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Conservation Practices in Iowa: Historical Investments, Water Quality, and Gaps

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Executive Summary

A few farmers' organizations in Iowa, led by the Iowa Farm Bureau, came together and formed a partnership to support an initiative to assess the "state of conservation" on Iowa's cropland. Other partners include the Iowa Corn Growers Association, the Iowa Soybean Association, and the Leopold Center for Sustainable Agriculture. The Iowa Department of Natural Resources and Iowa Natural Resources Conservation Service (NRCS), though not in the partnership, provided advice and expertise to the initiative. Specifically, the project's goal was to provide answers to three questions: 1) What conservation practices are currently in place in Iowa, what is their coverage, and what is the cost of these practices? 2) What are (and have been) the effects of these practices on water quality? 3) What would it take to improve water quality to obtain specific standards? With datasets available from the U.S. Department of Agriculture and other sources, some economic models, and a hydrological simulation model, the Center for Agricultural and Rural Development (CARD) at Iowa State University undertook the task of answering these questions.

To address the first question, CARD gathered county-level data for some major conservation practices with regard to their costs and coverage. A database of county average cost is established for terraces, grass waterways, land retirement, sediment control basins, grade stabilization structures, filter strips, wetland restoration, riparian buffers, contour buffer strips, and nutrient management. We estimated that the statewide cumulative annual cost was about $435 million for seven major conservation practices on

the ground and accounted for as part of 1997 and 2004 data-sets. ($37 million for terraces and grass waterways and $397 million for other five practices). [Directly related discussions can be found on pages 155 and 176.]

Table 3. Cost of practices currently in place.

Practice	Cost
Terraces*	$27,685,907
Grass Waterways*	$9,509,042
Contour Farming	$30,889,200
Contour Stripcropping	$3,552,000
No-Till	$104,308,740
Mulch-Till	$82,861,900
CRP	$175,878,365

*annual average of total installation costs divided by the life span of the practice. The assumed life span is 25 years for terraces and 10 years for grass waterways.

In order to answer the second question, a widely used biophysical model was utilized to estimate the water quality impacts of land use practices. We undertook the hypothetical experiment of removing all existing conservation practices from the landscape and performing a simulation with the calibrated Soil and Water Assessment Tool (SWAT) model. The resulting water quality values were then compared with the corresponding values of the current baseline results. The difference between these two provides an estimate of the water quality benefits that the existing conservation practices yield. Water quality indicators we focused on in this study are nitrogen and phosphorus. The size and environmental conditions of each watershed affect the predicted outcomes. In the model outputs, streamflow was estimated to increase in all watersheds, indicating that the existing conservation practices allow faster movement of water. Nitrate loadings were estimated to decrease significantly, especially for western watersheds. More specifically, the range of total nitrogen reductions in 13 watersheds representing the

majority of Iowa was 11 to 38 percent. Nitrate reductions range from 6 to 28 percent. Total phosphorus reductions were 25-58 percent. More details are provided on pages 21 and 22, and Table 7 which is copied below.

Table 7. Percentage reduction in average annual baseline values of flow and nutrient loadings due to existing conservation practices in Iowa watersheds.

	Flow	Nitrate	Org N	Min P	Org P	Total N	Total P
Boyer	-8	23	56	45	50	38	48
Des Moines	-8	14	39	29	37	15	33
Floyd	-4	19	42	41	44	25	42
Iowa	-5	10	41	0	40	13	25
Little Sioux	-7	20	52	40	50	24	47
Maquoketa	-1	8	42	37	42	17	39
Monona	-3	15	49	54	61	26	58
Nishnabotna	-3	21	52	45	47	33	46
Nodaway	-2	28	56	49	51	37	50
Skunk	-6	14	46	40	44	21	42
Turkey	-5	5	38	30	37	18	34
Upper Iowa	-3	7	48	38	47	18	45
Wapsipinicon	-8	6	46	34	45	11	40

To answer the third question, three different optimal nutrient targets were considered: reducing phosphorus loadings by 40%, reducing nitrate loadings by 25%, and reducing both phosphorus (by 40%) and nitrate (by 25%) concurrently. The targets were chosen subjectively and thought to be a reasonable starting point for the type of analyses this project calls for. The evolution algorithm was used to search for the least cost of reaching the targets. Focusing on nitrates exclusively without any regard to phosphorus levels led to an increase in total phosphorus loadings in 8 out of 13 watersheds. The total statewide gross cost of reducing nitrates was about $472 million annually. For the phosphorous target, the total gross cost was estimated to be almost $613 million a year. Implementing the phosphorous target would simultaneously result in a statewide reduction in nitrate loadings of over 31%. This means that meeting the target of a 40%

reduction in phosphorous would also meet the target of a 25% reduction in nitrogen. Details can be found on page 32 and Tables 11 and 12.

In addition to creating a reasonable baseline to evaluate the value of the work already completed by Iowans, this project also gives us an idea of the magnitude of the work remaining and the challenges of meeting aquatic life standards. In particular, we found that cost-effective measures are different across different watersheds and that targeting different pollutants will mean different land use options. These findings suggest that flexible policy, increased resources, targeted placement and strategic research are all necessary to ensure that we meet future water quality standards for the state. Limitations and future research needs are identified at the end of the report including the restricted number of land use options considered, the limited water quality modeling capacity, and the lack of current data on the cost and coverage of land uses. Additional discussions on the interpretations of the key findings and caveats of this research can be found on pages 37-41.

Finally, we emphasize that our scenario results were based on our first attempt at applying the genetic algorithm at the state level. As we were performing the simulations for the watersheds one by one, we recognized several important aspects that could be improved upon if we were to conduct the same research project again.

Introduction

Over the last two decades, conservation on cropland to improve water quality and provide other environmental benefits has been of growing interest. Federal government expenditures on conservation and environmental programs have been 80% higher under the current (2002) farm bill than under the previous bill and several new programs, including the Conservation Security Program (CSP) and the Grassland Reserve Program, were also introduced in the 2002 bill. As the expiration date for the current bill draws near, it is apparent that the total expenditures and priorities of conservation programs will again be at the heart of legislative debates. The likelihood of tight fiscal budgets over the coming years suggests that competition for federal funding of conservation programs will be at least as intense as in the past if not more so. Hard questions concerning the impacts of these programs on water quality and the environment will need to be answered if such funding is to be maintained or increased. However, there are currently no easy or clear answers to these questions.

The U.S. Department of Agriculture (USDA) is undertaking a multi-agency national effort, the Conservation Effects Assessment Project (CEAP), to quantify the effects of conservation expenditures on the environment. With funding from this project, the Center for Agricultural and Rural Development (CARD), in conjunction with a group of interdisciplinary researchers at Iowa State University, is currently working on several detailed watershed studies in Iowa. As a complement to these projects, a few farmers' organizations in Iowa have come together and formed a partnership to support an initiative to assess the "state of conservation" on Iowa's cropland by collecting and analyzing the records of a variety of conservation programs and other data on the use of

conservation practices in the state. The partnership includes the Iowa Farm Bureau, the Iowa Corn Growers Association, the Iowa Soybean Association, and the Leopold Center for Sustainable Agriculture. The Iowa Department of Natural Resources (IDNR) and Iowa Natural Resources Conservation Service (NRCS), though not in the partnership, provided advice and expertise to the initiative.

Specifically, the initiative tried to provide answers to three questions: 1) What conservation practices are currently in place in Iowa, what is their coverage, and what is the cost of these practices? 2) What are (and have been) the effects of these practices on water quality? 3) What would it take to improve water quality to obtain specific standards? CARD used datasets available from the USDA and other sources, some economic models, and a hydrological simulation model in this project. In this report, we detail the research process that CARD used to shed light on the above questions.

Question 1: What conservation practices are currently in place in Iowa, what is their coverage, and what is the cost of these practices?

To answer this question we have collected county-level cost data and developed county-level average cost estimates for twelve conservation practices and a statewide average cost estimate for another. In developing cost estimates for the practices, we primarily used data reported by conservation programs. To determine the reliability of our estimates, we also contacted conservation offices and questioned personnel. The offices contacted include county Natural Resources Conservation Service (NRCS) and Farm Service Agency (FSA) offices. However, contacting county offices was not the main method for collecting cost data and was of limited use in creating average cost estimates,

though very useful in testing reasonableness of costs reported by other sources. In fact, when we did obtain cost estimates from county conservationists they were generally based on either past conservation projects, often done under the major conservation programs, or current rates listed by the conservation programs. Therefore, we believe that utilizing cost information gathered by the major conservation programs is both a more efficient method and leads to greater accuracy in our estimates, and therefore this is the method we used.

While we believe our methodology provided reasonable cost estimates, it is important to note that they are only estimates of county averages, and individual cost numbers will vary. Also, many of the practices examined differ structurally across sites, so a relatively lower cost in one county does not necessarily indicate better cost management. For example, with filter strips, the lower-cost cool-season grass seed may be selected; however, while findings vary, some studies suggest that certain warm-season grasses are more effective than cool-season grasses in nitrogen, phosphorous, and sediment removal (Lee et al., 1999). Finally, it is important to note that we do not consider the full opportunity costs of conservation actions such as taking land out of production. This means that our cost numbers are likely to underestimate the true investments in conservation.

1.1 Methods

Several sources and methods were used to develop estimates of costs and usage of practices for Iowa's counties and statewide. The general methodology used is as follows:

1. Collect and analyze cost data from major conservation programs
2. Determine outliers that may reflect incorrect costs

3. Contact county and state conservationists to determine reasonableness of outliers
4. Fill in for counties with missing average costs
5. Calculate statewide average costs
6. Collect usage data

1.1.1 Collecting data and calculating costs

Data were collected from several major conservation programs in Iowa, including the Iowa Financial Incentive Program (IFIP), Conservation Reserve Program (CRP), and Environmental Quality Incentives Program (EQIP). A description of the programs is provided in Table 1.

IFIP is a voluntary state program that provides cost-share and incentive payments. It covers many of the practices listed in this report, including contour farming, grade stabilization structures, grass waterways, no-till, terraces, and water and sediment control basins. To qualify for assistance under the program a person must own at least 10 acres and produce $2,500 of an agricultural commodity. Under the program, each county is given an annual allotment based partially on its share of Iowa's most erosive cropland soils; counties are allowed to set their own priorities for application and practice selection.

CRP is a voluntary federal program that provides cost-share, incentive, and annual rental payments. It also covers many of the practices listed in this report, including contour buffer strips (contour grass strips), filter strips, grass waterways, and riparian buffers. Up to 50% of the cost to establish an approved conservation practice can be paid in cost-share payments by the Commodity Credit Corporation (USDA/FSA, 2007b). However, certain practices are also eligible for an incentive payment of 40% of the

practice installation cost (USDA/FSA, 2007a). To qualify for assistance under the program, generally, a person "must have owned or operated the land for at least 12 months prior to close of the CRP sign-up period." Land must also be capable of being cropped and have been planted to an agricultural commodity for four of the years between 1996 and 2001; however, marginal pastureland may also be eligible. Applications are prioritized using the Environmental Benefits Index, which is essentially the sum of scores given to improvements in different environmental factors including soil erosion, nutrient runoff, and wildlife habitat, etc. Continuous CRP and general CRP are two ways in which land can be enrolled in CRP (USDA/FSA, 2007c).

EQIP is a voluntary federal program that provides cost-share and incentive payments. All of the practices listed in this report are covered under EQIP. To qualify for assistance under the program a person must have eligible land on which they produce livestock or crops. Under the program, both state and local conservation practice priorities are set. Applications are prioritized for funding using a state or locally developed ranking worksheet that generally considers various factors, including cost-effectiveness, resources to be treated, meeting national EQIP priorities, and compliance with environmental regulations.

For IFIP, cost was directly reported, while for CRP and EQIP, it had to be calculated using cost-share payments and average cost-share rates. The IFIP data set contained contract-level data reported over the period 1997 to 2006. To calculate the average cost of a practice for a given county, the data was first aggregated within the county and over time; the average cost of the practice in the county was then calculated

as the aggregated actual cost divided by the aggregated amount installed of the practice in the county.

The CRP data set contained county-level data for CRP contracts installed as of December 2005. Under CRP, costs had to be indirectly determined since actual costs were not listed. To determine the average cost of a practice under CRP, we assumed an average cost-share rate of 50% for all practices. We were able to assume an average cost-share rate of 50%, as an expert economist with the USDA suggested that this was likely the actual rate used. Further supporting the use of this rate, the FSA states that the "FSA provides cost-share assistance to participants who establish approved cover on eligible cropland. The cost-share assistance can be an amount not more than 50% of the participants' costs in establishing approved practices (USDA/FSA, 2007c)."

For EQIP, we collected and used several data sets in order to address the limitations of each of these sets individually; these data sets contained different information for determining the county-level average cost under EQIP. One EQIP data set contained county-level data aggregated for the period 1997 to 2005. This set included information on the cumulative practice cost-share payment, average cost-share rate, and the total amount installed. To determine a practice's average cost, we first divided the cumulative cost-share payment by the average cost-share rate to determine cumulative cost. Average cost was then calculated by dividing cumulative cost by the total amount installed. A second data set contained county-level data non-aggregated for the period 1997 to early 2006 and included information on the total practice cost and amount installed. Records for this data set were first aggregated across time for the entire reported period. Average cost was then found by dividing the aggregated total practice

cost by the aggregated amount installed. The last EQIP data set we used was compiled from online EQIP county reports for 2004 and 2006; these reports included rates of certain practices. These rates were used as average cost estimates for nutrient management and contour farming under EQIP.

Once costs were calculated under these programs, we had to determine, for a given practice and county, which program would be used for establishing our average cost estimate. For most practices, IFIP data was first used because it generally had more counties with cost estimates, we believed the reported costs were more reliable, and we were able to check the data by directing any questions to the IFIP program administrators. Generally, in cases in which IFIP data was not available, we then used EQIP or CRP cost data, depending on the program's coverage of the specific practice.

1.1.2 Testing reasonableness of average cost

We next considered whether the calculated average costs from these programs seemed reasonable. To determine reasonableness, outliers were determined through mapping and querying. Determination of outliers was subjective; if there was a large break between a specific average cost observation and the other observations it was considered an outlier to be followed up on. For some practices, relevant literature was also available and considered in determining reasonableness. Next, county conservation offices were contacted for counties with outliers. In speaking with the county conservationists, we attempted to determine their estimate of the practice's average cost in the county and their opinion as to the reasonableness of the average cost we derived from the conservation program data. After we had concluded testing the reasonableness of costs, we moved on to addressing any missing costs.

1.1.3 Addressing missing costs

Because we collected information from a number of conservation programs, we were able to rely heavily upon the costs reported for most practices. However, even when costs could be determined for most counties using conservation program data, there were usually a few counties that did not have a cost reported. Also, a few practices did not have a significant number of counties with cost information or proxies (incentive paid) listed. There were several reasons why costs were not listed for these counties. These reasons ranged from little to no use of the given practice in the county to cost-share or incentive not being offered since the practice was already more widely adopted in the county. A practice that was widely used throughout most of the state might not be used in a small number of counties because each county sets its own priorities for practices. Since counties are allowed to prioritize practices, there would be little reason to emphasize a practice that didn't fit the county's specific environmental conditions, even if it was effective in most other counties. An example of this is in the "Prairie Pothole" region of Iowa where the landscape is extremely flat. Since the landscape is extremely flat in this region, there is little reason to install terraces even though they are used in the majority of Iowa's counties. However, this region has instead emphasized other practices such as conservation tillage and grass waterways as a way to reduce erosion.

Regardless of the reason, when cost estimates were missing, the first course of action taken to fill them in was contacting state or county conservationists. While contacting conservationists was very useful in determining reasonableness of outliers, it was more limited in filling in missing costs. Since cost information was usually missing because the practice was generally not used in the county, this also meant there were few

to no prior examples on which the county conservationist could base his or her estimate. At this point, the method for determining costs for missing values varied significantly depending on the reason the estimate was missing. For practices that had costs reported throughout most of the state, we used an average of surrounding county costs to fill in missing values. This seemed reasonable since counties in close proximity may have more similar characteristics that could impact the cost of the practice. With a few practices, costs were not listed in enough counties that average cost of surrounding counties could be effectively used. In this case, we used estimates from prior research for no-till and an average cost estimate for the entire state based on incentive payments for contour farming. At this point, county-level average cost estimates had been established for all counties. The cost estimates and further description by practices can be found in Appendix A.

1.1.4 Calculating statewide average cost

Along with the county-level average cost estimates, we also calculated a statewide average cost for the practices. In calculating this average cost, we gave each county equal weighting. Therefore, our statewide average cost estimate is calculated as a simple average of our county-level average cost estimates.

1.1.5 Pros and cons of the methodology

Overall, this method of determining average costs required using different sources for the same practice; however, we attempted to maintain consistency in selecting cost estimates. By establishing a ranking of sources for each practice, we could select a cost estimate from the source that we considered most relevant. If a cost existed and seemed reasonable for our preferred source, we used it; if these two criteria weren't met, we then moved on

to the next source. A benefit of this strategy was that it increased the number of cost estimates that were collected. Also, our statewide calculation for average cost should present a better picture of the average cost for practices that have high variability and a limited number installed.

Before continuing, it is important to note that the average costs for structural practices[1] are reported as the cost of construction and do not include land rental costs. They are also reported as one-time costs and have not been amortized over the life of the structures. Finally, the unit that average cost is calculated over is the amount or area of the practice installed/implemented and not the area impacted. Thus, for grass waterways an average cost of $2,000 per acre is the average cost of installing one acre of grass waterway and not the cost per acre impacted by the grass waterway.

1.1.6 Determining usage level

To determine the amount of the practice on the ground, we also relied on several sources, which are described in Table 2. The first data set used was from the National Resources Inventory (NRI). This covered practice usage for contour farming, filter strips, grass waterways, and terraces. One difficulty with using the NRI dataset is that NRI points do not report the amount of a given practice in the area represented by the point. Instead, they report if a given practice is located within the area. Since some practices, such as grass waterways and terraces, only account for part of the land area associated with an NRI point, the amount of the practice on the ground could not be directly determined. Instead, the amount of grass waterways can be indirectly calculated by assuming the practice takes up 2% of the land area in which they are reported; this follows the

[1] Structural practices include grass waterways, terraces, water and sediment control basins, grade stabilization structures, filter strips, contour buffer strips, riparian buffers, and wetland restoration.

conversion rate used in Secchi et al. (2007). Note that the maps in appendix A that are based on the NRI report the overall acres of the observation area that contained the given practice. These maps do not show the amount/area of the conservation practice, as they have not been converted to reflect this.

