions and their performance. Such an investigation is important, because land tenure conditions are always changing based on settlement patterns, land use changes, U.S. agricultural policies, and technological changes. What set of conservation practices might seem economically attractive to one land tenure, might not be economically viable for another land tenure. Such an investigation has been gravely missing in existing watershed optimization literature.

[68] In the third set of experiments (which addressed the third objective), the analyses on attitudes and preferences scores of practices (performed in the previous first set of experiments) were then used to demonstrate how the nondominated sets of alternatives found by the optimization analyses (in second set of experiments) would change in their effectiveness/performance, once the practices not preferred by landowner operators (with SBs operated by the three different land tenures and exhibiting different attitudes) were removed from the final set of these nondominated alternatives.

3.3.1. Comparative Analysis of Practices

[69] Figure 4 compares the scaled objective functions for all the seven practices, and demonstrates which practices perform better than the others when only one objective function/factor/criterion was considered to judge the overall effectiveness of individual practices. Note, again, that to calculate the economic cost functions, we assumed that all the SBs were occupied by one type of land tenure only. Positive values of net economic costs indicate that more economic costs were higher than economic revenues from incentives and rents, etc., whereas, negative net economic costs (e.g., those in the case of "landowner costs" and "share renter costs") indicate that economic revenues incurred by the landowner operators were higher for a specific practice than the cost of implementing and managing that specific practice.

[70] If the entire watershed was occupied by only one type of land tenure out of the three land tenure types, then the landowner operators who farm their own land and landowner operators who rent out part of their land to share renters would have a similar performance of practices with respect to net economic costs. Filter strips would yield

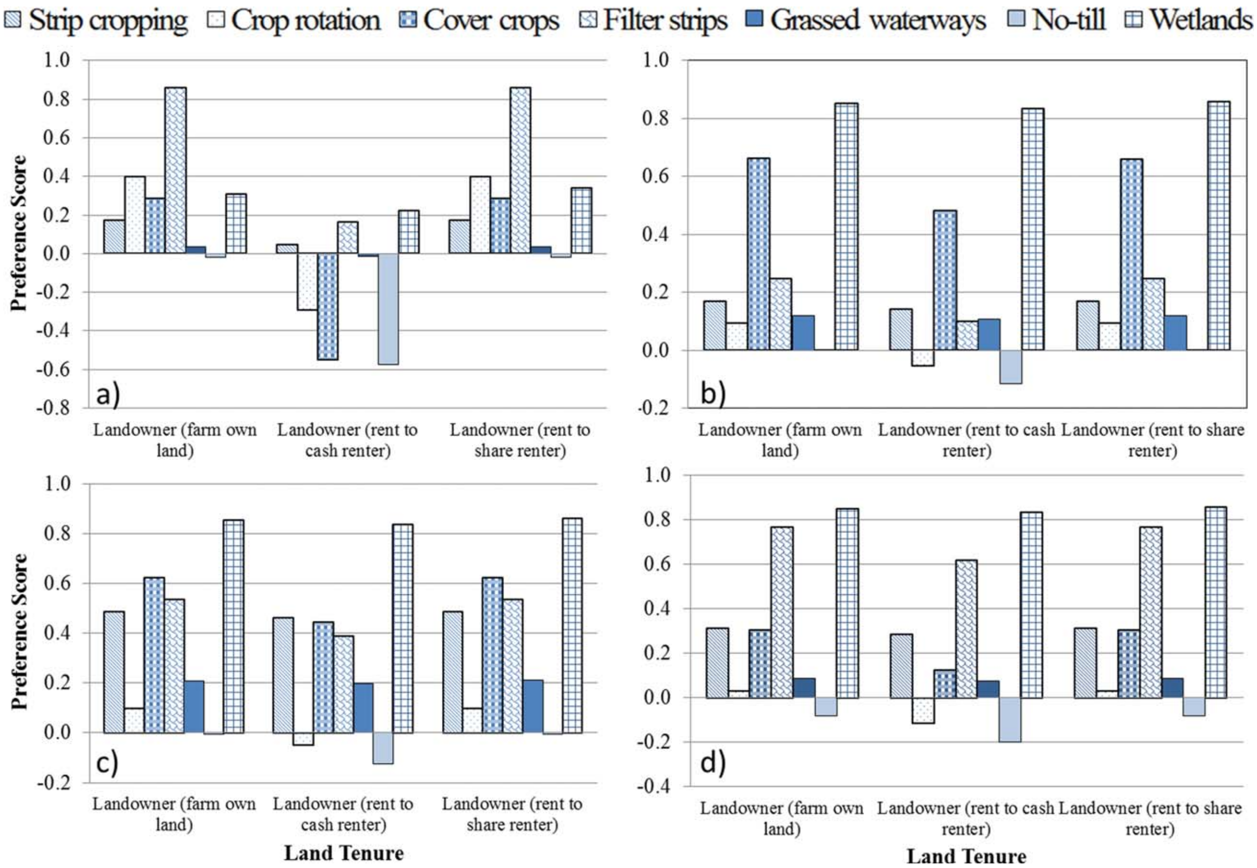

Figure 5. (a) Effect of attitudes driven by economic profits on the preference score of practices. (b) Effect of attitudes driven by flood reduction on the preference score of practices. (c) Effect of attitudes driven by soil fertility and conservation on the preference score of practices. (d) Effect of attitudes driven by fertilizer loss on the preference score of practices.

largest economic revenues, followed by crop rotation, cover crops, and then strip cropping. Costs and revenues would almost balance out for grass waterways, no-till, and wetlands. However, if the entire watershed was occupied by landowner operators who rent out their land to cash renters, then the all practices would incur economic costs higher than economic revenue, except for filter strips where economic costs and economic revenues would almost balance each other out. Hence, purely from the economic perspective, filter strips seem like the most economically viable practice for this watershed, for all three land tenure types. One assumption that needs to be noted here is that economic revenue estimated in these economic functions for the different land tenures are dependent on the crop yields estimated by the SWAT model. Hence, if the yield changes in the actual watershed, the performance of these practices would change between the land tenure types.

[71] For peak flow reduction, sediment reduction, and nitrate reduction, the results are different from economic functions. The three objectives show wetlands as the most effective practice with maximum reductions in peak flows, sediments, and nitrates (whereas based on the economic functions wetlands were one of the less favorable ones). Filter strips have the worst performance in reducing peak flows. For the short-term period of 4 years (2004–2008), No-till conservation practice has the least sediments reduction and nitrates reduction. Hence, for short-term impacts, no-till would not be a useful practice. As part of the next phase of this work, we plan to investigate how the performance of this practice would change when implemented for a long period of time.

[72] Figures 5a–5d compare the preference scores of the practices for the three land tenure scenarios, when the attitudes of the landowner operators are affected by all of the four factors/drivers, with variant biases toward specific factors. The weighting approach described earlier in equation (19) was used to obtain the preference scores based on biased factors. Variables γ_{costs}, γ_{Flood}, γ_{Seds}, and γ_{fert} are the weights assigned to the various factors based on how strongly a factor affected the landowner's attitude toward the conservation practice. The values of these weights were chosen based on the relative weighting approach shown in Table 7, and based on findings from multiple socioeconomic literature [e.g., *Luzar and Diagne*, 1999; *Söderqvist*, 2003], which indicate that economic costs and economic revenues are always a critical part of decision making and should not be completely unaccounted for as a driving factor (hence, the weights for economic costs and revenues in Table 7 was never set to be below "medium" weights). The higher the preferences score for a practice in these figures, the more it will be preferred by the landowner with the specific tenure and specific attitude.

[73] When landowner operators (Figure 5a) are biased by economic costs and revenue driver, filter strips remain

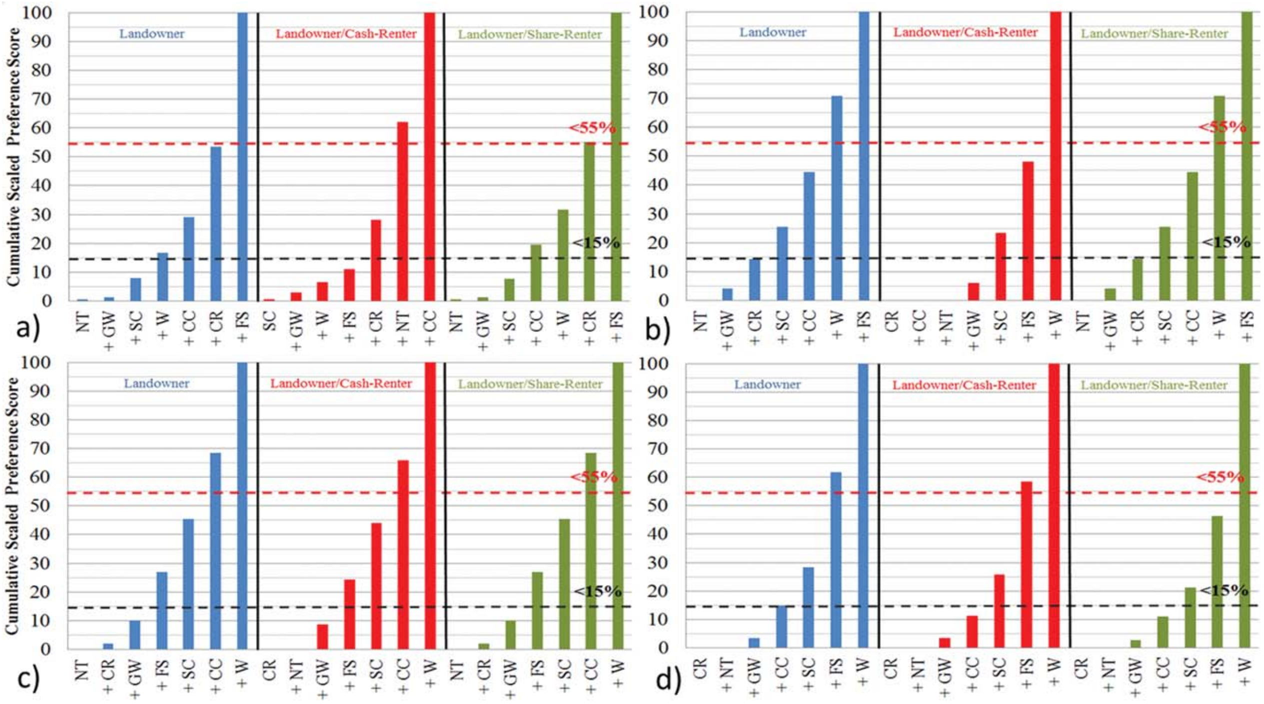

Figure 6. (a) Cumulative preference scores of landowners with attitudes driven by economic profits. (b) Cumulative preference scores of landowners with attitudes driven by flood control. (c) Cumulative preference scores of landowners with attitudes driven by soil fertility and conservation (or, erosion control). (d) Cumulative preference scores of landowners with attitudes driven by fertilizer loss (or nitrate loss).

to be the preferred choice for landowner operators who farm their own land and land owners who rent their land to share renters. However, landowner operators who rent out their land to cash renters prefer wetlands to other practices. This indicates that when these types of landowner operators considered all the benefits of wetlands, the net benefit of implementing wetlands in their watershed would outweigh the net investment they would need to make over the 4 year time period.

[74] When landowner operators are biased by flood control benefits (Figure 5b) or by soil fertility and conservation-related benefits (Figure 5c) or by fertilizer loss-related benefits (Figure 5d), wetlands outperform all other practices in their preference scores, in spite of the net economic costs (Figure 4). No-till always had the lowest preference score and did not appear to be a promising practice for the 4 year time period.

[75] The previous results (in Figures 5a–5d) were based on minimum value of "weight_high" for the range of weight values in Table 7. Hence, to test the effect of different values of weights within the possible ranges in Table 7, 100 random realizations of "weight_high" and the other dependent weights (i.e., the low and medium weights) were created. These 100 realizations of weights were then used to calculate 100 realizations of preference scores for each practice, for each attitude driver, and for each tenure type. The results of preference scores for these realizations of weights did not significantly vary from the results based on the minimum value of "weight_high" shown in Figures 5a–5d on how the practices were preferred in comparison to the others. For example, only 5 out of the 84 scenarios of practices, tenure types, and attitude drivers (i.e., less than 6% of the scenarios) in Figure 5 had their respective average preference score for the 100 realizations differ from the preference scores based on the minimum value of "weight_high" (that are shown in Figure 5) by a value greater than 0.1. Moreover, the standard deviation of the preference scores for all 100 realizations of the 84 scenarios varied from 0.001 to 0.15, with an average of maximum standard deviations for all the practices under all scenarios of 0.07.