The second data set was from the Conservation Technology Information Center (CTIC) and was used to determine usage of no-till. The map in appendix A based on CTIC data can be assumed to reflect the amount of no-till on the ground. The conservation programs (IFIP, CRP, and EQIP) also had information on practice usage; however, this information was limited to cases in which the practice was implemented under the given conservation programs. Listed in appendix A is the amount of the practice implemented under the main conservation program we used to develop our average cost estimates for the practice. This allows comparison between what was implemented under the conservation programs and what was reported in the NRI. It also provides a source on which to base practice usage when NRI or CTIC data is not available, such as with water and sediment control basins. The conservation programs report the amount/area of the practice implemented under the program.

1.2 Cost of practices currently in place

Statewide estimates of costs of practices currently in place were developed for several practices and are reported in Table 3. Practice usage is based on levels reported in the 1997 NRI and 2004 CTIC, and practice life span is based on those used in Secchi et al. (2007). When the NRI was used, the amount of practice used was considered to be the entire land area corresponding to the NRI point reporting practice usage. The exception to

this is terraces and grass waterways for which a conversion rate was used to estimate practice area from land area.

The cost estimate of contour stripcropping was determined by multiplying an assumed $15 average cost per acre (the flat rate incentive payment paid under IFIP) by NRI contour stripcropping acres. For contour farming, our statewide average cost estimate of $6 per acre was multiplied by NRI contour farming acres to determine cost. The NRI grass waterway acres in each county were multiplied by 0.02, based on the conversion rate suggested in Secchi et al. (2007), to determine grass waterway acres. Statewide cost was then calculated by multiplying grass waterway acres in each county by our county-level average cost estimates and then summing across counties. The conversion rate, 166.67 feet of terrace per acre, used in Secchi et al. (2007) for their low-cost estimate, was used to convert NRI terrace acres to feet of terrace. Calculated feet of terrace in each county were then multiplied by our county-level average cost estimates and summed across counties. The costs of no-till and mulch-till are based on average costs of $20 and $10 per acre, for respective practices, and usage levels reported in CTIC. Total cost is calculated as average cost multiplied by practice usage. CRP cost is determined by multiplying acres under CRP, reported in CTIC, for each county by our county-level average annual rental payment per acre estimates for general CRP and summing across counties. Since the first two practices in the table, terraces and grass waterways, are structural practices, their annual cost was derived as the cost calculated above divided by practice life span. Practice life span was considered to be 25 years for terraces and 10 years for grassed waterways, following practice life spans used in Secchi et al. (2007). This yields a statewide cumulative annual cost of $434,685,154 for the

seven practices listed ($37,194,949 for terraces and grass waterways and $397,490,205 for the other five practices listed).

It is important to note that the numbers Table 3 only reflect the costs to implement the practices. It does not account for the technical assistance needed to apply the practices nor the agencies administrative cost. It is also important to point out that the project only accounts for conservation applied through 1997, except for conservation tillage which is as applied through 2004. Finally, it should be noted that given the increase spending due to 2002 Farm Bill we would anticipate the annual $435 million public cost to increase as more conservation has notably been applied.

Question 2: What are (and have been) the effects of these practices on water quality?

A watershed level of the process-based model, the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Arnold and Forher, 2005; Gassman et al., 2007), is used in this study to estimate changes in water quality due to changes in conservation practices. SWAT is a hydrologic and water quality model developed by the USDA's Agricultural Research Service (ARS). It is a long-term continuous watershed scale simulation model that operates on a daily time step and is designed to assess the impact of different management practices on water, sediment, and agricultural chemical yields. The model is physically based, computationally efficient, and capable of simulating a high level of spatial detail. Major model components include weather, hydrology, soil temperature, crop growth, nutrients, pesticides, and land management. In SWAT, a watershed is divided into multiple subwatersheds, which are further subdivided into unique soil/land use characteristics called hydrologic response units (HRUs). The water balance of each

HRU is represented by four storage volumes: snow, soil profile, shallow aquifer, and deep aquifer. Flow generation, sediment yield, and pollutant loadings are summed across all HRUs in a subwatershed, and the resulting loads are then routed through channels, ponds, and/or reservoirs to the watershed outlet. Description of some of the processes involved in the SWAT model is provided in appendix B. Major limitations of the SWAT model are pointed out in the conclusions.

2.1 SWAT model setup

Watershed delineation of the study region is the first step in the SWAT application. Watersheds in Iowa are divided into 13 major watersheds, as shown in Figure 1, based on the criterion that the watershed outlet should drain watersheds within the state of Iowa. Delineation of each watershed into smaller spatial units required for the SWAT simulations consists of two steps: (1) subdividing each major watershed into smaller units such as U.S. Geological Survey (USGS) 8-digit Hydrologic Cataloging Unit (HCU) watersheds (Seaber et al., 1987) or smaller 10-digit watersheds (as described in http://www.igsb.uiowa.edu/gsbpubs/pdf/WFS-2001-12.pdf), and (2) further subdividing subwatersheds into HRUs. Larger 8-digit subwatersheds were used for the Des Moines and Iowa River Watersheds (Figure 1), which were the two largest watersheds included in the analysis. The smaller 10-digit subwatersheds were used for those watersheds that consist of 1 to 3 8-digit watersheds (Figure 1), to avoid potential distortions in predicted pollutant indicators when only a small number of subwatersheds are used in a SWAT application, as discussed by Jha et al. (2004).

Historical precipitation, maximum temperature, and minimum temperature data obtained from Iowa Environmental Mesonet (http://mesonet.agron.iastate.edu/COOP/)

were used for the SWAT simulations. Key input data required for SWAT simulation are land use, soil, management, and climate data. A data source for the land use, soil, and management information is the USDA 1997 NRI database (Nusser and Goebel, 1997; http://www.nrcs.usda .gov/technical/NRI/), which was briefly discussed above and which contains soil type, landscape features, cropping histories, conservation practices, and other data for roughly 800,000 U.S. nonfederal land "points" including 23,498 in Iowa. Each point represents an area that is assumed to consist of homogeneous land use, soil, and other characteristics, which generally ranges from a few hundred to several thousand hectares in size. Table 4 provides the characteristics of each watershed.

The NRI clusters serve as HRUs in the SWAT simulations. All of the points within a given category were clustered together within each 8-digit watershed for the Des Moines and Iowa River Watershed simulations, except for the cultivated cropland. For the cultivated cropland, the NRI points were first aggregated into different crop rotation land use clusters within each 8-digit watershed, based on the NRI cropping histories. These crop rotation aggregations were then subdivided based on permutations of rotations; e.g., corn-soybean versus soybean-corn. The tillage implements simulated for the different levels of tillage (conventional, reduced, mulch, and no-till) incorporated in the analysis were obtained from the USDA 1990-95 Cropping Practices Survey (CPS), which is located at http://usda.mannlib.cornell.edu/usda/ess_entry.html. The soil layer data required for the SWAT simulations are input from a soil database that contains soil properties consistent with those described by Baumer et al. (1994), with the additional enhancement of ID codes that allow direct linkage to NRI points.

A more complex procedure was developed to construct the HRUs for the SWAT baseline simulations for the other 11 watersheds, because the NRI data is not spatially referenced at the 10-digit watershed level. To overcome this limitation, Iowa Soil Properties And Interpretations Database (ISPAID) soil data (http://extension.agron.iastate.edu/soils/pdfs/ISP71MAN.pdf) and 2002 IDNR land use data were used to help determine which HRUs should be placed in each 10-digit subwatershed. The initial step in the procedure consisted of attempting to match soil IDs shown in the ISPAID soil map for a 10-digit watershed to soil IDs listed in the NRI for points located within the respective 8-digit watershed that the 10-digit watershed was located in. A positive match indicated that the NRI point could be located in that 10-digit watershed. The 2002 IDNR land use data was then used to help further verify which 10-digit watershed an NRI point was most likely to be located in, based on whether the land use was cropland, CRP, forest, urban, and so forth.

The effect of conservation practices is accounted for by adjusting the "support practice (P) factor," which is one of the factors used in the original USLE equation (Wischmeier and Smith, 1978) and also in the MUSLE equation that is used in SWAT. The P factors used for contouring and terraces are based on values reported by Wischmeier and Smith (1978) as a function of slope range (Table 5). The choice of a P factor value of 0.4 for grassed waterways is based on the methodology used by Gassman et al. (2006) for simulating the impact of grassed waterways in the Mineral Creek Watershed in eastern Iowa. The effect of grassed waterways was further accounted for in SWAT by adjusting the Manning's N values for the affected HRUs.

To estimate the water quality changes, it is necessary to calibrate SWAT to existing baseline data on the watersheds and to accurately represent the current land use, land management, and weather conditions of the region using data obtained from several sources. A calibration and validation exercise was performed with SWAT2005 for all 13 Iowa watersheds. Results are provided in appendix B. The SWAT model was calibrated very well, especially for streamflow, because of the abundance of measured data availability. Water quality components were also calibrated but with lower confidence because of a lack of sufficient measured data.

2.2 Impacts of existing conservation practices

We undertook the hypothetical experiment of removing all existing conservation practices from the landscape and perform the simulation with the calibrated SWAT model. The resulting water quality values were then compared with the corresponding values of the current baseline results. The difference between these two provides an estimate of the water quality benefits that the current existing conservation practices yield. Water quality indicators focused in this study are nitrogen and phosphorus. Table 6 shows the baseline average annual values of the water quality parameters, averaged over a 20-year period from 1986 to 2005. Total N is total nitrogen, which includes nitrate and organic nitrogen (Org N). Similarly, total phosphorus (Total P) includes organic phosphorus (Org P) and mineral or soluble phosphorus (Min P).

Removal of existing conservation practices includes removal of all CRP land, conservation tillage, terracing, contouring, strip cropping, and grassed waterways. CRP lands were converted into corn-soybean cropland; conservation tillage was switched to conventional tillage; and other conservation practices were just removed. These

conservation practices are basically designed to prevent erosion. Reducing sediment transport helps reduce sediment-bound organic compounds of nitrogen and phosphorus. Additionally, taking land out of production removes all fertilizer application and hence reduces nutrients overall. Table 7 shows the percentage change in flow and nutrient loadings when all conservation practices, listed above, are removed from the existing baseline. Streamflow was estimated to increase in all watersheds, indicating that such conservation practices allow faster movement of water. Nitrate loadings were estimated to decrease significantly, especially for western watersheds. Nitrate reductions are greater than 10% for nine watersheds. The estimated reductions for Org N, Org P, and Min P were much greater. The size and environmental conditions of each watershed also affect the predicted outcomes.

Question 3: What would it take to improve water quality to obtain specific standards?

3.1 Background on watershed pollution control

Studying the efficient control of pollution in the watershed context is fraught with difficulty. In the past few decades, economists as well as researchers in other fields have made tremendous progress toward understanding the complex watershed process and how this process will shape policy design and determine the effectiveness of control measures. In this section, we provide some background information about the methodologies used in our analysis.

The effectiveness of a given conservation practice on a given field depends on the placement of other conservation practices and cropping systems in the watershed,

conditional on the physical characteristics of the watershed location and the watershed itself. In other words, off-site impacts of land use on any parcel in a watershed tend to be endogenous to land use choices on other parcels of the watershed. However, earlier studies on the economics of water pollution control on a watershed scale essentially followed Montgomery's (1972) conceptual model of fixed, exogenous pollution delivery coefficients. Studies by Carpentier, Bosch, and Batie (1998), Kramer, McSweeny, Kerns, and Stravros (1984), and Ribaudo (1986, 1989) assume that off-site impacts can be accurately described as a proportion of on-site pollution generated. Given such assumptions, it is straightforward to solve for cost-efficient allocations of pollution abatement using calculus-based constrained optimization techniques.

Development of realistic, physically based, spatially distributed hydrologic simulation models highlighted the fact that parcel-level off-site impacts are endogenous and moved the researchers dealing with nonpoint source pollution issues to incorporate some features of these models into their analyses. Until recently, there were essentially two types of studies: studies that attempted spatial optimization (but incorporated only some parts of the hydrologic modeling), and studies that incorporated full hydrologic simulations but relied on comparison of scenarios without explicit optimization.

Of the former type, studies undertaken by Braden, Bouzaher, Johnson and colleagues (Braden, Johnson, Bouzaher, and Miltz, 1989; Bouzaher, Braden, and Johnson, 1990; Bouzaher, Braden, Johnson, and Murley, 1994) in the late 1980s and early 1990s are excellent examples. Braden et al. (1989) attempt to find cost-efficient sediment control strategies, incorporating management practices of downslope parcels. The authors separate a watershed into hydrologically independent flow paths and use a

hydrologic model to estimate the impact of various management alternatives for the flow paths onto the resulting sediment yield. As a result, a problem of finding cost-efficient sediment reduction solutions becomes a variant of the knapsack model in operations research. By focusing on hydrologically independent flow paths, the authors are able to use dynamic programming to allocate the sediment reductions across flow paths.

A study by Khanna, Yang, Farnsworth, and Onal (2003) provides another good example of the ingenuity that was demonstrated by researchers in attempting to cope with the complexity of water pollution dynamics. In this study, the authors focus on fairly narrow hydrologically independent flow paths that are adjacent to streams and attempt to fully capture the interdependencies between upslope and downslope parcels by using a hydrologic model. They restrict their attention to three parcels up from a stream, and to two alternatives on each parcel: crop production and land retirement. Even in the stylized model they present, the problem becomes highly nonlinear and is likely to be non-convex; thus, they need an empirical simplification in order to make the model tractable for calculus-based optimization.

A major drawback to these approaches is that hydrologic models developed for the entire watershed are broken up; hence, one does not get the full benefit of a hydrologic simulation model. Therefore, the studies of the latter type utilize complete hydrologic simulation models and focus on several land use change scenarios that achieve the pollution reduction goals. For example, Secchi, Jha, Kurkalova, Feng, Gassman, and Kling (2005) consider retirement of land in proximity to waterways and with high erodibility and analyze the resulting water quality benefits using a hydrologic simulation model.

Conceptually, if one could analyze all possible (and feasible) scenarios and evaluate the cost and the pollution outcomes, picking cost-efficient solutions would be trivial. However, for any realistic watershed problem, a brute force approach appears infeasible. Specifically, if there are N conservation practices possible for adoption on each field and there are F fields, this implies a total of N^F possible watershed configurations to compare. In a watershed with hundreds of fields and more than a couple of conservation practices, this comparison quickly becomes unwieldy. The combinatorial nature of the problem was already recognized by Braden et al. (1989), and was one of the reasons for Khanna et al.'s (2003) decision to focus on a narrow band of land around streams.

3.2 The search algorithm

Recently, however, several researchers have found a tool that appears to be able to deal with the combinatorial nature of a watershed simulation-optimization problem. Evolutionary algorithms provide one systematic way for searching through large search spaces. Evolutionary algorithms aim to mimic the process of biological evolution, which, in the words of Mitchell (1996), "in effect, is a method of searching for solutions among an enormous amount of possibilities." Researchers, beginning with Srivastava, Hamlett, Robillard, and Day (2002) and Veith, Wolfe, and Heatwole (2003), have used genetic algorithms (GA) in order to search for single cost-efficient watershed-level pollution reduction solutions. Appendix B provides some (by no means complete) background on evolutionary computation and genetic algorithms.[2]

[2] See, for example, Mitchell (1996), for more history of evolutionary computation.

In our application, three major components were integrated to arrive at the algorithm used to generate results. The first component is the logic and the fitness assignment method of a multiobjective evolutionary optimization algorithm, SPEA2. The second component is a publicly available C++ library of genetic algorithms, GALib, originally developed by Wall (1996), with the current version available online. The third component is a hydrologic model, Soil and Water Assessment Tool (SWAT), 2005 version, coupled with a Windows-based database control system, i_SWAT (CARD, 2007; Gassman et al., 2003). SPEA2 provides the fundamental multiobjective optimization logic, while GALib provides the tools that are needed to implement an evolutionary search algorithm. Finally, SWAT and i_SWAT provide a way to model the different conservation practices considered in this paper and model their watershed-level environmental impacts. Figure 2 provides a conceptual flow diagram of the algorithm.

In GALib, a steady-state genetic algorithm is implemented, that is, the population size remains the same through the generations. At every generation, a percentage of population is replaced, so a new temporary population (a mating pool) is created. Its size, on average, is equal to the product of population replacement percentage and the size of the original population.[3] Individuals are selected from the population into the mating pool with probability that is proportional to their fitness (roulette wheel fitness-proportional selection). Two offspring are created from two parents via single-point crossover with a specified crossover probability.[4] Finally, offspring is subject to random mutation.

3.3 Land use options and costs

[3] Thus, in this implementation, the original population is an "archive" in Zitzler and Thiele's (1999, 2002) terms, while the temporary population is the "population."

[4] That is, when the crossover probability is 0.8, two parents produce offspring with probability 0.8, and with probability 0.2, both parents become "offspring" without the crossover operation.

To answer the question of what it takes to improve water quality, one run with a genetic algorithm was performed on all 13 watersheds. Table 8 presents the set of options available at each HRU used in the application presented. There are a total of 13 options available, which represent a particular conservation-compatible strategy by interacting the choice of a tillage practice, a structural conservation practice (contouring or terracing), and a reduction in nitrogen fertilizer application. Corn-soybean crop rotation is the prevalent rotation in the state; thus, this is the crop rotation modeled. This rotation with conventional tillage is presumed to be profit-maximizing while all other options carry an incremental cost. All HRUs in a watershed are presumed to face the same per acre cost of land use change options. This is one of the limitations of the current analysis. However, an effort was made to draw upon existing literature and expert opinion to provide realistic cost estimates.[5]

All cost numbers were drawn from Kling et al. (2005) except for fertilizer reduction. For the nitrogen fertilizer reduction option, yield curves for corn-soybean rotation as a function of fertilizer applied were constructed using the data from Iowa field experiments, available through ISU Extension. Then, following the reduction in the baseline application, the resulting reduction in yield was computed. The reduction in yield was multiplied by the price of corn to get the revenue reduction effect. While this is a fairly rough estimate, it does provide a way to capture some financial consequences of fertilizer reductions without having to deal explicitly with modeling farmers' nitrogen input decisions, which is outside the scope of this application. In the current application, we utilized nitrogen application rates, which differ by the hydrologic coding unit,

[5] For most land use options, data was adapted from Kling et al. (2005). Because of time limitations, we did not refine the genetic algorithm runs with the detailed cost estimates we obtained in Section 1.

developed by Wolter (2006). Therefore, the costs of nitrogen fertilizer reduction varied across HUCs based on the baseline nitrogen application rate reported in the data.