[76] Based on the sensitivity of the practices to the attitudes of landowner operators, we then used a threshold approach for every landowner type and specific attitude to remove practices that clearly had a low preference score. The preference scores of each practice and tenure type and attitude were first averaged across all 100 realizations. These average score for every practice (under a particular landowner type and attitude) was then scaled by a total preference score ($TScore_{K,\ m}$, equation (22)) for all practices (under the same landowner type and attitude) to calculate a scaled preference score.

$$TScore_{K,m} = \sum_{l=1}^{num\ Practices} \left(Score_{K,l,m}\right) \tag{22}$$

where m represents each land tenure type with a specific attitude. Note, that here, maximum value of $m = number\ of\ land\ tenures\ (i.e., 3) \times number\ of\ attitudes\ (i.e., 4)$. Scaling preference scores in this manner allowed us to assess what percent of the total preference score across all practices is the preference score of a specific practice. Hence, if a

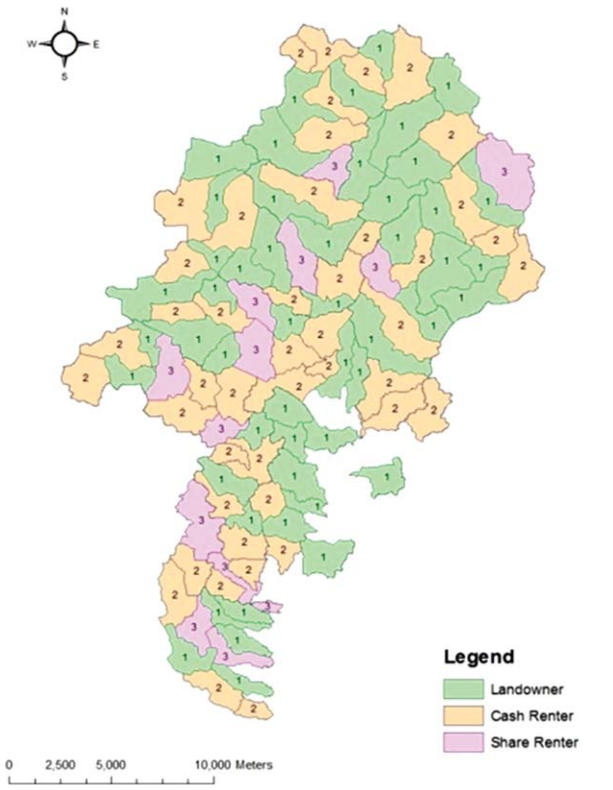

Figure 7. Random distribution of land-tenures in the Eagle Creek Watershed, Indiana.

landowner with a specific attitude and a specific land tenure on her/his land wanted to disregard practices with low preference scores, she/he could use this scaled preference score to remove low-scoring practices. We used a cumulative score approach to remove these low performing practices by removing only those low-scoring practices whose cumulative value of scaled preference score was less than a threshold of the total preference score.

[77] Figures 6a–6d show the cumulative values of the scaled preference scores of practices, for each of the three land-tenure types and each of the four attitudes. The horizontal lines show two thresholds (i.e., a low value of 15% and a medium value of 55% for exploratory purposes) for cumulative scores that were used to remove the low-scoring practices. For all the attitudes of different land-tenure types that are environmentally oriented (flood control, soil fertility and conservation, and fertilizer loss and nitrates control), a wetland practice prevailed irrespective of the threshold selected. However, if the attitude of landowner operators toward conservation practices are driven by economic costs, then wetland scores much lower than many other practices, and can be eliminated from the preferred practices of all types of landowners if the 55% threshold is used to select practices. In most cases, in spite of the attitudes and thresholds, filter strip was selected as a preferred practice by landowner operators. Cover crops were clearly one of the top two preferred practices, besides wetlands, when erosion, soil fertility, and soil conservation were important drivers of the landowner attitude, whereas filter strips and wetlands were the top two preferred practices for attitudes driven by flood control and fertilizer loss. When attitudes were driven by economic criteria, there were no clear patterns in top two practices.

3.3.2. Effect of Distribution of Land Tenure on Optimization

[78] In the second experiment, we optimized the spatial design/allocation of all the seven practices across the entire watershed. This is a typical approach for optimization of conservation practices that has been commonly used in the past by multiple researchers [e.g., *Bekele and Nicklow*, 2005; *Artita et al*., 2008; *Maringanti et al*., 2009]. We, however, demonstrated the differences in the outcomes of the optimization when land tenure was included in the optimization formulations. Three "uniform distribution" optimization experiments were performed, one for each land tenure type, in which it was assumed that the entire watershed was operated by the same land-tenure type in all the SBs. Hence, the actual function for the economic objective function was different for the three experiments based on which land tenure was used to represent the watershed in the particular experiment.

[79] In practical application, there could be multiple land-tenure types present in the watershed, and they would all be distributed at the farm scale. Hence, a fourth optimization experiment was also tested, in which the distribution of land tenures operating the land was randomly chosen ("random distribution"). Actual data on the distribution of land tenures on a specific land/farm is challenging to obtain since it is not commonly collected for multiple watersheds, and usually involves exhaustive surveys. Hence, we used a report based on Iowa's leasing trends [*Duffy et al*., 2008] to estimate a similar leasing distribution for the Eagle Creek watershed, IN. Though, the report provides estimates for a different state, we assumed that it is likely that Indiana, which is also a typical agricultural Midwestern state that has been influenced by similar drivers in the agricultural rental market, would have a similar leasing distribution. Using the same statistics as that in the Iowa data (i.e., 46% of area is landowner operated, 42% of area is cash-renter operated, and 12% of area is share-renter operated), Figure 7 shows the random distribution of the three land tenure types in the watershed at SB scale (i.e., land tenures operating the farm varied at SB scale). Also, the economic cost function in equation (3) would have different values of variable m for every SB for this experiment. Figures 8a–8c show the differences in Pareto front when distribution of land tenure in the watershed changes. When the distribution of land tenures operating the watershed was uniform, the alternatives on the Pareto front for landowner-operated watershed received the maximum economic revenues (as apparent by the negative net economic costs), and the highest benefits in peak flow reduction, sediment reduction, and nitrate reductions. This land tenure type yielded the best Pareto front of alternatives in comparison to others.