3.4 Results

3.4.1 The selection of nutrient reduction goals

Applying the evolutionary algorithm to the 13 watersheds proved to be a difficult and time consuming task. As can be seen from Table 9, many watersheds in Iowa were delineated to consist of several thousand HRUs, which had two effects that made the analysis more difficult. First, the run time of the SWAT model was increased significantly, and second, the search space for the evolutionary algorithm grew exponentially. Despite these setbacks, the results appear promising: the algorithm was able to identify watershed management scenarios, which significantly reduced the loadings of both nitrates and phosphorus. At the same time, the results have to be used with caution: because of the difficulties outlined above, we cannot fully claim that the scenarios presented are truly efficient. That is, we cannot rule out the possibility that, given enough computer power and time, one could improve upon the presented scenarios on one or more of the relevant dimensions of interest: nitrates, phosphorus, and cost. The computing requirements for the project were significant. The results presented are based on over 91 days of CPU time, and on over 116,000 SWAT model runs.

Table 10 provides some summary information about the effort. Each of the watersheds was analyzed using a population of size 50. The number of generations that was run for each of the watersheds is in the second column of the table. As can be seen from the table, the percentage reduction in nitrates and phosphorus varies across the

watersheds, ranging from 25% to 56.1% for nitrates and from 28.7% to over 70% for phosphorus.[6]

As explained above, at final generation, we obtain 50 watershed management scenarios. Therefore, for the presentation of results, we have to focus on certain scenarios of interest. In this report, we focus on three potential water quality targets. The first target is to reduce nitrate loadings in each watershed by 25% from the baseline level. The second target is to attempt to reduce total phosphorus load by 40% from the baseline level. The third target is to simultaneously reduce nitrate loadings by 25% and phosphorus loadings by 40%. The choice of these target levels was made at the intermediate stages of the process of running the evolutionary algorithms and, while somewhat arbitrary, represents the minimum of the maximum of nitrate loading reductions and the average maximum phosphorus loading reduction observed in the search process. While all of the watersheds achieve the nitrate target, 5 out of 13 watersheds fall somewhat short of the phosphorus target (the maximum shortfall is 28% for the Turkey Watershed, with a mean shortfall of 18.5%). It is unclear as to why that is the case, but it may be due either to the limited computer power available or to the watershed characteristics or both. However, as this phosphorus target is more than achieved in two-thirds of the watersheds in the state, we maintain the 40% target as a benchmark in the analysis. Moreover, the total phosphorus loadings from the state are reduced by exactly 40%.

One attractive feature of the evolutionary algorithm approach employed is that we obtain a range of pollution reductions at the end of the model run. Thus, a decisionmaker

[6] The differences between the loading in Table 6 and Table 8 were due to the fact that different simulation periods were used.

may have a menu of pollution/cost options for each watershed. The current set of targets is chosen mainly to provide consistency across the watersheds in the state. Clearly, watersheds in the state differ based on feasible pollution reductions as well as on their costs. Therefore, any practical implementation of pollution reductions would involve taking a much more detailed stock of the menu of pollution reduction strategies for each of the watersheds than is reasonable to provide in a statewide report of preliminary findings.

Furthermore, in this report, we are focusing on pollution reduction targets and then provide an estimate of costs of achieving those targets. An equally valid approach would be to set a target cost level and ask: what, given this cost, is the menu of pollution reductions available? For instance, a given level of costs may be able to reduce nitrogen loadings by 50% (and not reduce phosphorus) or reduce phosphorus by 50% (and not reduce nitrogen) or reduce both by 30%. These kinds of questions are undoubtedly interesting, and our modeling approach could be in a position to address them.

3.4.2 State-level results

Given the choice of the target levels and the fact that we are considering two water quality objectives, we potentially have three distinct watershed management scenarios: one focusing exclusively on nitrates without any regard to phosphorus, the other focusing exclusively on phosphorus without any regard to nitrates, and the third focusing on achieving both. In all the watersheds except for the Des Moines Watershed, we have been able to identify a distinct scenario that focuses on nitrates. However, the scenario that focuses on phosphorus also achieves the nitrate target. We believe that the reason for this finding lies in the definition of the land use option set used for the study. Out of 13

options, 6 include a 20% nitrogen fertilizer reduction. This means that the N reduction is oftentimes coupled with conservation practices that we anticipate to have a positive impact on phosphorus loadings through sediment reductions (e.g., terracing). It appears likely that the algorithm, in the process of searching for a way to reduce phosphorus loadings, comes across an option that does well for phosphorus but also includes the N reduction and therefore is able to reduce nitrate loadings.

For instance, consider an algorithm picking an option that includes terracing coupled with 20% N fertilizer reduction to be implemented on an arbitrary HRU. Now consider a purposeful mutation that replaces this allele with one that gets rid of the N reduction and implements terracing only. Assuming away any complex interactions between N, biomass, and phosphorus, we would see that such a mutation would produce a Pareto-nondominated individual, which results in more nitrate loading, the same phosphorus loading, and lower cost. However, since such a mutation *does not* produce a Pareto-dominant individual relative to the original individual, we would not expect the SPEA2 algorithm to necessarily eliminate the original individual in future iterations. Moreover, since the actual algorithm is an inherently stochastic search process, we do not expect such "convenient" mutations to take place very often. Therefore, it is not surprising that in an overwhelming majority of the watersheds, the N reduction option is present to a great extent in the solutions focusing on phosphorus. This "free-riding" phenomenon appears to be the reason that once we focus on phosphorus reductions, we also achieve the nitrate reduction target.

Based on the observation that whenever phosphorus is targeted, the nitrate target is achieved as well, the selection of the individuals that achieve both targets was based on

how close they are to achieving both targets, as well as on how inexpensive a particular individual is predicted to be. For example, if we found a scenario in a watershed in which phosphorus was reduced 40%, nitrates were reduced 35%, and the cost of that reduction was $20 million annually, and subsequently found an individual for which phosphorus was reduced 40%, nitrates were reduced by 27%, and the cost was $17 million annually, the latter individual was chosen for analysis.

When we focus on 25% reduction in nitrate loadings, we look for individuals in final populations that lie closest to the plane defined by the reduction target. For most watersheds, we are able to identify individuals that are quite close to the nitrate target. For some smaller watersheds, however, the final population contained only the individuals that lie further away from the target and, in fact, over-achieve it.

Tables 11 and 12 highlight the statewide results for the watersheds scenarios in which we attempt to reduce phosphorus loadings by 40% and nitrate loadings by 25%. Focusing on nitrates exclusively, without any regard to phosphorus levels, leads to an increase in total phosphorus loadings in 8 out of 13 watersheds. Adding up the gross costs of nitrate reductions yields a total statewide gross cost of reducing nitrates of about $472 million annually. However, if we consider this cost relative to the baseline, we obtain a significantly smaller number, about $181 million annually. Overall, the SWAT model suggests that should the Iowa watersheds be made to look as prescribed by the scenarios in which nitrates are the only focus, the total loading of nitrates from the state would be reduced by 27%, while the loadings of phosphorus would increase by about 12%.

When both phosphorus and nitrogen reductions are desired, following the prescriptions of the algorithm for each of the watersheds results in a statewide reduction

in phosphorus loadings of over 36%. The total gross cost of implementing the management scenarios is estimated to be almost $613 million a year, while the net cost is estimated to run just under $322 million annually. The implementation of the algorithm's prescriptions would simultaneously result in a statewide reduction in nitrate loadings of over 31%.

3.4.3 Patterns across watersheds and in relation to baseline

The subsequent section and appendices D and E will present the detailed results for each of the watersheds. From the charts in appendix E, some patterns can be noted that appear to hold across the entire state. We must again note that the algorithm implemented was free to vary land use and conservation practices for each of the cropland HRUs in all of the watersheds. This, of course, implies that the existing conservation practices noted in the baseline data could be replaced by any one of the 13 options. This also implies that any land retirement prescribed by the algorithm is to be in addition to baseline CRP area.

The first noteworthy pattern is that the additional land retirement acreage called for by the algorithm results is smaller for scenarios that target nitrates as opposed to scenarios that target both nitrates and phosphorus in the majority of the watersheds (except Des Moines and Floyd). However, it is difficult to interpret this finding as suggesting that land retirement is necessarily more effective for phosphorus control as opposed to nitrates control, since we get a higher average N reduction in the phosphorus-focused scenarios. The second pattern is that the area of each watershed where corn-soybean crop rotation is coupled with conventional tillage is higher in all of the watersheds for the N-targeting scenarios both relative to the P-targeting scenario and relative to the baseline. The third pattern observed is that the area in which no-till is used

is significantly smaller for the N-targeting scenarios across all of the watersheds relative to the P-N-targeting scenarios. The same is true relative to the baseline in all of the watersheds except Floyd. The area in which terracing is used is consistently smaller in the N-targeting scenarios than in the P-N-targeting scenarios. Comparing the solutions to the baseline acreage involving terracing yields no strong pattern and yields a different answer across the watersheds. Roughly the same holds true for contouring: while in all the watersheds except Des Moines, the area where contour cropping is used is smaller in the N-targeting scenarios than in the P-N-targeting scenarios, no consistent pattern is observed in comparing those areas to the baseline data.

3.4.4 Watershed-level results

To facilitate discussion, the location of each sub-watershed within the watersheds is indicated in Figure 3. In the following, we discuss the results for two representative watersheds, the Des Moines Watershed and the Nodaway watershed. The discussions on all other watersheds and related charts can be found in Appendices D and E.

Des Moines Watershed. Des Moines Watershed is the largest watershed in the state by drainage area (37,496 km^2), running from southwestern Minnesota to the southeastern part of Iowa. It is delineated into 9 subbasins, each of which is an 8-digit HUC. It is second only to the Iowa Watershed in baseline nitrate loadings, and fourth (behind Iowa, Skunk, and Nishnabotna watersheds) in total phosphorus loadings. However, it is estimated to be the most expensive watershed in terms of both gross and net abatement costs for the N-targeting solution, and it is second only to the Iowa Watershed in the gross abatement costs for the P-N-targeting solution (it still has the highest net abatement cost). The gross cost of reducing nitrates by 25% is estimated to be

over $182 million annually. The net cost is around $138 million annually, which comprises 77% of the total statewide net cost. The gross cost of reducing phosphorus by 40% and reducing nitrate loadings by 25% is estimated to be $190 million annually, while the net cost is predicted to be just under $146 million annually. While the large gross costs can be explained by the watershed's 25,000 square kilometers of cropland on which conservation-compatible practices are introduced by the evolutionary algorithm, the large net costs can be explained by the relative dearth of terracing and contouring observed in the baseline data (see the chart describing baseline land use and management).

Compared to the baseline, the general pattern noted above holds, with the exception of additional land retirement area. In this watershed, the additional land retirement acres prescribed by the algorithm are higher for the N-targeting scenario relative to the P-N-targeting scenario. Otherwise, Figures 4 and 5 are representative of the pattern observed in other watersheds in the state. In the final population, a scenario that comes closest to achieving the 25% nitrate loading reduction also reduces phosphorus loadings by almost 32%. Thus, when we compare the distribution of practices for the N-targeting scenario with the P-N-targeting scenario (where phosphorus loadings are reduced by around 41%, and nitrate loadings are reduced by 24%), the two scenarios do not appear to be drastically different.

Analyzing Figures 4 and 5 of the two solutions, we see that the largest differences between the two solutions are in the increased use of terracing in subbasin 3 (HUC 07100003) and in the outlet subbasin, subbasin 9 (HUC 07100009) in the P-N-targeting scenario relative to the N-targeting scenario. This increase appears to drive the increase in

costs between the two scenarios (the P-N scenario costs about $7.5 million more a year). It is somewhat intuitive that the algorithm identifies the outlet subbasin for an increased use of terracing for the control of phosphorus loadings, which are measured at the outlet.

Nodaway Watershed. Nodaway watershed is the smallest watershed out of the 13 in its total drained area (2,051 km^2). This watershed provides perhaps the most striking example of the fact that targeting nitrates in isolation results in a very different land use and conservation practice mix in the watershed than does targeting both phosphorus and nitrates.

The N-targeting scenario achieves a reduction in nitrate loadings of 24.2%, while phosphorus loadings rise by 21.2%. The gross cost of the scenario is just over $4 million annually, while the net cost is negative and is estimated to be -$757 thousand annually. The negative net cost is not surprising if we look at the chart describing the distribution of practices in Figure 6. A very large portion of the watershed cropland is allocated to a corn-soybean rotation/conventional tillage option, which in our modeling carries a zero incremental cost. At the same time, a smaller area of the watershed is allocated to no-till and contouring relative to the baseline. Therefore, the control costs are smaller relative to the assumed cost of the baseline. Further, all the areas observed to be in alternative crop rotations in the baseline data contribute to the larger cost of the baseline and thus contribute to the negative difference between the cost of the N-targeting scenario and the baseline.

While it may appear counterintuitive that the corn-soybean/conventional tillage option is utilized so extensively in the solution that aims to reduce nitrate loadings, the answer may lie in the effect of many of the conservation practices on the nitrate losses. In

particular, conservation tillage and terraces may in fact increase nitrate leaching, which is followed by subsequent increases in nitrate losses via tile drains. Given this phenomenon, it is not surprising that the algorithm solutions that focus solely on nitrates do not utilize such conservation practices to a great extent.

However, once we turn our attention to the P-N-targeting solution, the conservation practices (which are quite effective at controlling sediment, and therefore, phosphorus which is bound to soils) are used to a much greater degree. This is most apparent in the case of Nodaway Watershed. The P-N-targeting scenario achieves a 38.4% reduction in the total phosphorus loadings while at the same time reducing nitrate loadings by 27.1%. The gross cost of the scenario is estimated to be around $8 million annually, while the net cost is roughly $3.4 million annually. The higher cost is due to the solution's much greater reliance on no-till, terracing, and land retirement than the N-targeting solution. Relative to the baseline, the general pattern holds: while the total area with no-till and contouring is smaller than in the baseline, the total terraced area is significantly higher.

Comparing Figures 6 and 7, we see that targeting for different pollutants produces quite different watershed management implications. Uniformly across the subbasins, the area devoted to the corn-soybean/conventional tillage option is higher under the N-targeting scenario. It is especially interesting to consider the distribution of land use options in subbasin 7, which is the outlet subbasin. We see that when phosphorus loadings matter, the algorithm places a great deal of emphasis on no-till, terracing, contouring, and land retirement in order to trap sediment and to reduce phosphorus

loadings at the watershed outlet. In contrast, the N-scenario places the overwhelming majority of crop land into a corn-soybean rotation with conventional tillage.

Concluding remarks

The complex nature of nonpoint pollution control on a watershed scale requires the adoption of innovative tools for finding (or at least approximating) cost-efficient solutions. To accomplish such tasks, it is necessary that we have a reasonable cost estimate for each conservation practice. The combinatorial nature of the watershed optimization problem also requires an evaluation of a potentially enormous number of scenarios, while the use of hydrologic, physically based models is needed to model appropriately the impact of land use change and pollution abatement activities on the resulting water quality indicators. These considerations surround a policy decision aimed at reducing water pollution cost-efficiently with a great deal of uncertainty. The approach taken in this project represents one reasonable way of dealing with such uncertainty by providing an integrated method for searching for cost-efficient pollution reduction solutions. By employing an evolutionary algorithm coupled with a hydrologic model, it becomes possible to provide decisionmakers with a menu of Pareto-optimal solutions. This information is indispensable in designing an inter-watershed pollution trading program.

Current research can be improved, however, by incorporating finer-scale land use data, by refining the conservation options considered, and by recognizing additional environmental objectives. It must be noted also that the scenario results were based on a first attempt at applying the genetic algorithm to identify optimal solutions for water

quality improvement at the state level. This was essentially an exploratory effort at such a scale. Consequently, there were many aspects of the simulation that seemed to be too aggregated or incomplete. Specifically, to put the results into perspective, a reader should be aware of the following limitations of our research approach.

Caveats:

- The corn price was not current. If it stays at the current level or increases, then model results can differ. A sustained increase in the price of corn would be expected to affect our results in several ways. First, a direct effect would be to increase the cost of the N fertilizer reduction option, which would likely increase the costs of reducing nitrate loadings. An indirect but potentially much more important effect would be due to the change in crop rotations. A higher price of corn may mean that our assumption that the corn-soybean rotation is associated with the highest economic net return and thus carries a zero incremental cost may no longer be valid. Thus, a cost of the rotation would have to be added. Further, a move to continuous corn or a corn-corn-soybean rotation would immediately mean a higher amount of nitrogen fertilizer applied on the land, which would likely make it increasingly difficult to reduce nitrates relative to the baseline assumed in the simulations. Undoubtedly, future work should address the possibility of a sustained corn price increase.
- The same price is used for all land use options across the whole state. While we have some data on finer spatial scales, we did not incorporate such information in our application of the genetic algorithm.

- Due to limited computational power, the number of generations we ran probably was not able to approximate the least costs. As run time increases, it is very likely that more efficient solutions will be identified.
- We only considered 13 land use options, which were different combinations of five conservation practices. In these options, only a corn-soybean rotation was considered. While this rotation is the predominant rotation for Iowa, focusing solely on this rotation would undoubtedly be too simplistic for some watersheds. The choice of the 13 options was mainly decided by the modeling capacity of our water quality model, the SWAT. As other conservation practices are considered (e.g., wetland, different levels of nitrogen control), the optimal solutions are likely to change.