[80] The nondominated alternatives for cash-renter-operated watershed had the maximum net economic costs (approximately around 4.7×10^7 \$/Watershed). The distance, *D(A,B)* (equation (19)), with respect to the "optimal set" (landowner operated) is 0.86 (solid arrow in Figures 8a–8c). This value is approximately 1.7 times greater than the distance of 0.52 between the optimal set and the alternatives for share-renter-operated watershed. These differences may be attributed to a higher increasing in

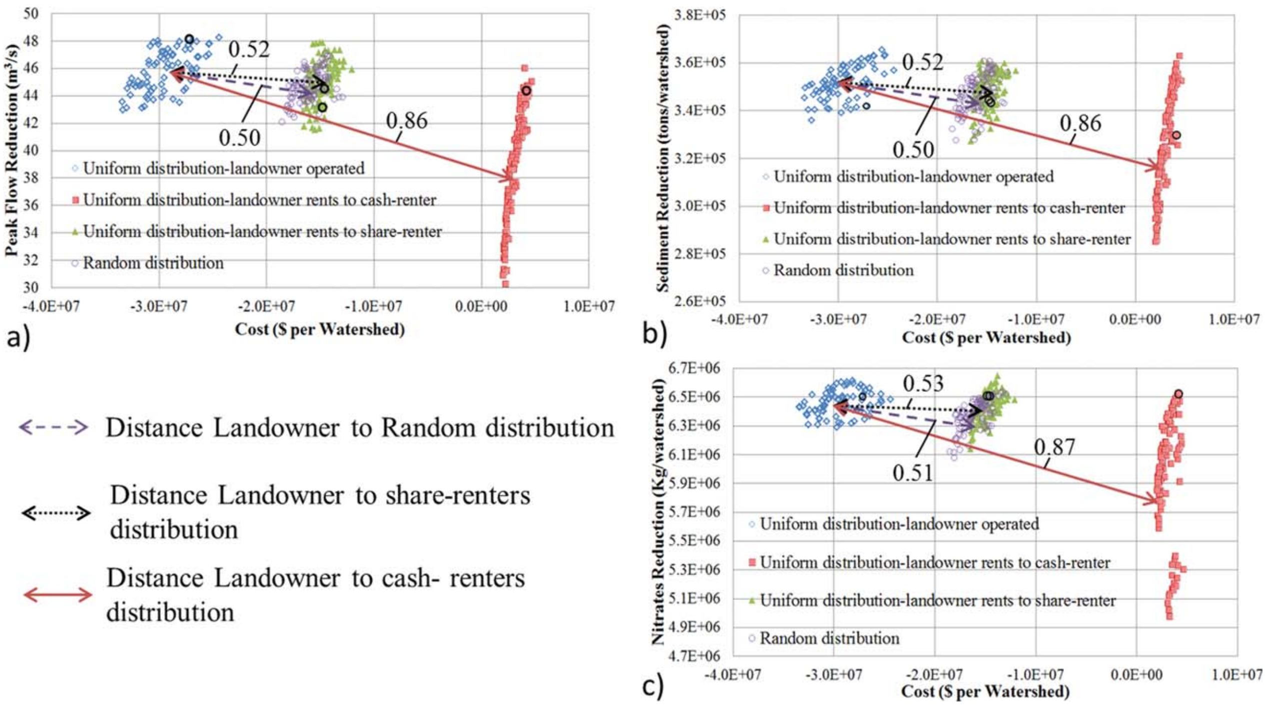

Figure 8. (a) Comparison of final Pareto fronts based on land owner net economic costs vs. maximum peak flow reductions, for uniform distributions of land tenures and random distribution of land tenures. (b) Comparison of final Pareto fronts based on land owner net economic costs vs. sediment reductions, for uniform distributions of land tenures and random distribution of land tenures. (c) Comparison of final Pareto fronts based on land owner net economic costs vs. nitrates reductions, for uniform distributions of land tenures and random distribution of land tenures. The arrows indicate the overall shift and distance *D(A,B)* between the fronts.

productivity (PI in equation (6)) for the landowner operators who operate their own land or share their operation costs with share renters, than the rent-based income (equation (12)) received by landowner operators who rent their land to cash renters.

[81] For a random distribution, the results are similar to the share-renter-operated watershed, with a calculated distance *D(A,B)* of 0.50 from the optimal set of "uniform distribution-landowner operated" scenario. This can be attributed to the fact that in "Random distribution" about 46% of the area is landowner operated and 12% of the area is operated by landowner operators who rent to share renters, and, hence, these landowner operators obtain significant positive net revenues (or negative net economic costs) from the increase in productivity and incentives. The other 42% of the area is occupied by landowner operators who rent to cash renters and hence have net positive economic costs for investing in conservation practices. Hence, the overall watershed-scale costs are reduced to a net cost, which is approximately between the two extreme cases "Uniform distribution-landowner operated" and "Uniform distribution-landowner operators rent to cash -renters."

[82] Hence, by investing in practices, landowner operators who operate their own land or operate via share renting can achieve not only better net economic returns but also obtain better environmental benefits. Landowner operators who rent their land to cash rents, on the other hand, have a very vertical Pareto front, indicating limited variation in net economic costs, whether they invest in many or few conservation practices. And, in order to obtain environmental benefits (i.e., reductions in peak flows, etc.) of the magnitude achieved by other land tenure, these landowner operators would not receive as high revenues via just land rent as they would if they operated their own land and used the profit from the increase in productivity to add up to their revenues. Hence, landowner operators renting their land to cash renters would not find conservation practices economically attractive.

[83] A combination of practices yield much better benefits than implementing only one practice in the entire watershed. Figure 9 compares the best benefits that can be achieved at watershed scale, if the entire watershed was occupied by only one practice (first seven bars in the graphs) or when the watershed was occupied by a combination of practices found via optimization of these practices for various land-tenure distributions in Figure 7. As clearly apparent, that optimization of combination of practices yield alternatives that have clearly the highest peak flow reduction benefits, sediment reduction benefits, and nitrate reduction benefits for the short-term period of 2005–2008 in the watershed. For example, among the individual practices, wetlands attain the highest peak flow reductions, sediment reductions, and nitrate reductions. However, when a combination of practices are applied, the optimized alternatives can attain 13.5% higher peak flow reductions than just wetlands (*i.e., in the case of "Optimized practices*

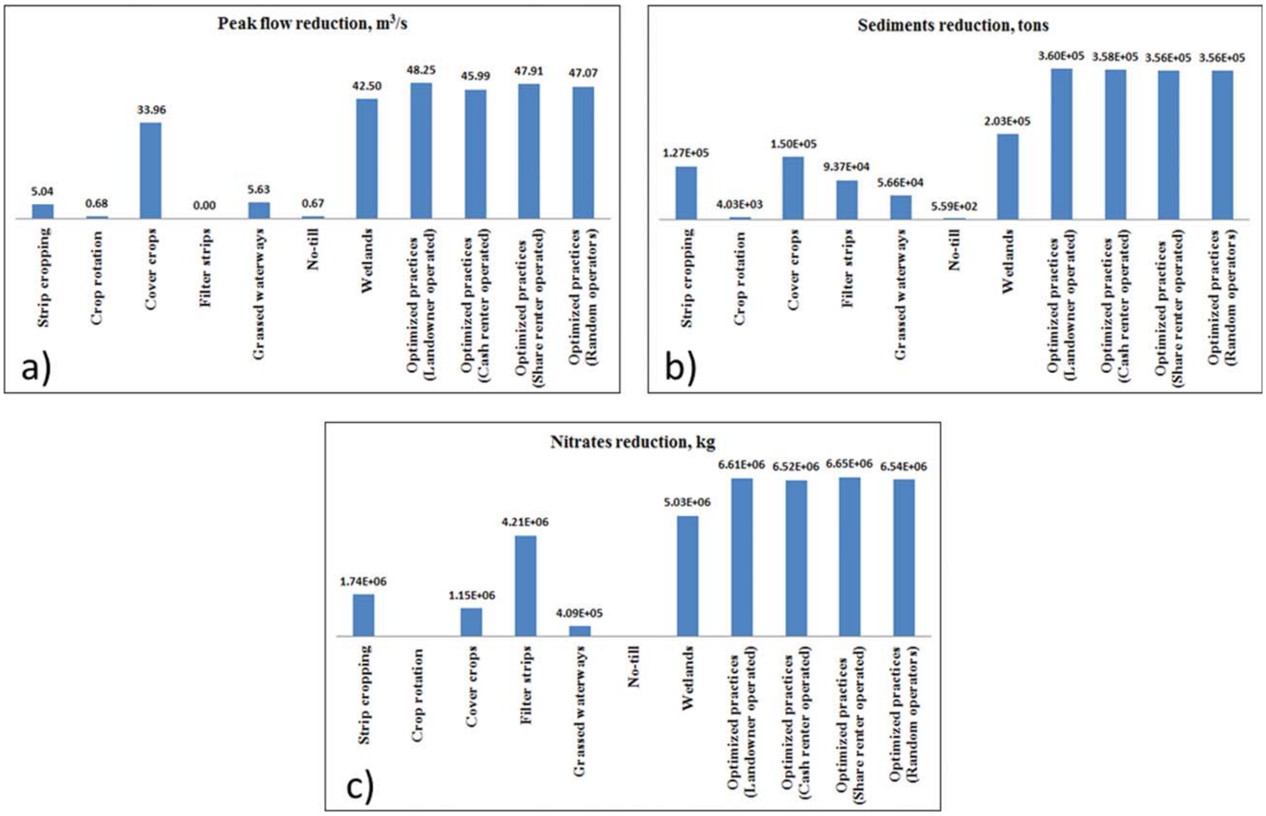

Figure 9. Comparison of practices based on the noneconomic benefits. (a) Peak flow reduction. (b) Sediments reduction. (c) Nitrates reduction.

(Landowner operated)"), 77.6% higher sediments reductions than just wetlands (*i.e., in the case of "Optimized practices (Landowner operated)"*), and 32.2% higher nitrates reductions than just wetlands (*i.e., in the case of "Optimized practices (Share renter operated)"*). The best benefits of combination of practices when the type and/or distribution of land-tenure changes is very similar for all types of land tenures, with a slight better performance in benefits when the entire watershed is occupied by just landowner operators (*i.e., in the case of "Optimized practices (Landowner operated)"*).

[84] Figure 10 show the actual distribution of alternatives from the four optimized Pareto fronts in Figures 8a–8c (*alternatives surrounded by black circles in Figures 88a-88c*), which had approximately the same nitrate reduction of 6.5×10^6 kg. All alternatives have a good spatial distribution of practices over all possible 108 SBs that have agriculture. However, some interesting differences also exist in the alternatives. For example, grassed waterways and crop management practices (such as strip cropping, cover crops, crop rotations, and no-till) are distributed over the entire watershed in these alternatives, whereas the conservation practices related to wetlands and filter strips have larger wetlands and wider strips respectively, mostly in the northern half of the watershed. All four alternatives also identified two medium size wetlands for the southwest corner of the watershed in two of the SBs of School branch. Additionally, the scenario with uniform distribution of landowner who operates on her/his own farm had the maximum number of wetlands with areas larger than 8.4 ha.

3.3.3. Effect of Attitudes on Nondominated Alternatives Found Via Optimization

[85] Figure 11 compares the differences between the original Pareto fronts identified in the second set of experiments and the modified Pareto fronts when the attitudes are biased by soil conservation, soil fertility, and/or erosion control and are used to eliminate less-preferred practices (i.e., based on 15% and 55% threshold criteria examined in the first set of experiments) from the optimized alternatives. Figure 44 shows results from scenarios when the watershed is either occupied by landowner operators who farm their own land (Figures 11a–11c) and when the watershed is occupied by landowner operators who rent their land to cash renters for crop production (Figures 11d–11f). For both kinds of landowner operators, crop rotation, no-till, and grassed waterways were removed when 15% threshold was used for identifying low-scoring practices (see Figure 6c), and filter strip and strip cropping were also additionally removed when the 55% threshold was used.

[86] There is a clear decrease in the performance of the overall Pareto front ("optimal solutions" in the Figure 11) when both thresholds criteria are used to remove low-scoring practices. The decrease in performance can vary as per the criteria and as per the tenure type. For example, when the watershed is occupied by only landowner operators who farm their own land, the elimination of less-preferred practices ends up making the modified alternatives more expensive (because, these modified alternatives have lesser economic revenue due to decreased crop yields and loss of incentives) than the original optimized