Recommendations for policies:

- Our results indicated that conservation practices that are efficient for erosion and phosphorous control are not in general efficient for nitrogen control. In general, conservation practices that have been implemented on the ground tend to focus on erosion control. Based on this, our recommendation is that to reduce nitrogen pollution in the waterways, measures that directly target nitrogen might be necessary. This has implications for policies that are designed to alleviate the hypoxic problem in the Gulf of Mexico.
- Our results also indicate that the cost-effective measures are different across different watersheds. The message for stakeholders in the watersheds is that they should gain a good knowledge of their watersheds before adopting any control policies that have been proving to be promising in other watersheds.

- A clear result from our analysis is that targeting different pollutants will mean different land use options. Thus, the needs of stakeholders in the watersheds should be identified before any policy discussions take place. While our results indicate that targeting phosphorous would also achieve the nitrate goal in our scenarios, we think it is highly likely that this particular result will not hold as more practices are considered and a more thorough search is conducted through the genetic algorithm.

Recommendations to facilitate future research:

To better answer Question #1:

- *Information gathering on the cost and use of conservation practices*— Data availability and consistency for this kind of modeling work needs to be improved at various scales, so that we can be more effective in targeting limited resources in the future. We have found that intermittent data collection and the lack of a central data source make cost data difficult to acquire/interpret. There are several things that we decided not to model because we did not think we had sufficient data, for example, the cost of changing the timing of fertilizer application, and manure management.
- *Computation of full costs problematic because of opportunity cost of farmer's time, risk attitudes*—Additional work needs to be done regarding opportunity costs for farmers. For example, as the price of corn increases, so does the opportunity cost for various alternatives identified. To estimate costs in all dimensions, we need farm-level data that are combined with field-level data, including farmers characteristics, farm conditions, and physical environment of the farm.

To better answer Questions #2 and #3:

- Mainly because of the limitation of our water quality model, wetland and riparian buffers are not included in our study.
- Limited monitoring data makes water quality calibration challenging.
- Modeling at the NRI point scale will miss some heterogeneity.

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Table 1. Sources for practice cost.

Source	IFIP	CRP	EQIP
Description	State Conservation Program	Federal Conservation Program	Federal Conservation Program
Program Function	Cost-Sharing and Incentive Payments	Cost-Sharing, Maintenance and Other Incentive Payments, and Rental Payments	Cost-Sharing and Incentive Payments
Practices Used	Contour Farming GSSs Grass Waterways No-Till Terraces WSCBs	General CRP Continuous CRP Contour Buffer Strips Filter Strips Grass Waterways Riparian Buffers Wetland Restoration	Contour Buffer Strips Contour Farming GSSs Grass Waterways No-Till Nutrient Management Terraces WSCBs
Years Included in Data Set	1997 to 2006	CRP Contracts as of December 2005	1997 to 2006 & 1997 to 2005 & 2006 & 2004
Positives	1. All practices that received financial assistance from 1997 to 2006 under IFIP are included. 2. During the contract period the practice is required to be maintained in working condition. 3. Each contract is reported individually allowing for greater in-depth analysis.	1. The entire population of CRP land is included. 2. Practices are required to be maintained according to the conservation plan. 3. Practices have payments broken down into cost-share, incentive, and rental payments.	1. The entire population of practice contracts that received assistance under EQIP is included. 2. During the contract period the practice is required to be maintained in working condition.
Negatives	1. Only records where the practice received assistance under IFIP are included.	1. Only records where the practice received assistance under CRP are included. 2. Possibility that maintenance costs may be listed under incentive payments rather than cost-share payments. 3. Similar to the problem with maintenance costs, other costs could possibly fall under payment categories other than cost-share and thus be missing from our estimates.	1. Only records where the practice received assistance under EQIP are included. 2. Available records are more highly aggregated than IFIP records.

Table 1. Sources for practice cost (continued).

Source	Surrounding County Average Cost Calculation
Description	A calculation of the average cost of the practice in adjacent counties
Practices Used	Contour Buffer Strips GSSs Grass Waterways Nutrient Management Riparian Buffers Wetland Restoration WSCBs
Years Included in Data Set	The years included in this calculation vary as the average cost estimates in surrounding counties may be based on different conservation programs and time periods.
Positives	1. Allows for average cost estimates to be established in counties where information on a practice's cost was not available. 2. This method seemed logical since counties in close proximity may have more similar environmental conditions impacting practice cost.
Negatives	1. Costs were based on other counties' estimates and other than spatial location the county had no unique information that was used in developing its cost estimate.

*WSCBs = Water & Sediment Control Basins
**GSSs = Grade Stabilization Structures

Table 2. Sources of practice usage and erodibility measures.

	Surveys		Conservation Programs
	NRI	CTIC	IFIP, CRP, and EQIP
Description	USDA Survey	Reported findings from the USDA's Crop Residue Management Survey	State and federal conservation programs
Program Function	Report survey findings	Report survey findings	
Coverage	Contour Farming Filter Strips Grass Waterways Terraces Erodibility Measures	No-Till	General CRP Continuous CRP Contour Buffer Strips Filter Strips GSSs Grass Waterways No-Till Nutrient Management Riparian Buffers Terraces Wetland Restoration WSCBs
Years	1997	2004	1997-2006
Drive-by field sampling	no	yes	no
Positives	1. Records all conservation practices sampled (both those that received financial assistance and those that were installed voluntarily without financial assistance).	1. Records all conservation practices sampled (both those that received financial assistance and those that were installed voluntarily without financial assistance).	1. Practice cost and usage/implementation amounts are reported under one source.
Negatives	1. Conservation practice usage is calculated from a sample and so assumptions are made about the population. 2. Assumptions and conversions must be made to determine practice usage since it is not directly reported	1. Conservation practice usage is calculated from a sample and so assumptions are made about the population.	1. Practice usage is only recorded for practices implemented under the given conservation program.

*WSCBs = Water & Sediment Control Basins
**GSSs = Grade Stabilization Structures

Table 3. Cost of practices currently in place.

Practice	Cost
Terraces*	$27,685,907
Grass Waterways*	$9,509,042
Contour Farming	$30,889,200
Contour Stripcropping	$3,552,000
No-Till	$104,308,740
Mulch-Till	$82,861,900
CRP	$175,878,365

*annual average of total installation costs divided by the life span of the practice. The assumed life span is 25 years for terraces and 10 years for grass waterways.

Table 4. Characteristics of the 13 study watersheds.

Watershed	# of Delineated Subwatersheds	Drainage Area		Key Land Uses (% of watershed)			
		mi^2	km^2	Cropland	Grassland (CRP and Pasture)	Forest	Urban
Boyer	5	1,089	2,820	68	26	4	2
Des Moines	9	14,477	37,496	71	16	6	7
Floyd	5	917	2,376	84	13	0	3
Iowa	9	12,663	32,796	77	12	4	8
Little Sioux	10	3,553	9,203	86	13	1	0
Maquoketa	10	1,864	4,827	56	32	10	3
Monona	5	947	2,452	78	19	2	1
Nishnabotna	11	2,980	7,718	84	15	1	0
Nodaway	7	792	2,051	52	41	5	3
Skunk	12	4,342	11,246	69	25	5	1
Turkey	9	1,699	4,400	56	25	16	3
Upper Iowa	7	992	2,569	51	26	19	3
Wapsipinicon	11	2,542	6,582	77	19	3	1

Table 5. Original P-factor values for contouring, strip-cropping, and terraces.

Slope ranges	Contouring[a]	Terraces[a,b]	Grassed Waterways[c]
1 to 2	0.6	0.12	0.4
3 to 5	0.5	0.1	0.4
6 to 8	0.5	0.1	0.4
9 to 12	0.6	0.12	0.4
13 to 16	0.7	0.14	0.4
17 to 20	0.8	0.16	0.4
21 to 25	0.9	0.18	0.4

[a]Source: Wischmeier and Smith (1978).
[b]Based on expected sediment yield for terraces with graded channels and outlets.
[c]Source: Gassman et al. (2003).

Table 6. Baseline average annual values (metric tons) of water quality parameters, averaged over a 20-year period (1986-2005).

	Flow (mm)	*Nitrate*	*Org N*	*Min P*	*Org P*	*Total N*	*Total P*
Boyer	167	2,699	1,409	418	640	4,108	1,059
Des Moines	177	60,406	3,057	1,299	885	63,463	2,184
Floyd	115	3,625	962	195	174	4,587	368
Iowa	276	65,639	5,122	1,330	1,287	70,761	2,616
Little Sioux	167	14,699	1,395	220	434	16,094	654
Maquoketa	251	8,516	1,965	326	101	10,482	427
Monona	119	2,143	599	50	72	2,741	121
Nishnabotna	231	8,848	3,307	1,303	1,597	12,155	2,900
Nodaway	213	1,984	614	221	313	2,598	534
Skunk	230	13,609	2,166	1,324	1,200	15,775	2,524
Turkey	261	6,354	2,803	476	652	9,157	1,127
Upper Iowa	253	2,335	482	45	135	2,817	180
Wapsipinicon	284	14,253	1,166	275	268	15,419	543

Table 7. Percentage reduction in average annual baseline values of flow and nutrient loadings due to existing conservation practices in Iowa watersheds.

	Flow	*Nitrate*	*Org N*	*Min P*	*Org P*	*Total N*	*Total P*
Boyer	-8	23	56	45	50	38	48
Des Moines	-8	14	39	29	37	15	33
Floyd	-4	19	42	41	44	25	42
Iowa	-5	10	41	0	40	13	25
Little Sioux	-7	20	52	40	50	24	47
Maquoketa	-1	8	42	37	42	17	39
Monona	-3	15	49	54	61	26	58
Nishnabotna	-3	21	52	45	47	33	46
Nodaway	-2	28	56	49	51	37	50
Skunk	-6	14	46	40	44	21	42
Turkey	-5	5	38	30	37	18	34
Upper Iowa	-3	7	48	38	47	18	45
Wapsipinicon	-8	6	46	34	45	11	40

Table 8. Land use options and the incremental costs.

Option number	***Option description***	***Assumed per acre cost, $iacre***
1	*CRP (land retirement)*	*110*
2	*Corn-Soybeans, Conventional Tillage*	*0*
3	*Corn-Soybeans, Conventional Tillage, 20% Fertilizer Reduction*	*1.89*
4	*Corn-Soybeans, No-Till*	*20*
5	*Corn-Soybeans, No-Till, 20% Fertilizer Reduction*	*21.89*
6	*Corn-Soybeans, Conventional Tillage, Terracing*	*18*
7	*Corn-Soybeans, Conventional Tillage, Terracing, 20% Fertilizer Reduction*	*19.89*
8	*Corn-Soybeans, No-Till, Terracing*	*38*
9	*Corn-Soybeans, No-Till, Terracing, 20% Fertilizer Reduction*	*39.89*
10	*Corn-Soybeans, Conventional Tillage, Contouring*	*15*
11	*Corn-Soybeans, Conventional Tillage, Contouring, 20% Fertilizer Reduction*	*16.89*
12	*Corn-Soybeans, No-Till, Contouring*	*35*
13	*Corn-Soybeans, No-Till, Contouring, 20% Fertilizer Reduction*	*36.89*

Table 9. Predicted annual loadings and associated mean daily concentrations for nitrate and total phosphorus. (1997-2001)

Watershed	HRUs	Base Cost, in million $	Base NO3, in thousand kg	Base Phosphorus, in thousand kg	Baseline NO3 conc., mg/L	Baseline P conc., mg/L
Boyer	425	$10	2,478.96	1,086.54	3.78	1.22
Des Moines	1223	$44	70,250.40	2,538.70	5.83	0.24
Floyd	524	$5	2,420.40	566.18	6.55	0.92
Iowa	2055	$84	80,908.00	3,623.26	7.96	0.28
Little Sioux	1879	$21	11,512.80	1,392.48	5.02	0.73
Maquoketa	2041	$18	490.02	36.66	5.77	0.19
Monona	379	$9	1,974.40	331.73	6.20	0.80
Nishnabotna	2997	$30	9,996.12	3,075.18	3.86	0.98
Nodaway	593	$5	1,967.58	574.36	3.09	0.71
Skunk	3284	$21	13,882.40	2,896.46	3.70	0.80
Turkey	1640	$15	7,277.00	1,376.38	4.30	0.54
Upper Iowa	664	$7	2,760.78	215.80	2.32	0.16
Wapsipinicon	3141	$21	16,150.80	610.96	5.70	0.20

Table 10. Statewide highlights of the algorithm runs.

Watershed	Generations	HRUs	Max NO3 reduction,%	Max P reduction,%
Boyer	646	425	35	49
Des Moines	782	1223	27	51
Floyd	1161	524	55	70
Iowa	625	2055	25	33
Little Sioux	596	1879	41	43
Maquoketa	500	2041	50	67
Monona	2074	379	56	60
Nishnabotna	501	2997	36	33
Nodaway	612	593	30	43
Skunk	526	3284	26	36
Turkey	460	1640	27	29
Upper Iowa	692	664	29	42
Wapsipinicon	588	3141	32	32

Table 11. Statewide results, focus on 25% reduction in nitrate loadings from baseline.

Watershed	NO3, in % of baseline	NO3 concentration, in % of baseline	Gross Cost, in thousand $	Cost relative to baseline, in % of baseline	P loadings, in % of baseline	P concentration, in % of baseline
Boyer	75	62	$7,847	77	112	124
Des Moines	75	82	$182,563	414	68	63
Floyd	49	62	$5,705	108	85	96
Iowa	75	77	$164,070	196	84	83
Little Sioux	72	82	$14,264	67	89	105
Maquoketa	56	64	$569	3	163	179
Monona	59	70	$5,837	63	83	100
Nishnabotna	75	69	$23,731	79	127	126
Nodaway	76	70	$4,013	84	121	119
Skunk	75	72	$37,496	177	100	95
Turkey	75	69	$10,207	66	120	122
Upper Iowa	74	69	$7,227	99	130	133
Wapsipinicon	76	75	$8,321	40	168	171

Table 12. Statewide results, focus on 40% reduction in phosphorus loadings AND 25% reduction from nitrate loading from baseline.

Watershed	P loading, in % of baseline	P concentration, in % of baseline	Gross Cost, in thousand $	Cost relative to baseline, in % of baseline	NO3 loadings, in % of baseline	NO3 concentration, in % of baseline
Boyer	60	61	$14,951	146	66	59
Des Moines	58	54	$190,010	431	76	77
Floyd	52	61	$8,057	153	64	69
Iowa	67	73	$193,576	232	75	78
Little Sioux	58	67	$33,142	156	64	72
Maquoketa	40	166	$2,219	12	61	64
Monona	60	68	$7,753	84	55	67
Nishnabotna	67	64	$43,580	146	65	62
Nodaway	62	57	$8,140	171	73	66
Skunk	64	60	$50,380	238	75	70
Turkey	71	71	$17,057	111	74	70
Upper Iowa	61	61	$11,038	151	76	70
Wapsipinicon	68	68	$33,030	158	70	68

Figure 1. The study area and watershed delineations.

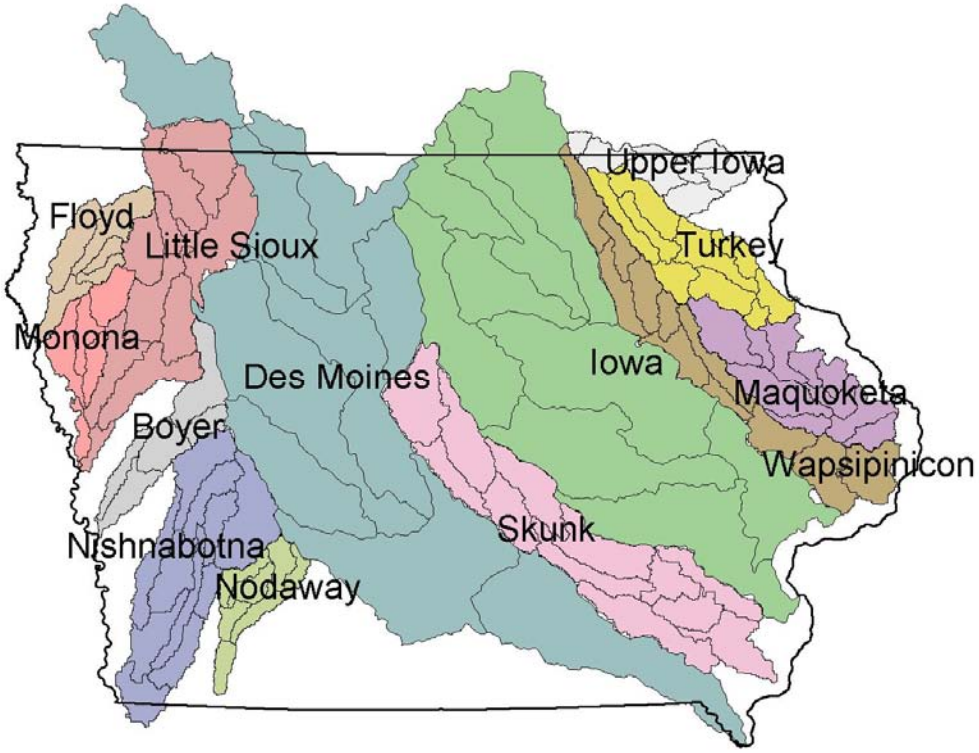


Figure 2. Simulation-optimization algorithm flow diagram.

Figure 3. Numeration of subbasins.