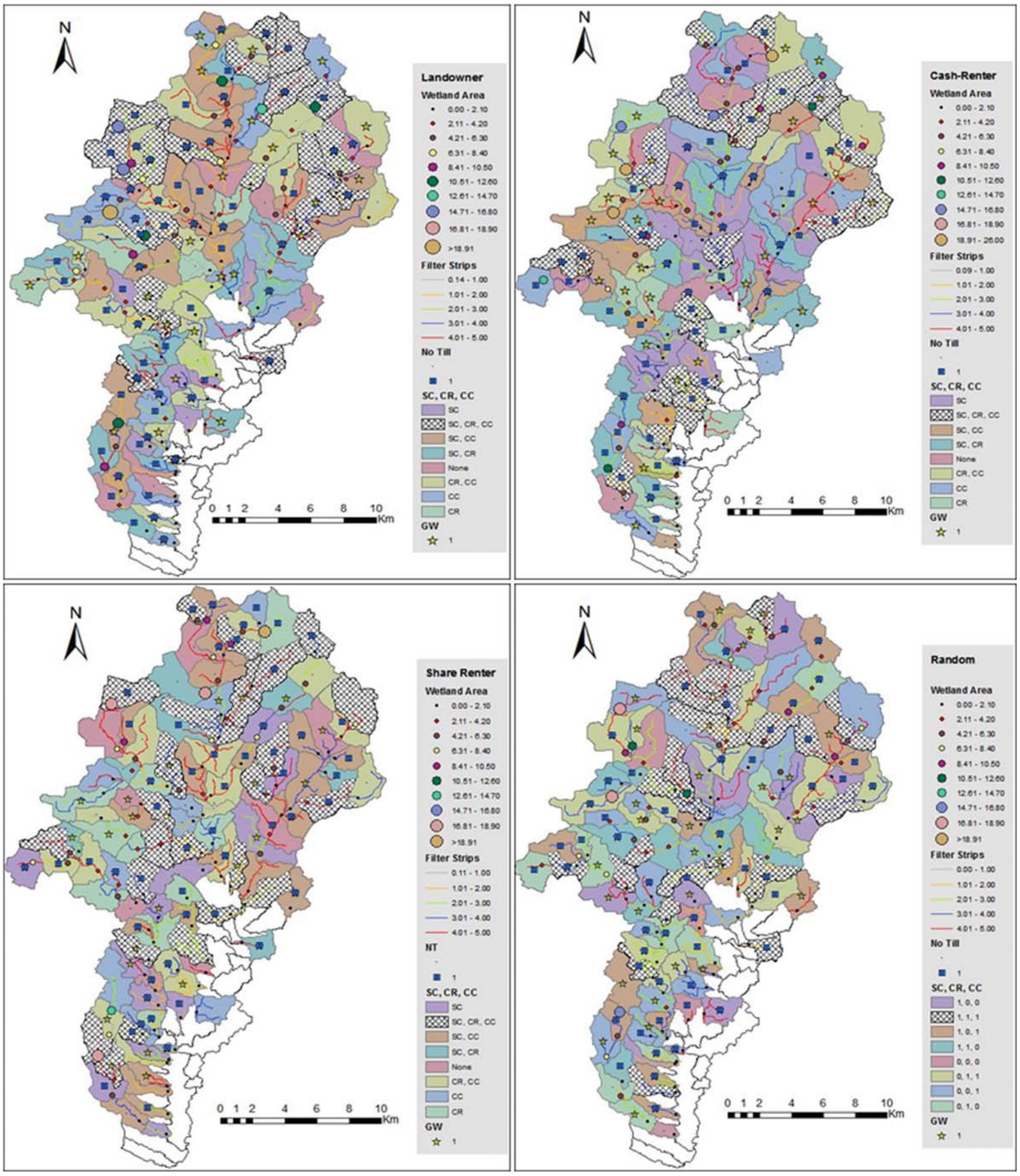

Figure 10. Distribution of practices depending on land tenure type and same nitrates reductions of approximately 6,500,000 kg. NT = No Till, SC = Strip Cropping, CR = Crop Rotation, and CC = Cover Crop.

alternatives with all the practices. Whereas when landowner operators rent their land to cash renters, the modified alternatives become cheaper for landowner operators because of absence of cost of implementation, and since for these landowners the overall economic function is mainly driven by the cost of implementation and increased rent from productivity.

[87] Also, note that for cash-renter-operated watershed, the net economic benefits improve for cases (d), (e), and (f) in Figure 11 when practices are removed; however, the remainder of the benefits (e.g., peak flow reductions and sediment reductions) actually worsen on their effectiveness. Interestingly, nitrate reduction benefits worsened when the 55% threshold criteria that removed five of the low-preferred practices was used, but slightly improved for most of the solutions when the 15% threshold criteria was used. Table 8 shows the distance, *D(A,B)* (equation (19)), between optimized Pareto front and modified Pareto fronts (for 15% and 55% threshold criteria), for various land tenure operators and farmer attitude drivers. In this table, *A* was chosen to be the scaled economic cost objective function, and *B* was chosen to be the scaled objective function