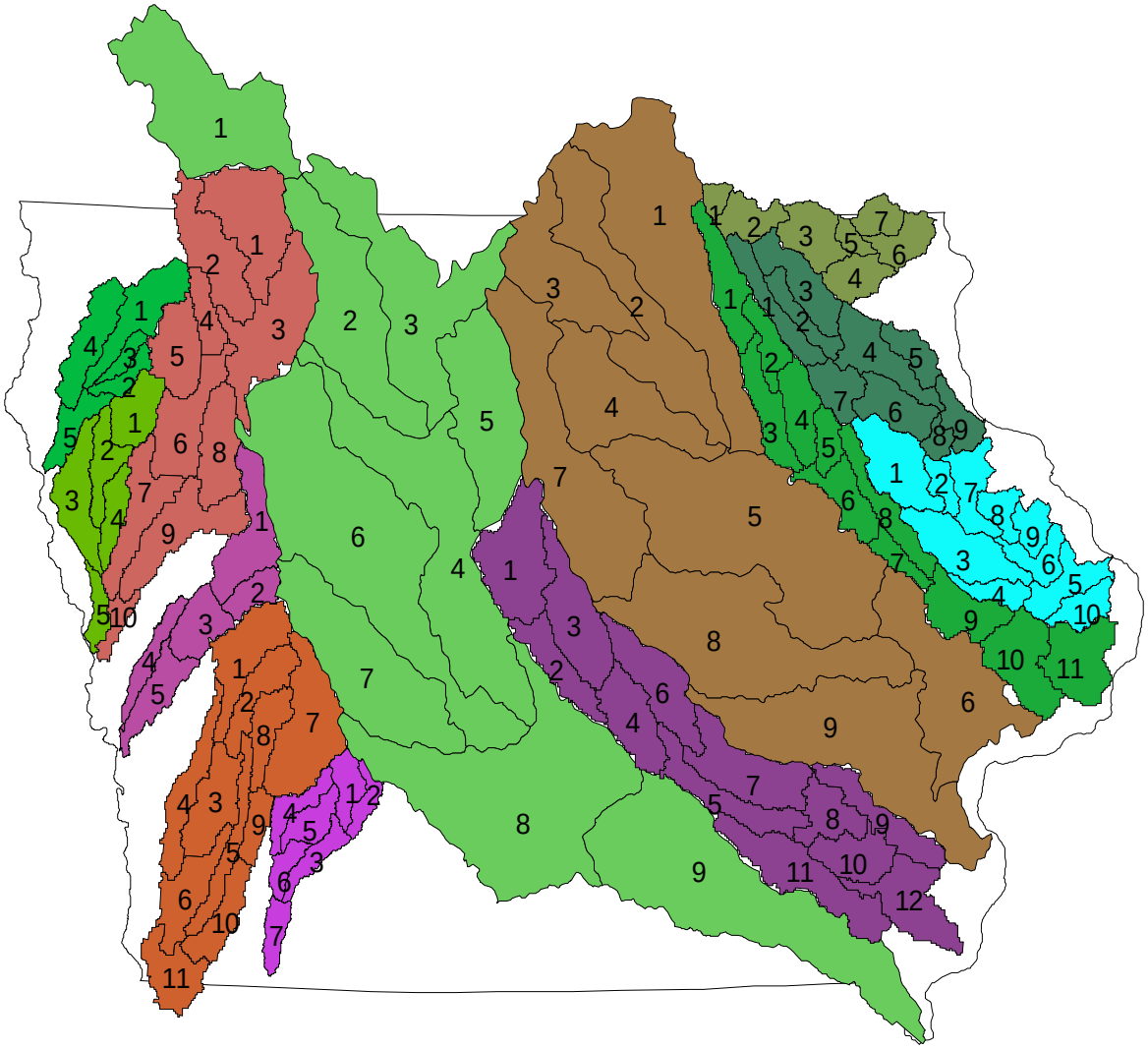


Figure 4. Distribution of land use options for Des Moines Watershed for the scenario of targeting N reduction.

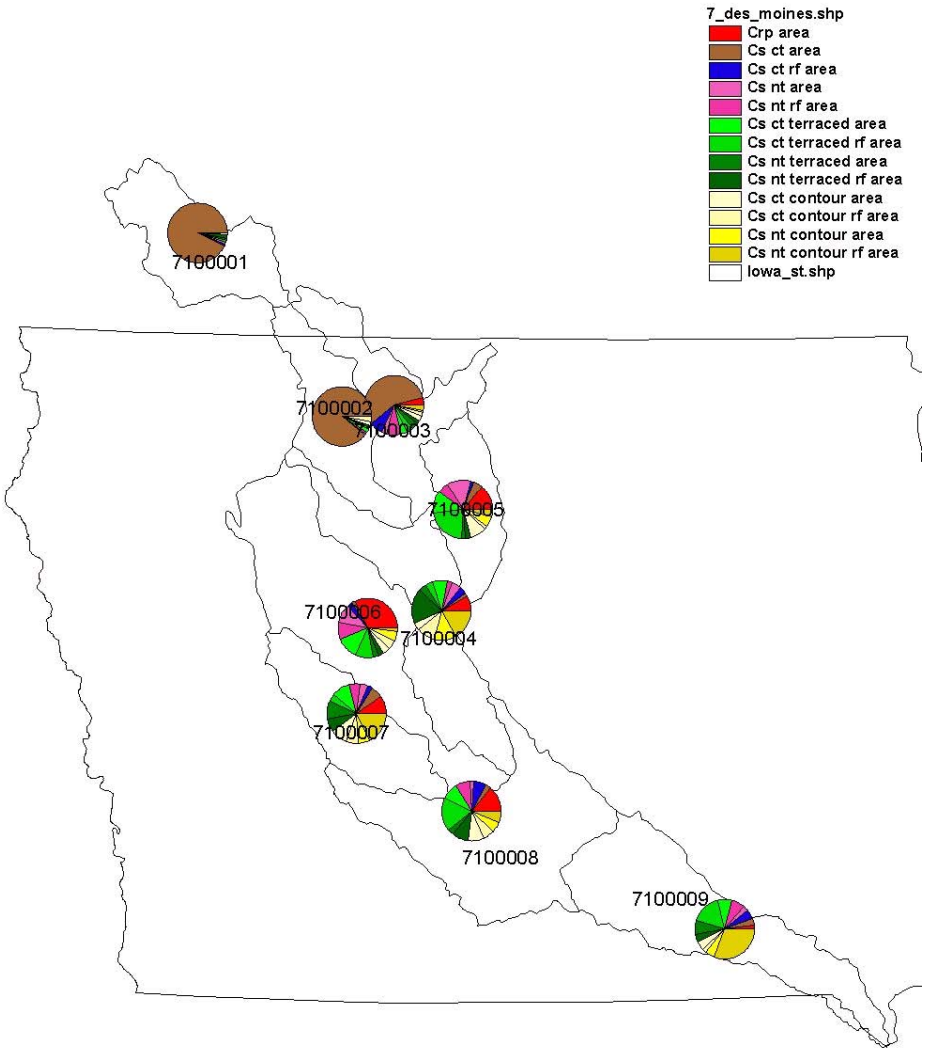


Figure 5. Distribution of land use options for Des Moines Watershed for the scenario of targeting both N and P reduction.

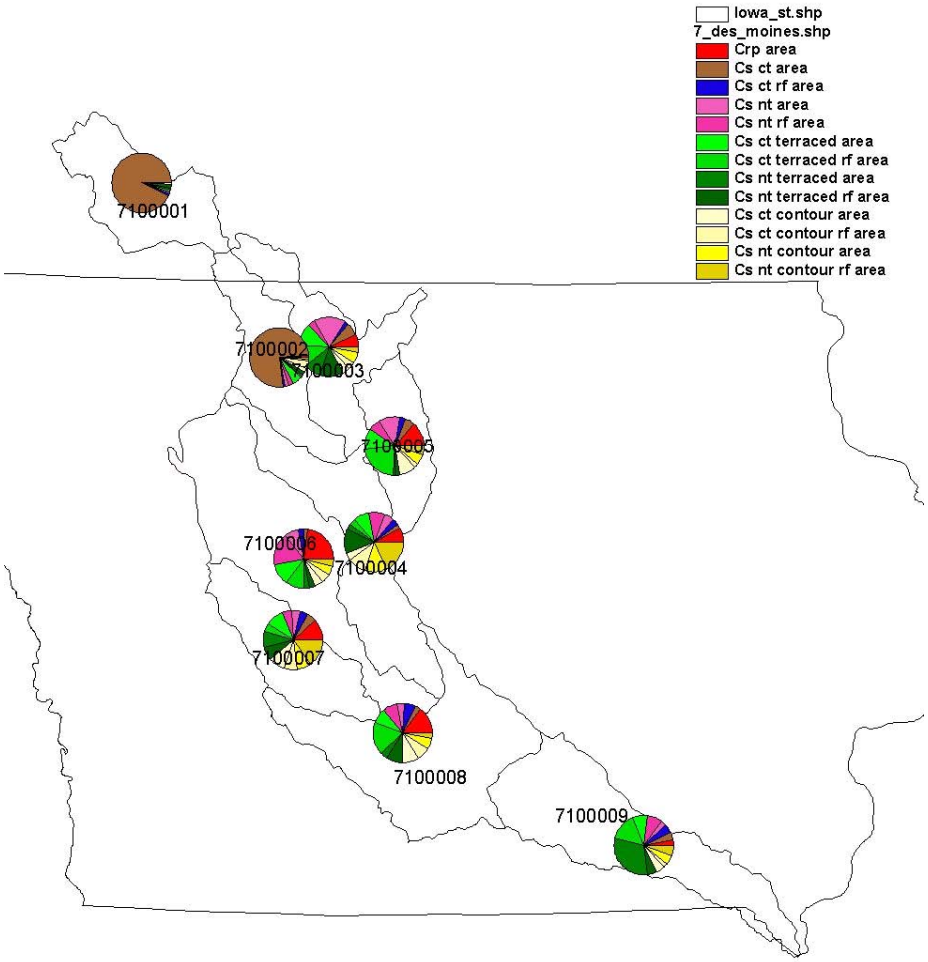


Figure 6. Distribution of land use options for Nodaway Watershed for the scenario of targeting N reduction.

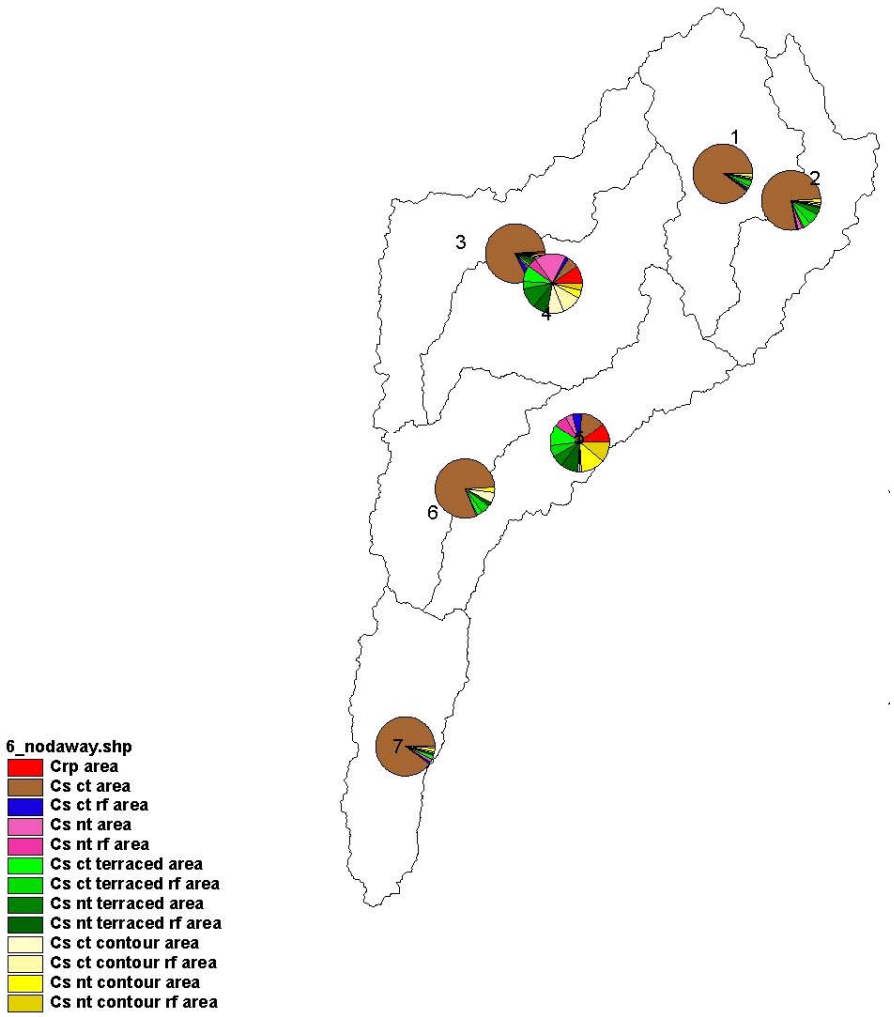
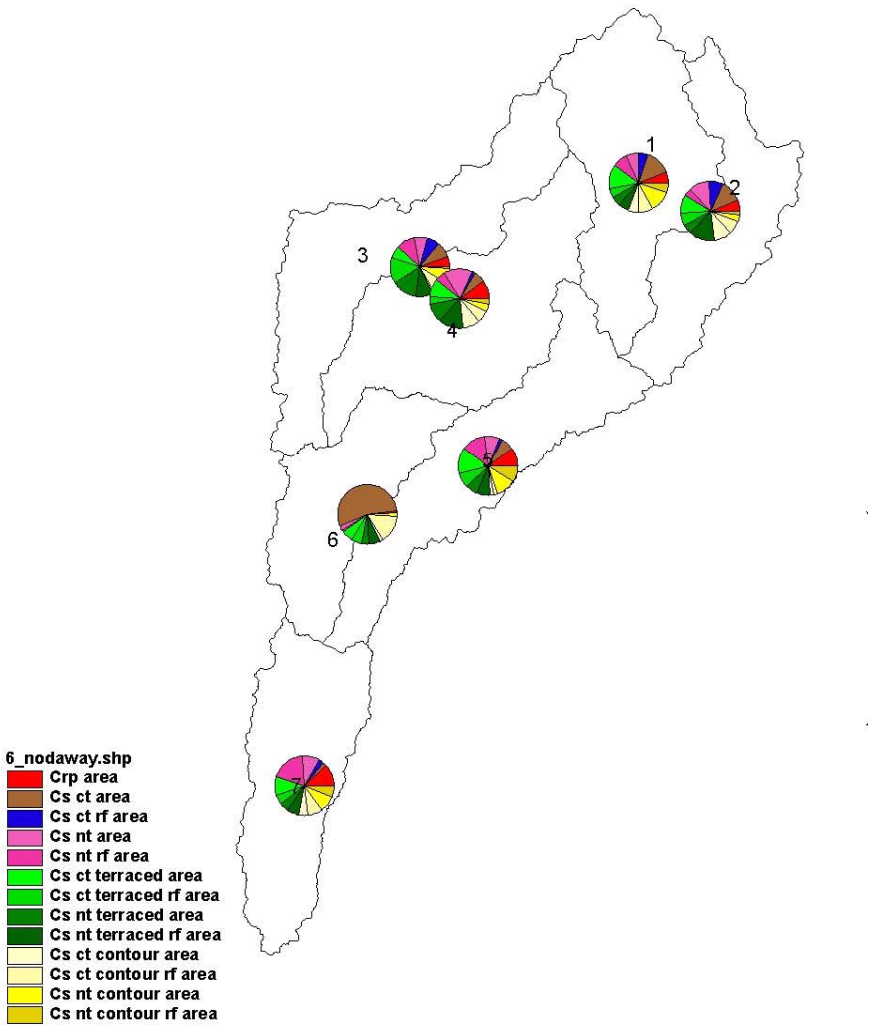


Figure 7. Distribution of land use options for Nodaway Watershed for the scenario of targeting both N and P reduction.



Appendix A: Practices and cost estimates in detail

Grass Waterways

Our average cost estimates for grass waterways relied primarily on IFIP data. If IFIP could not be used then CRP was used, then EQIP, and lastly surrounding county average cost. Only records with an average cost greater than $400 but less than $10,000 were considered. While we estimated the overall average cost of grass waterways, there are several important inputs/cost drivers that we identified. These include construction expenses from tile, earthwork, fabric strips, and seeding and also land rental expenses for land occupied by the grass waterway (land rental expenses are not included in our cost estimates). The role these inputs play in driving cost is important because they can lead to significant variability and may have significant impacts on the overall cost of grass waterways as the costs of these inputs change over time.

The issue of cost variability due to inputs is illustrated by the effect that the number of lines of tile used has on cost. Using a cost estimate for 5-inch tile of $1.65 per foot and a grass waterway length of 1,089 feet (equivalent to 1 acre of grass waterway for a 40-foot wide grass waterway[1]) results in an additional cost of approximately $1,797 per acre for each line of tile installed. We found the number of lines of tile could be expected to range from no tile to two lines in general. Other factors that affect the average construction cost of the grass waterway are the size/diameter of tile used, width of the waterway, distance to an outlet for the drained water, seed type used, usage and spacing of fabric strips, ability to use existing tile, and price of each input. It seems reasonable to believe that the NRI has underreported the usage of grass waterways, at least in some

[1] Grass waterway length / acre = (43,560 ft^2 / acre) x (1 / 40 ft) = 1,089 ft / acre.

counties, since almost all counties cost-shared on grass waterways under at least one of the programs we used. Statewide average cost was estimated to be $2,127 per acre.

Terraces

Our average cost estimates for terraces relied primarily on IFIP data, but if IFIP was not available we used EQIP. Only records with average cost greater than $0 but less than $14 were considered. With terraces, two primary issues affecting cost are the type of terrace constructed and the use of tile. There were four main types of terraces identified: broad-based, narrow-based, grass front-slope, and grass back-slope. A conservationist in one county estimated that the average cost for the different terraces ranged from $2.31 to $3.30 per foot for narrow-based, the least expensive, to $8 to $10 per foot for broad-based, the most expensive. There were different reasons for selecting a specific type of terrace, such as weed control and farming considerations; however, slope may be a primary factor as the different types of terraces have differing slope limitations.

To make the average cost estimates and the NRI usage estimates for terraces compatible, per foot average costs should be translated to per protected acre average costs. [2] A method for translation was reported in Secchi et al. (2007). This method utilized a high and low estimate for feet of terrace required to protect 1 acre. The high estimate was 435.6 feet per protected acre and the low estimate was 166.67 feet per protected acre. Our estimates of terrace usage relied on NRI data; however, terraces appeared to be underreported in the NRI for some counties. This was indicated as cost-share was reported by conservation programs for several counties that did not have any terraces reported in the NRI. Statewide average cost was estimated to be $3.57 per foot.

Water and Sediment Control Basins

[2] Cost per protected acre = (Cost per ft) x (ft per protected area)

Our average cost estimates for water and sediment control basins relied primarily on IFIP data. If IFIP could not be used, we then used EQIP and then surrounding county average cost. Only records in which the average cost was between $300 and $500,000 were considered. The upper limit of $500,000 was used to avoid over-refining the data and excluding accurate records; however, the most expensive of these structures should not come close to our upper limit of $500,000 according to an Iowa state conservationist. According to the same conservationist, most water and sediment control basins cost less than $50,000 but a few do cost more. The large range for what we considered reasonable was thus needed because of the high variability that is inherent in these structures and their average costs. When attempting to analyze counties with extreme average cost estimates, it is important to consider the high cost variability of these structures. It is also important to note that several counties reported very few water and sediment control basins, resulting in a small sample for some counties on which their average cost estimate was based. This may indicate that our county-level average cost estimates do not accurately represent the true average cost for counties with extreme values reported, and our statewide average cost estimate may be a better estimate in cases of extreme values. Statewide average cost was estimated to be $3,989 per structure.

Grade Stabilization Structures

Our average cost estimates for grade stabilization structures relied primarily on IFIP data, but if IFIP could not be used, we then used EQIP and then surrounding county average cost. Only records with average costs between $500 and $1,000,000 were considered. While it was suggested by an expert state conservationist that $500,000 should be an acceptable upper limit for the cost of a grade stabilization structure, the

conservationist also mentioned that it is possible that a specific structure could cost more than that. Therefore, we set our upper average cost limit at $1,000,000 to avoid over-refinement of the data; the $500 lower limit used was also based on what was suggested to be an acceptable lower limit. The conservationist also mentioned that most of these structures tend to fall within the range of $5,000 to $10,000. When analyzing counties with extreme average cost values, caution should be taken regarding the high cost variability of these structures and the small number of structures reported in some counties. Statewide average cost was estimated to be $15,018 per structure.

Filter Strips

CRP was the source used for our average cost estimates for filter strips. Land rental rate is a major cost for this practice; however, other costs include seed, seed bed preparation, cost to seed, and possibly fertilizer. As with other structural practices, the land rental rate is not included in our cost estimates. Choice of seed type can have a significant affect on costs. The lowest cost grasses, introduced grasses, cost slightly over $8 per acre while tall native grasses cost around $100 per acre and short native grasses with native forbs or legumes can cost around $200 per acre. Seed type also influences the cost of other inputs. Seeding costs vary from approximately $15 per acre for a grain drill to $30 per acre for a native grass drill. Seed bed preparation is around $40 per acre and fertilizer was listed as a possible cost since warm-season grasses really don’t use fertilizer but cool-season grasses sometimes do. The cost estimate for 30-30-40 fertilizer is around $25 per acre. When introduced grasses are used, CRP requires that a nurse crop be planted in the first year; the estimated cost for nurse crops is around $9 per acre. The cost estimates reported above for the various inputs of filter strips were based on flat rates

reported in a CRP report; these flat rates were doubled to determine cost since they are based on 50% cost-share according to a county conservationist. Statewide average cost was estimated to be $116.83 per acre.

Contour Buffer Strips

CRP was the primary source relied on for our average cost estimates for contour buffer strips. However, if data were not available from CRP we then used EQIP and lastly surrounding county average cost. For CRP we used information from practice CP15, contour grass strips, as our average cost estimates for contour buffer strips. The general inputs and costs for contour buffer strips were the same as those for filter strips. Other than the land rental rate, costs include the cost of seed, seed bed preparation, cost to seed, and possibly fertilizer. Statewide average cost was estimated to be $78 per acre.

Riparian Buffers

Our average cost estimates for riparian buffers relied primarily on CRP data, but if CRP could not be used we then used surrounding county average cost. Only records with average cost greater than zero were considered. Statewide average cost was estimated to be $486 per acre.

Wetland Restoration

CRP was the primary source relied on for our average cost estimates for wetland restoration, but if data were not available from CRP we used surrounding county average cost. The average costs derived seemed plausible when the only major process needed for wetland restoration was to cease cropping. However, these estimates are likely too low if other major processes/inputs are needed for wetland restoration. We arrived at this conclusion after doing a comparison with reported EQIP rates and contracting county and

district conservationists. In one case, an NRCS wetland specialist suggested that average costs of wetland restoration in that specialist's area might be around $3,000 per acre with earthwork being the major cost. General estimates mentioned were $300 per acre for locating old tile lines, and $2,500 to $3,000 per acre for earthwork. Other counties, such as Wright, do not need a lot of earthmoving in wetland restoration. However, there are costs from locating old tile and replacing any perforated tile with non-perforated; a county conservationist estimated that tile might be encountered 70% of the time with wetland restoration in the county. The conservationist also said the cost of seeding may be around $100 to $125 per acre in the county. We believe our average cost estimates, derived from CRP data, may be accurate when the only major step in restoring wetlands is to cease cropping. However, when other major processes/inputs are required, such as removing and replacing old tile lines or earthwork, we believe these estimates are likely too low. Statewide average cost was estimated to be $245 per acre.

Nutrient Management

Our average cost estimates for nutrient management relied primarily on EQIP data, with surrounding county average cost being the only other data source used. Since EQIP has flat rate incentive payments for nutrient management, rather than cost-sharing, our average cost estimates are based on incentive payment rates. There are two important issues to note with EQIP nutrient management incentive payment rates. First, the payments are primarily used as an incentive for adoption of nutrient management, which means that the incentive is generally only paid for the first three years of adoption. Second, the number of acres that can receive an incentive payment was generally capped at 320 acres for 2006. To be confident that these flat-rate incentive payments could be accurately

used as proxies to average cost, we reviewed literature to help determine a plausible range for average cost. The "National Management Measures to Control Nutrient Source Pollution from Agriculture" reported cost estimates for nutrient management in surrounding states ranging from approximately $1 to $20 and reported that in 1989 and 1990 savings in fertilizer cost for Iowa corn was about $2.25 per acre (EPA, 2003). This led us to conclude that the incentive payment rates used for our average cost estimates were at least within an acceptable range of reasonableness. Statewide average cost was estimated to be $4.09 per acre.

Contour Farming

Our estimated average cost for contour farming is a single average cost for the entire state because of limited cost information available on the practice. After gathering information from both IFIP and EQIP we had average costs for less than one-third of Iowa's counties. Moreover, the IFIP and EQIP numbers reported were flat-rate incentive payments. The flat-rate incentive payment for contour farming under IFIP is $6 per acre for all counties in which it is offered and the flat rate under EQIP is generally similar for most counties. While we recognize that certain land characteristics in parts of Iowa make contour farming unrealistic, such as short slopes that quickly change direction, we chose $6 per acre as our average cost estimate for contour farming, as it was the best estimate available for counties in which contour farming was practical.

No-Till

Incentive payments for the adoption of no-till under IFIP and EQIP were primarily reported in the northern half of Iowa and not the southern half. Since no-till is already more widely used in southern Iowa, an incentive for practice adoption is generally not

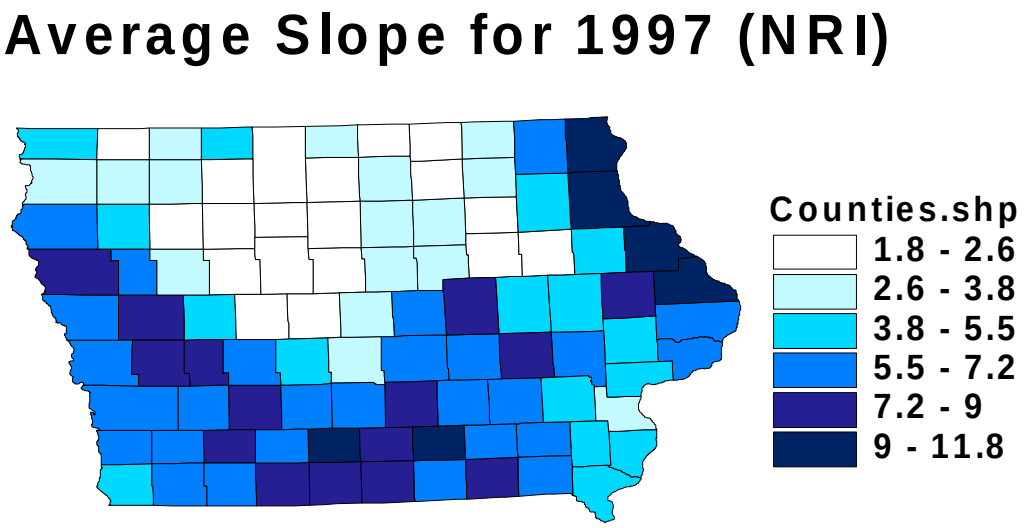
offered. Because of the limited information on average cost/incentive payments for no-till in southern Iowa under the various conservation programs, we instead relied on estimates developed on the social cost of no-till for each of Iowa's counties. The number of no-till acres reported in Map1b is from CTIC. Statewide average cost was estimated to be $17.94 per acre.

Continuous CRP and General CRP

Our average annual rental payment estimates for both continuous CRP and general CRP relied exclusively on CRP data. With general CRP, "producers can offer land for CRP general sign-up enrollment only during designated sign-up periods." With continuous CRP, "land devoted to certain practices may be enrolled at any time under CRP continuous sign-up (USDA/FSA, 2007c)." Conservation practices under continuous CRP include contour grass strips, grass waterways, filter strips, living snow fences, riparian buffers, salt-tolerant vegetation, shallow water areas for wildlife, shelterbelts, wetland buffers, wetland restoration, and wildlife habitat buffers. Statewide average annual rental payment was estimated to be $142 per acre for continuous CRP and $97 per acre for general CRP.

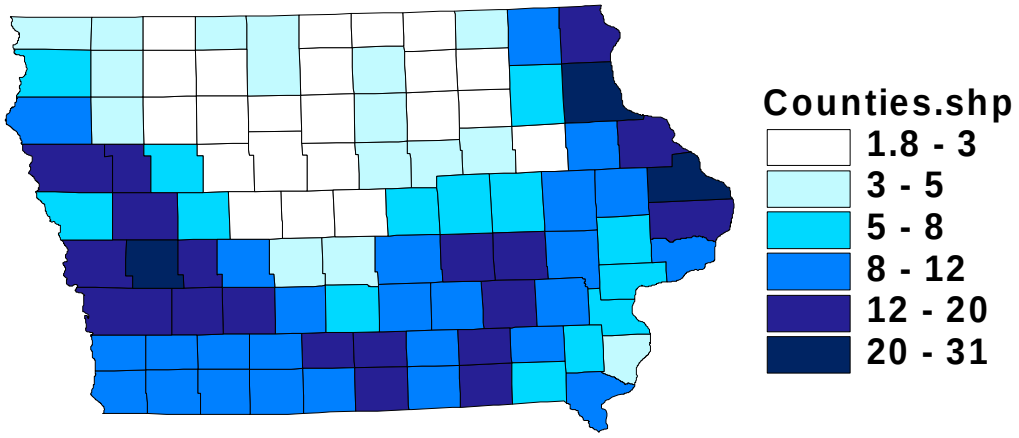
Tables and maps from appendix

Map A.1.



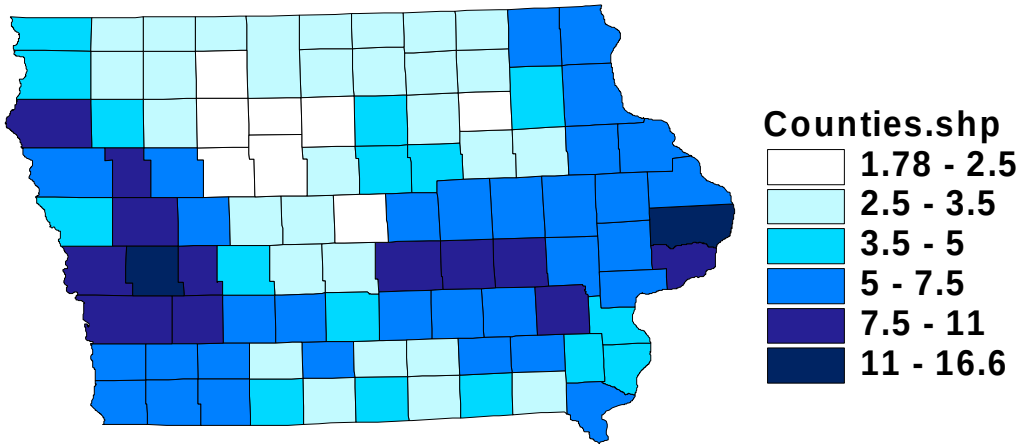
Map A.2.

Weighted Average Erodability Index for 1997 (NRI)

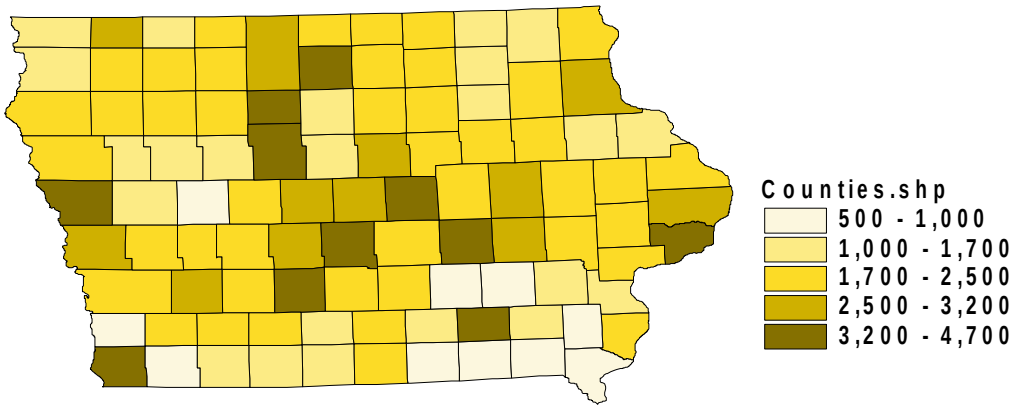


Map A.3.

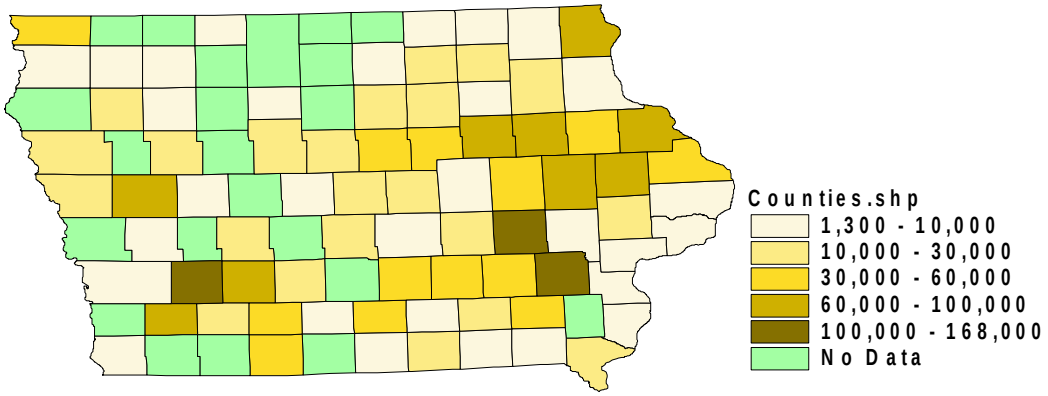
Weighted Average USLE for 1997 (NRI)



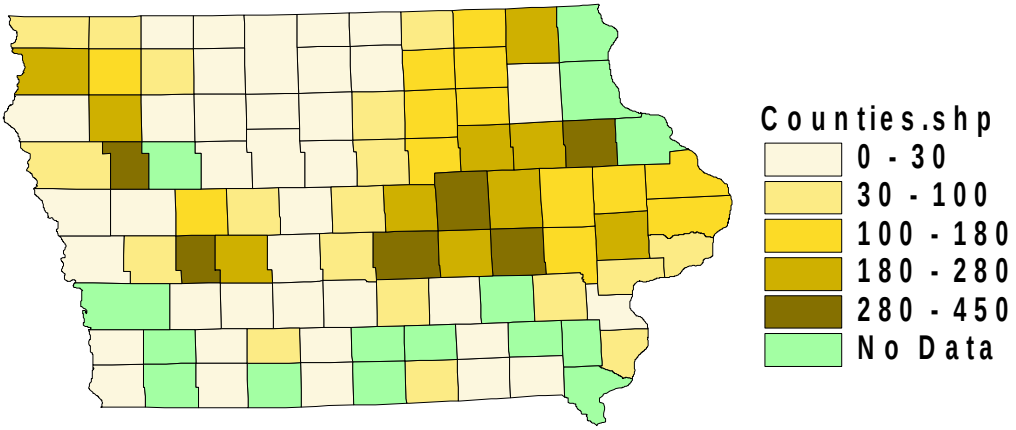
Map A.4. Average Cost per Acre



Map A.5. Total Acres (NRI)

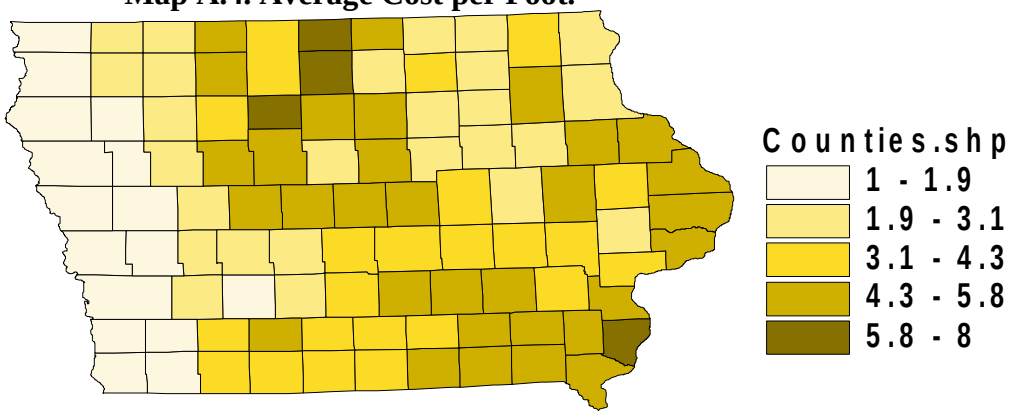


Map A.6. Total Acres Installed (IFIP)