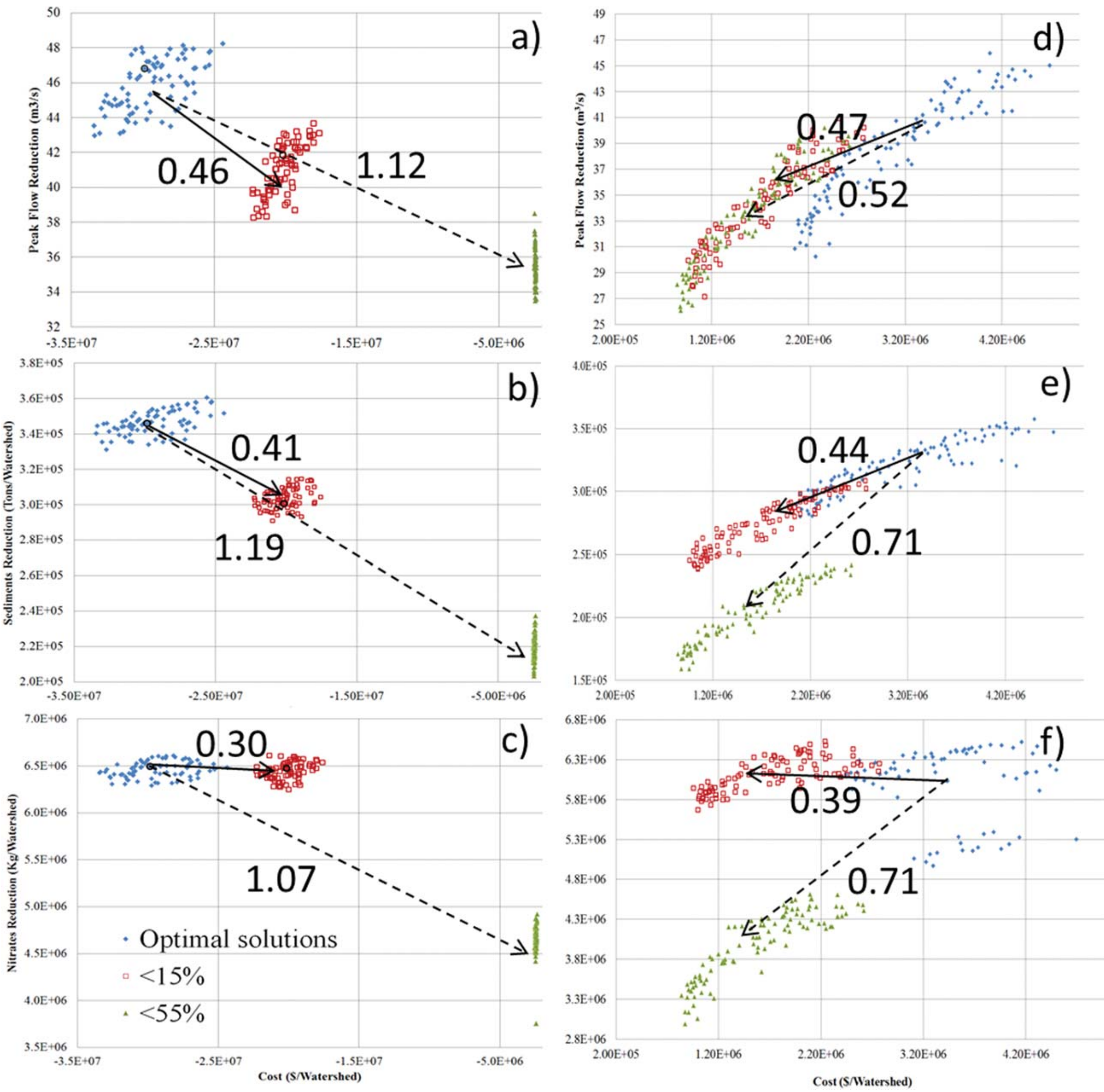

Figure 11. Effect of removing practices from optimized alternatives, when attitudes biased by soil conservation or erosion concerns affect the preferences for practices. (a)–(c) show when the watershed has a uniform distribution on "landowner operated" tenures, and (d)–(f) show when the watershed has a uniform distribution of "cash renter operated" tenures. The arrows indicate the overall shift and distance *D(A,B)* between the fronts.

related to various environmental benefits. Direction of change from optimized to modified Pareto fronts, for every objective function A and B, are given by the vertical arrows in the table.

[88] For landowner operators who farm their own land, the distances *D(A,B)* varied from 0.16 to 1.19 (Table 8), with a clear tendency of increase in costs (or degradation of economic revenue) and degradation of environmental benefits/objectives. However, there are four cases where this tendency is not followed. When the applied threshold is <15% and the landowner's preferences are driven by economic concerns, we can have solutions that increase the net economic revenue for the landowner with only a slight decrease in peak flow reduction, sediment reductions and nitrate reductions. A similar situation was found when the landowner operator is concerned about the erosion of the land and his preferences for practices are driven by this concern. For this case the objective function on nitrates reduction for the modified set of alternatives have reduction values that are very similar to the ones calculated for the original optimal set.

[89] For cash renter operators, the distances *D(A,B)* varied from 0.29 to 0.97 (Table 8). The economic cost for this land tenure type decreased when the practices were removed from the optimal solutions, unlike the scenario for uniformly distributed landowners operated watershed

Table 8. Distance, *D(A,B)*, Between Optimized Pareto Front and Modified Pareto Fronts (for 15% and 55% Threshold Criteria), for Various Land Tenure Operators and Farmer Attitude Drivers[a]

		Economic Concerns		Flood Concerns		Erosion Concerns		Fertilizer Concerns	
		<15%	<55%	<15%	<55%	<15%	<55%	<15%	<55%
Landowner									
B = PFR	*D(A,B)*	0.20	1.11	0.61	0.95	0.46	1.12	0.87	0.95
	A	↓	↑	↑	↑	↑	↑	↑	↑
	B	↓	↓	↓	↓	↓	↓	↓	↓
B = SR	*D(A,B)*	0.31	1.10	0.61	1.04	0.41	1.19	0.87	1.04
	A	↓	↑	↑	↑	↑	↑	↑	↑
	B	↓	↓	↓	↓	↓	↓	↓	↓
B = NR	*D(A,B)*	0.16	1.07	0.55	0.86	0.30	1.07	0.68	0.85
	A	↓	↑	↑	↑	↑	↑	↑	↑
	B	↓	↓	↓	↓	≈	↓	↓	↓
Cash renter									
B = PFR	*D(A,B)*	0.67	0.69	0.71	0.77	0.47	0.52	0.71	0.77
	A	↓	↓	↓	↓	↓	↓	↓	↓
	B	↓	↓	↓	↓	↓	↓	↓	↓
B = SR	*D(A,B)*	0.82	0.85	0.71	0.97	0.44	0.71	0.77	0.94
	A	↓	↓	↓	↓	↓	↓	↓	↓
	B	↓	↓	↓	↓	↓	↓	↓	↓
B = NR	*D(A,B)*	0.88	0.91	0.29	0.49	0.39	0.71	0.67	0.73
	A	↓	↓	↓	↓	↓	↓	↓	↓
	B	↓	↓	≈	↓	↑	↓	≈	≈
Share renter									
B = PFR	*D(A,B)*	0.23	1.00	0.61	0.92	0.55	1.00	0.67	1.10
	A	↓	↑	↑	↑	↑	↑	↑	↑
	B	↓	↓	↓	↓	↓	↓	↓	↓
B = SR	*D(A,B)*	0.34	1.00	0.61	1.01	0.44	1.14	0.56	1.21
	A	↓	↑	↑	↑	↑	↑	↑	↑
	B	↓	↓	↓	↓	↓	↓	↓	↓
B = NR	*D(A,B)*	0.20	0.93	0.56	0.80	0.33	1.15	0.37	1.18
	A	↓	↑	↑	↑	↑	↑	↑	↑
	B	≈	↓	≈	↓	≈	↓	↓	↓

[a]Note: A is scaled economic cost, B is the scaled objective function in the first column. PFR is peak flow reduction, SR is sediment reduction, NR is nitrate reduction.

where an increase in economic cost was observed. In this case, we observed an evidence of degradation in various environmental objective functions. However, we also observed a similarity of nitrate reductions between alternatives in the original optimized Pareto front and the modified front, when the modified front was created for preferences driven by flood concerns (for the 15% threshold case) and also when the modified fronts were created for preferences driven by fertilizer concerns (for both 15% and 55% threshold cases). This indicates the insensitivity of the removed practices to any measurable change in nitrate reduction benefits for this land tenure and these preference scenarios.

[90] In the case of share renter operators, the distance varies from 0.20 to 1.21 (Table 8), similar to the landowner operators. When the attitude and preferences are driven by economic concerns, the threshold of <15% produced a modified Pareto front with alternatives with lower economic costs, unlike all the other modified Pareto fronts for this land tenure. When the attitudes and preferences were driven by economic concerns, flood concerns, and erosion concerns, the <15% threshold also produced a modified Pareto front with similar nitrate reductions.

[91] Figure 12 shows the two alternatives (surrounded by black circles) in the original and modified Pareto fronts for 15% threshold criteria in Figure 11 (cases (a)–(c)). The right figure shows the clear loss in the diversity of practices across the entire watershed in comparison to the original diversity and combination of practices in the left figure. Among the practices removed, crop rotation was removed mainly in the central zone of the watershed in less than 4% of the total SBs area. However, grass waterways and no-till were removed almost uniformly across the watershed.