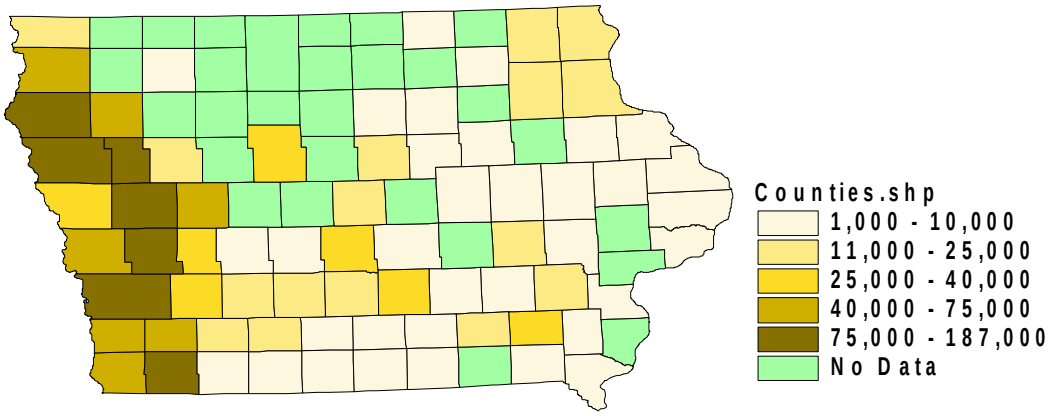


Terraces

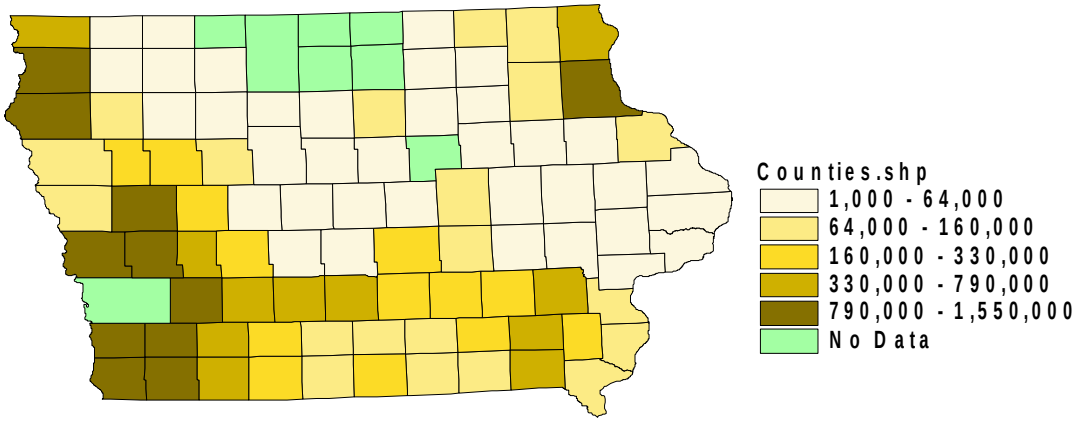
Map A.4. Average Cost per Foot.



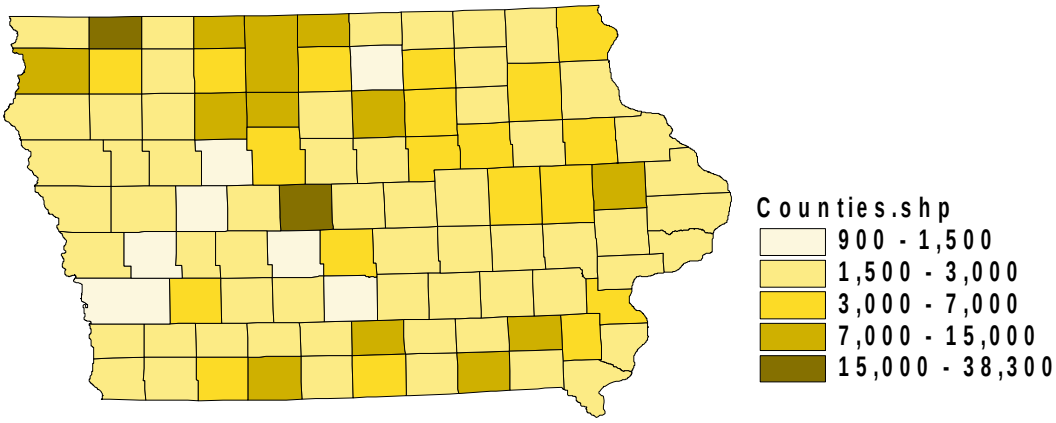
Map A.5. Total Acres (NRI).



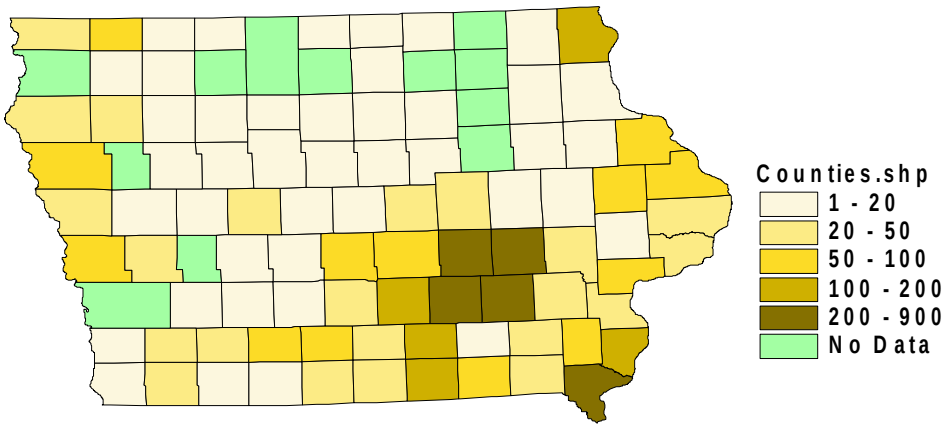
Map A.6. Total Feet Installed (IFIP).



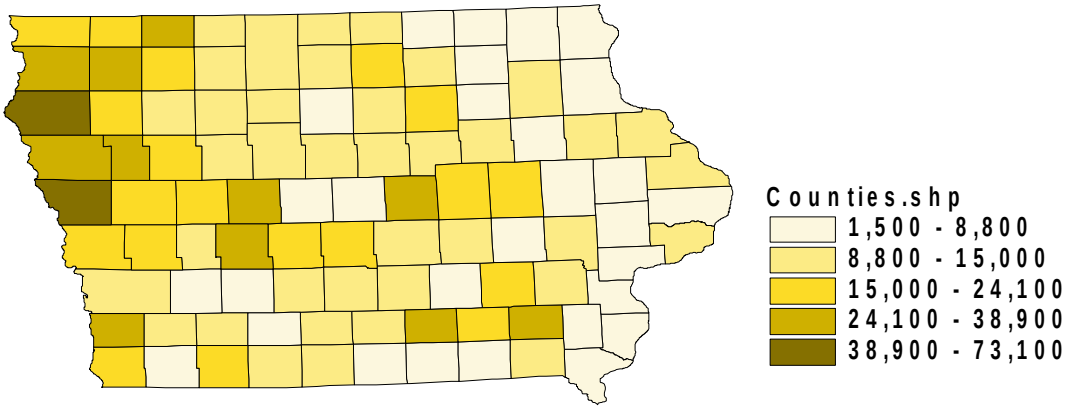
Map A.7. Average Cost per Structure.



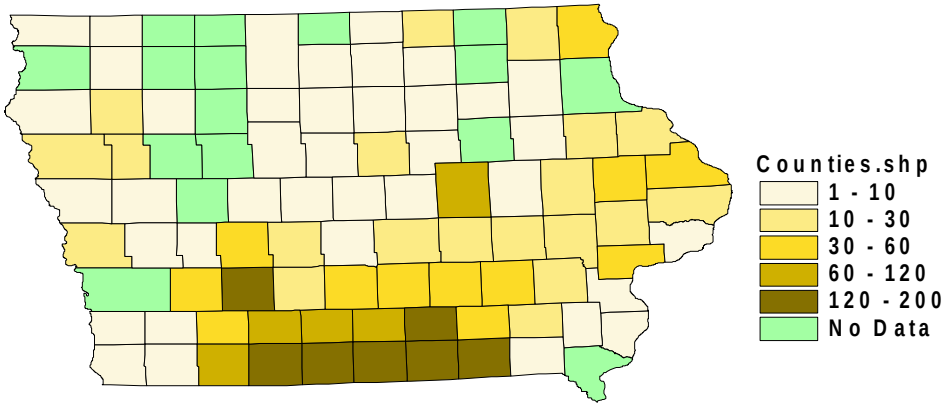
Map A.8. Total Structures Installed (IFIP).



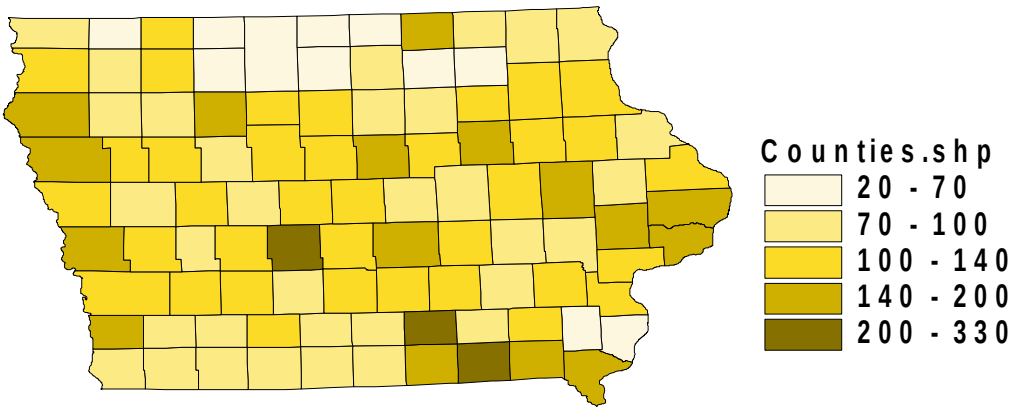
Map A.9. Average Cost per Structure.



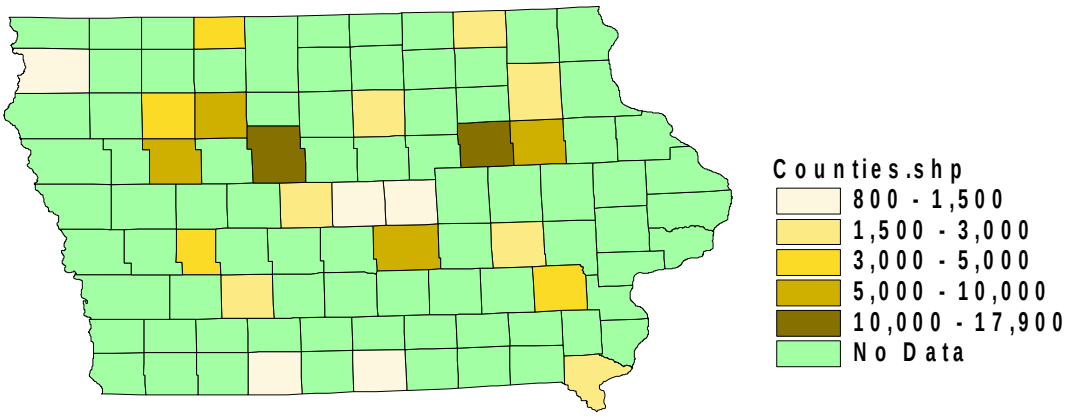
Map A.10. Total Structures Installed (IFIP).



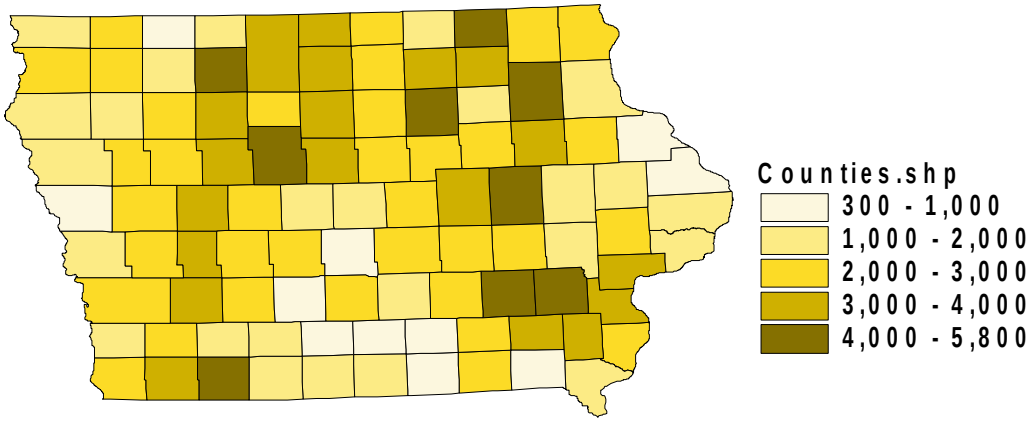
Map A.11. Average Cost per Acre.



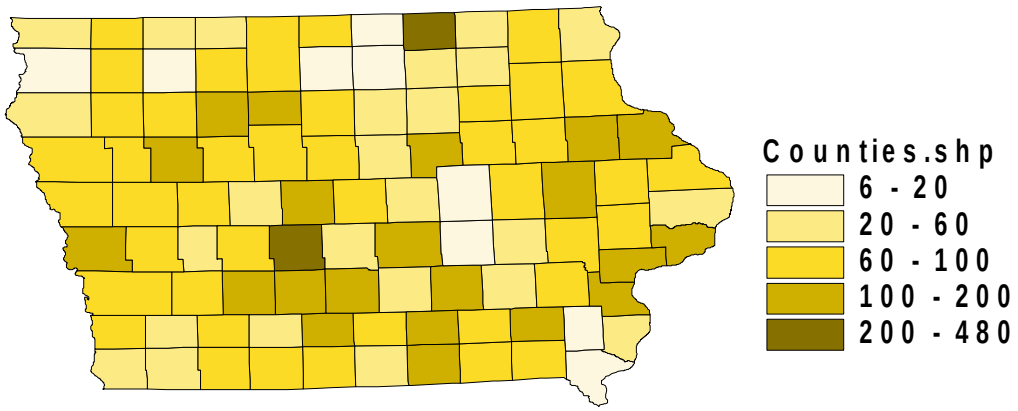
Map A.12. Total Acres (NRI).



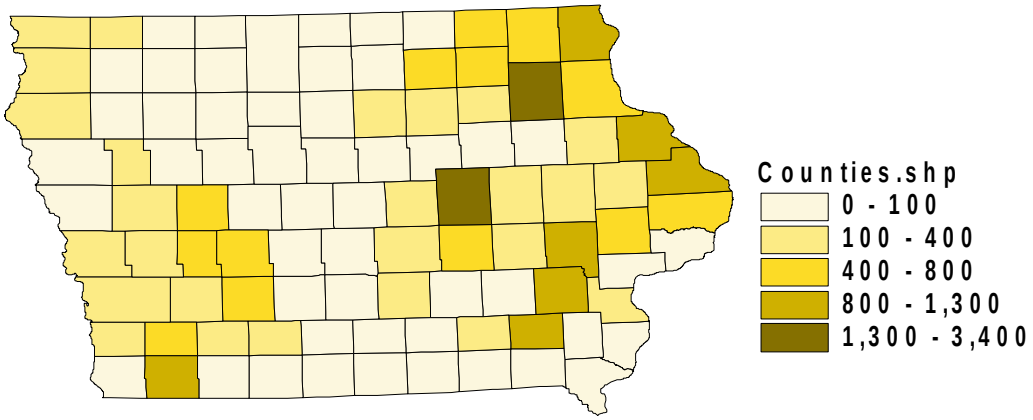
Map A.13. Total Acres Installed (CRP).



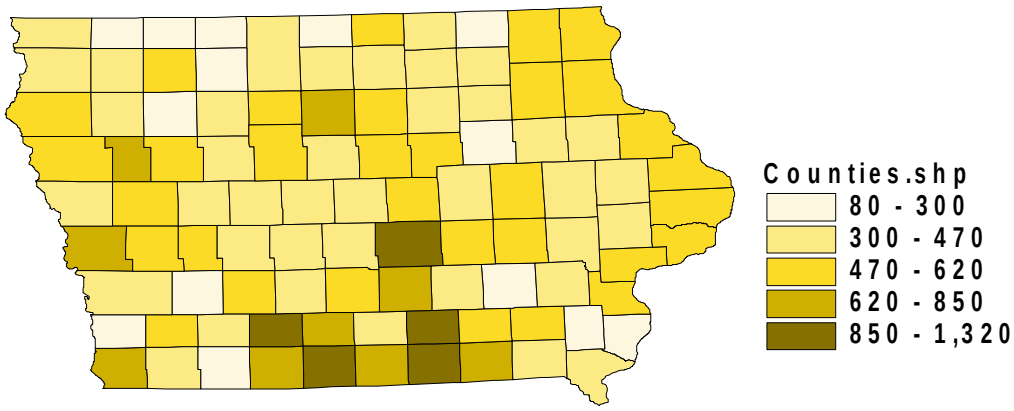
Map A.14. Average Cost per Acre.



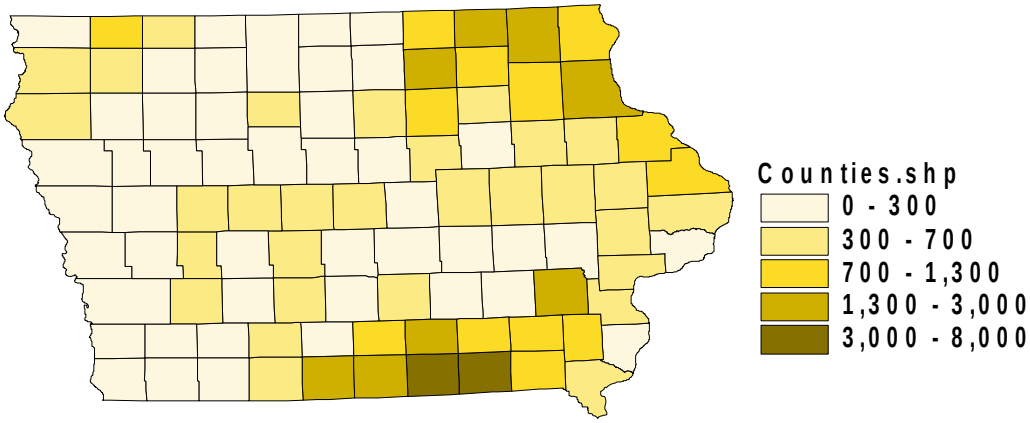
Map A.15. Total Acres Installed (CRP).