4. Conclusions

[92] Most existing optimization approaches in watershed planning and management studies have focused on incorporating physical features and economic consequences, without estimating how sociological conditions in watersheds can affect the adoption of "optimized" watershed plans. Even though one can argue that obtaining sociological data is extremely challenging and time consuming, it has become imperative to assess the value of such data on the design and optimization of watershed plans.

[93] In this study, we investigated the value of sociological data on the design of conservation practices in a midwestern agricultural watershed impacted by flooding and water quality problems. The effect of hypothetical watershed stakeholder attitudes on the conservation practices was investigated using an attitude model based on belief strengths, since we do not have detailed sociological data in this watershed to assess actual attitudes using methods proposed by researchers [*Lynne et al.*, 1988; *Weaver*, 1996; *Luzar and Cosse*, 1998; *Luzar and Diagne*, 1999; *Soule et al.*, 2000; *Söderqvist*, 2003; *Ahnström et al.*, 2009; *Reimer et al.*, 2010]. We specifically investigated the effect of sociological data (related to land tenure types and

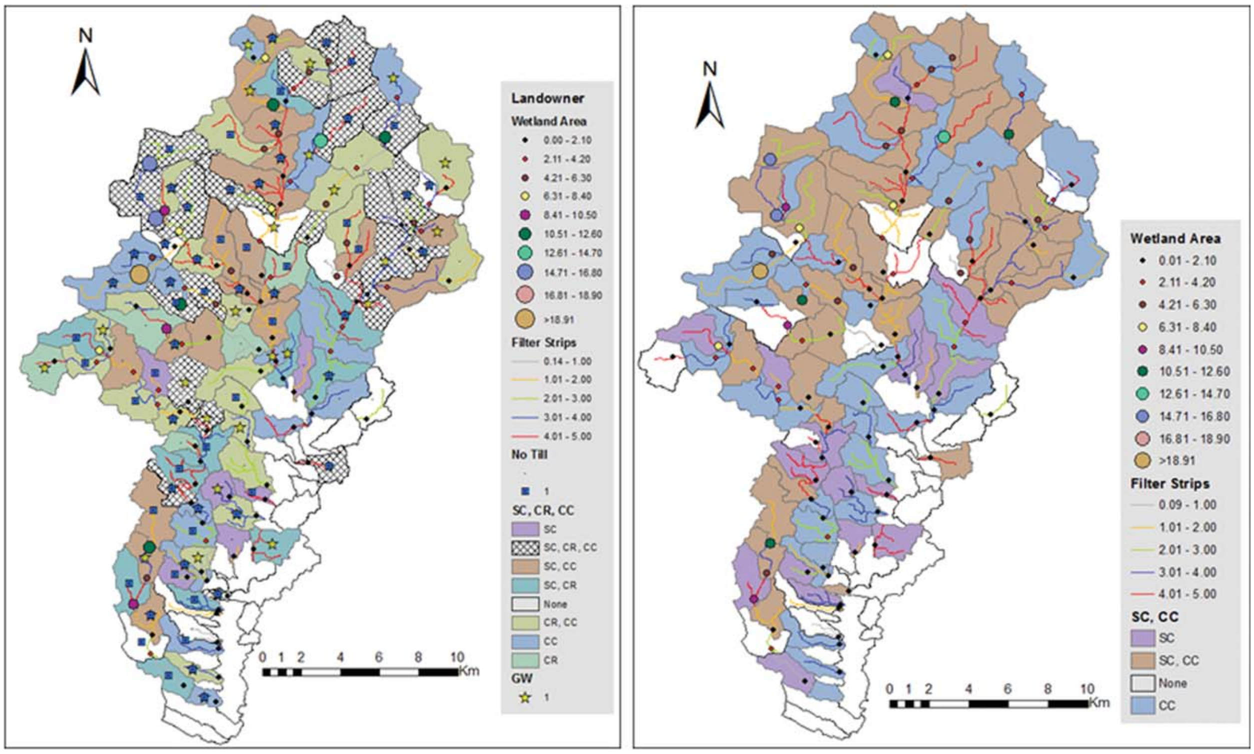

Figure 12. The change in the spatial distribution of practices for the optimized alternative affected by attitudes driven by preference for soil conservation and erosion control in Figures 11a–11c. The left figure is the optimized alternative in the original Pareto front ("optimal solutions") for landowners who farm their own land, and the right figure is the modified alternative in the modified Pareto front ("<15%").

landowner attitudes) on the modifications of alternatives found via standard optimization methods. Stakeholder preferences for individual conservation practices were estimated based on documented attitudes of landowner operators toward typical watershed management objectives (e.g., net economic profits, peak flow reduction, sediment reduction, and nitrate reductions). In the scenarios explored in this paper, it was found that when practices with low preferences were removed from original optimized alternatives, the effectiveness of the original optimal set reduced in most of the cases; producing new Pareto fronts that range in distances (measured by an average scaled distance metric *D(A,B)*) between 0.16 and 1.10 for economic concerns, 0.29 and 1.04 for flood concerns, 0.3 and 1.19 for erosion concerns and 0.37–1.21 for fertilizer concern, among the different land tenure types. However, when the land is operated by cash renters, and practices were removed from the set of solution, there was an improvement on the net economic cost, with some slight degradation on nitrate reduction. This suggests that for landowners who cash rent their land, there is a possible set of solutions that will offer similar results on the environmental objectives, reducing the investment on the implementation of a complete set of decision variables.

[94] There is also evidence that is land tenure changes (from landowner operated to either cash renter or share renter (uniformly or randomly)) the driver of Pareto fronts modifications; mainly drifted by the change in how the economic components affect the optimization of alternatives. For example, in our experiments for test watershed, we found that the performance (measured by *D(A,B)*) of Pareto fronts for land tenures other than uniformly distributed landowner operated decreased from 0.50 to 0.87.

[95] This paper provides an important insight into how existing spatially varying sociological conditions can change the effectiveness of optimized alternatives, and thereby, makes a strong case for future watershed optimization studies to collect and incorporate sociological data in the design of alternatives. If practices proposed by optimized alternatives are less attractive to stakeholders/landowner operators because of the sociological conditions, the actual adoption of various practices will be lower and the planned benefits will be reduced. The authors also propose that assumptions such as random distributions, market prices, and motivation of adoptions should be further investigated and modeled by integrating real stakeholder agents into the optimization process.

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