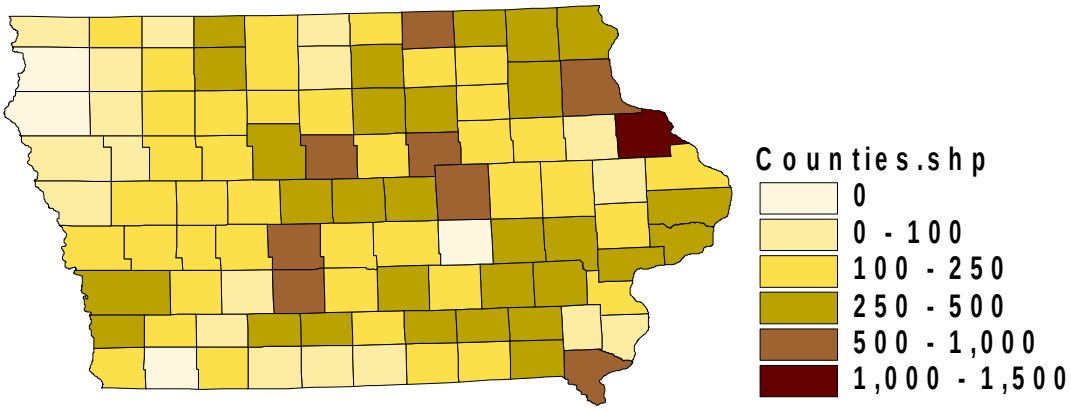
Map A.16. Average Cost per Acre.



Map A.17. Total Acres Installed (CRP).

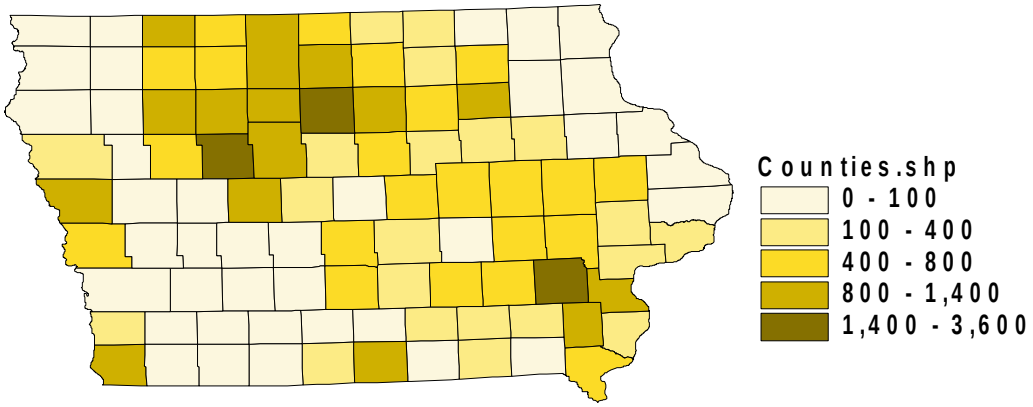


Map A.18. Average Cost per Acre.

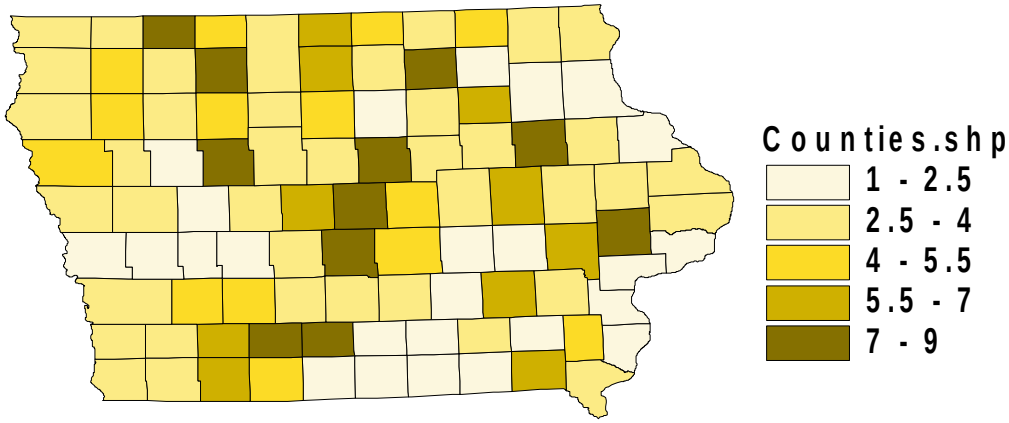


*Note: See wetland restoration section for a discussion on average cost estimates.

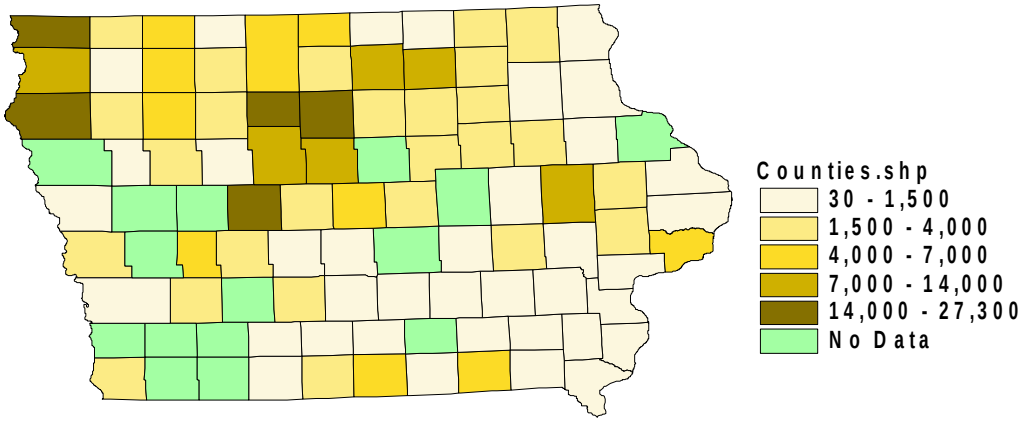
Map A.19. Total Acres Installed (CRP).



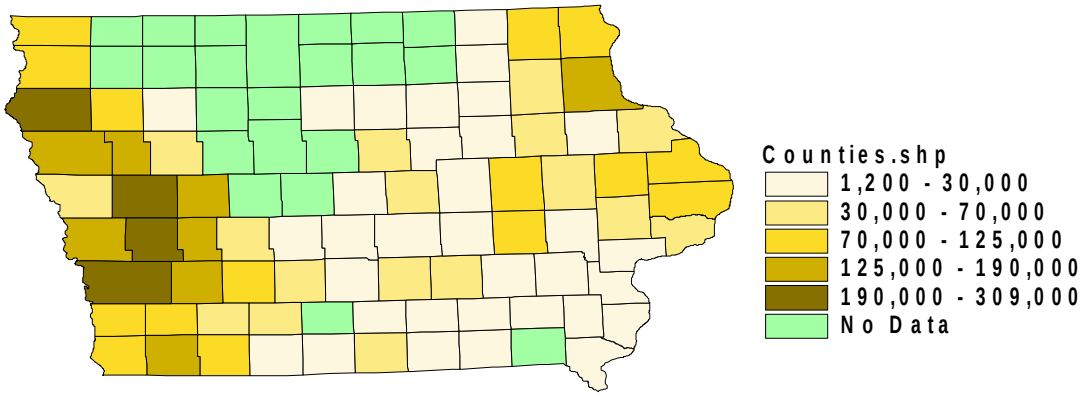
Map A.20. Average Cost per Acre.



Map A.21. Total Acres Implemented (EQIP).

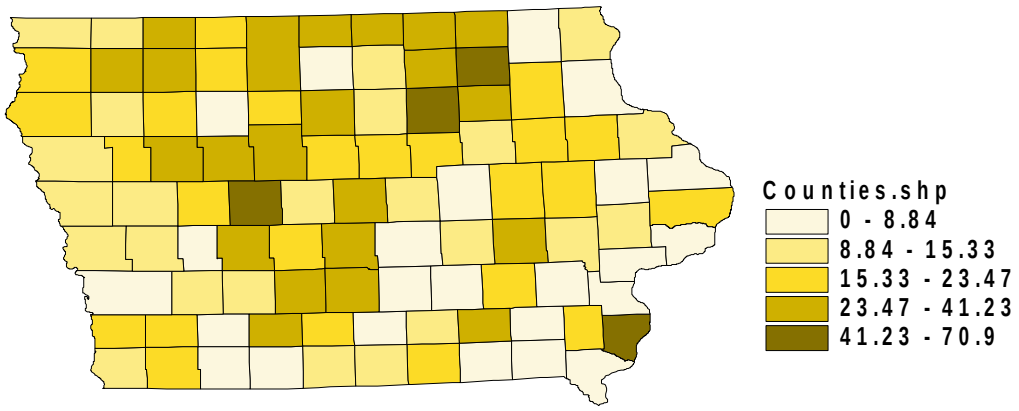


Map A.22. Total Acres (NRI).

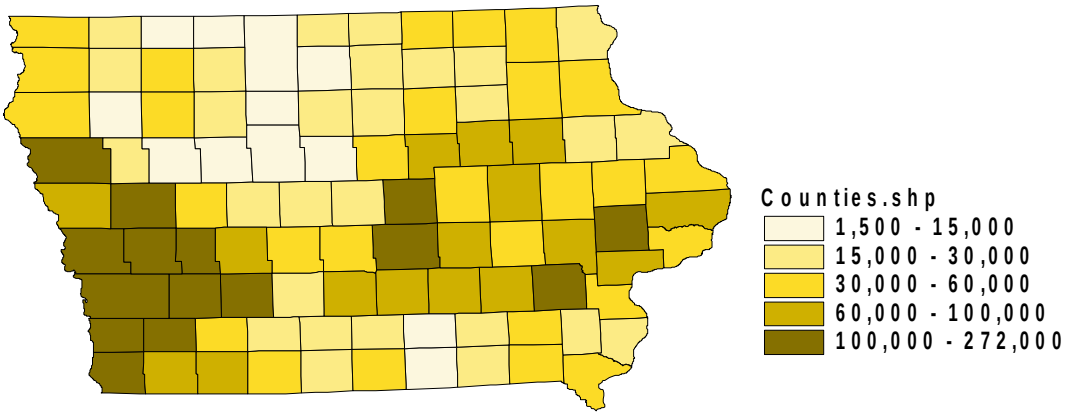


No-Till

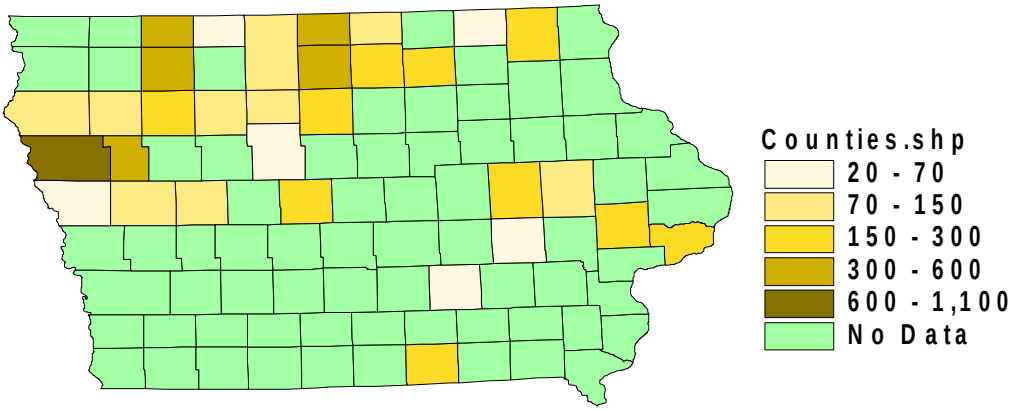
Map A.23. Average Cost per Acre.



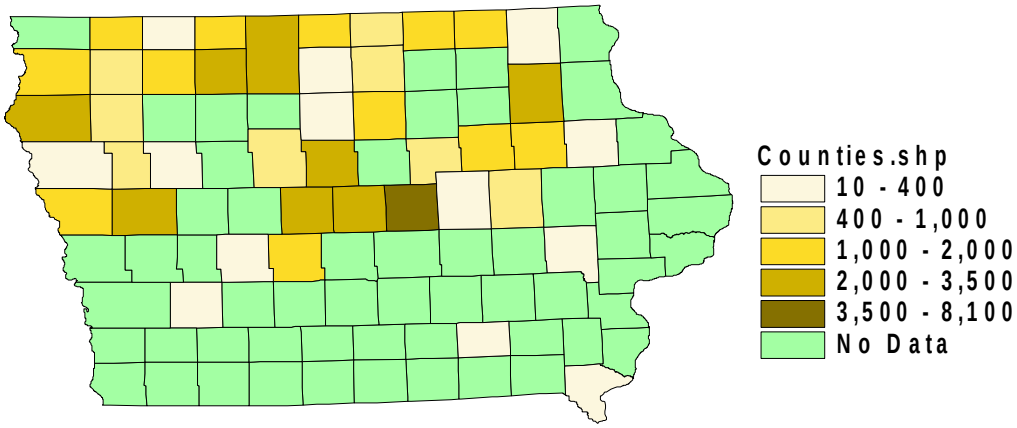
Map A.24. Total Acres (CTIC).



Map A.25. Total Acres Implemented (IFIP).

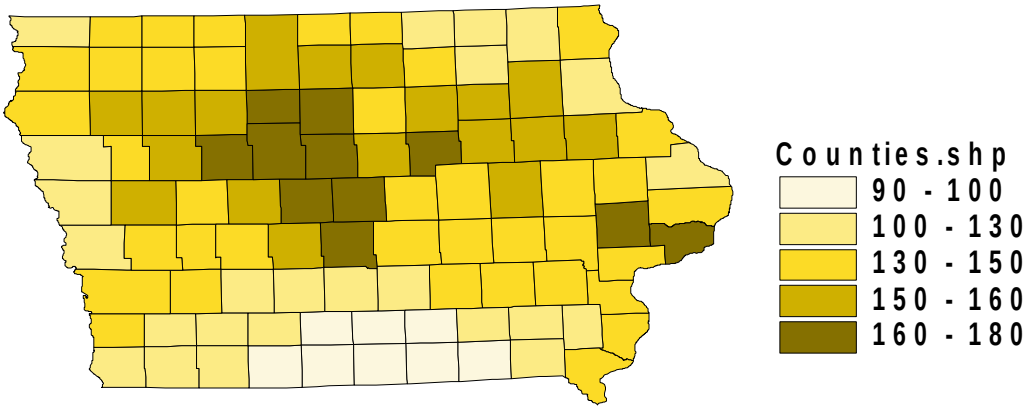


Map A.26. Total Acres Implemented (EQIP).

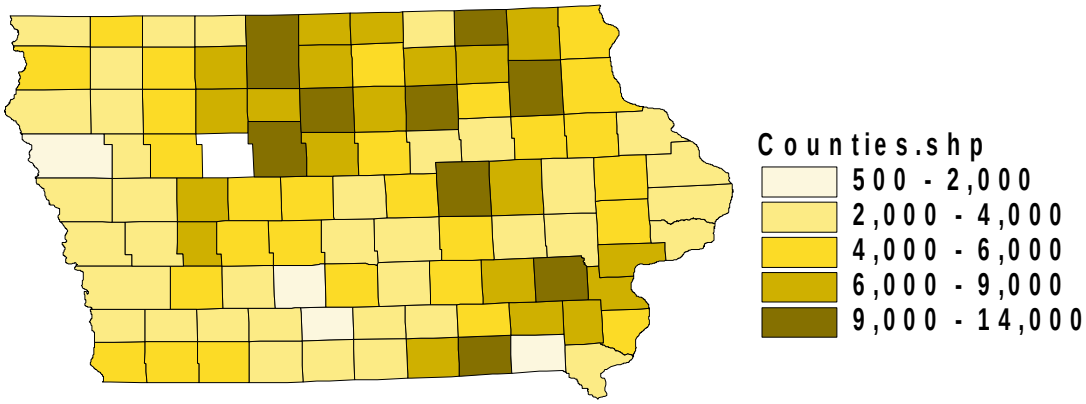


* Note: IFIP and EQIP were not used for no-till average cost estimates; maps of the no-till acres implemented under the programs are listed for comparison to CTIC.

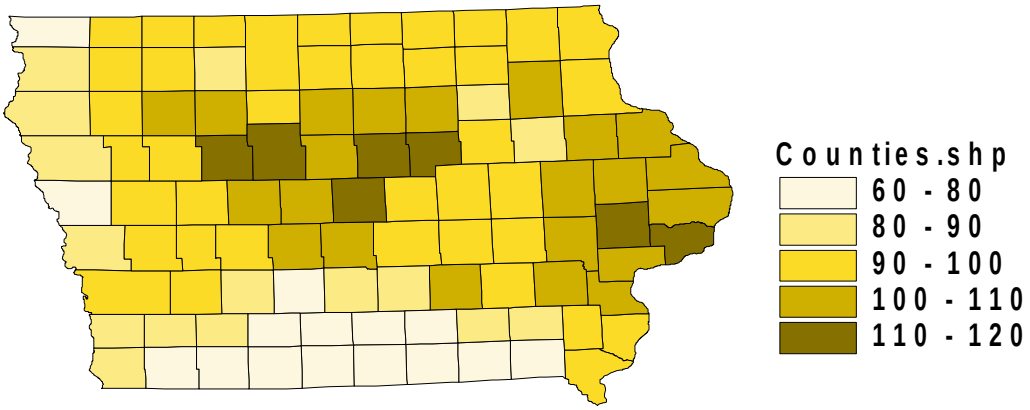
Map A.27. Average Annual Rental Payment per Acre.



Map A.28. Total Acres (CRP).



Map A.29. Average Annual Rental Payment per Acre.



Map A.30. Total Acres (CRP).

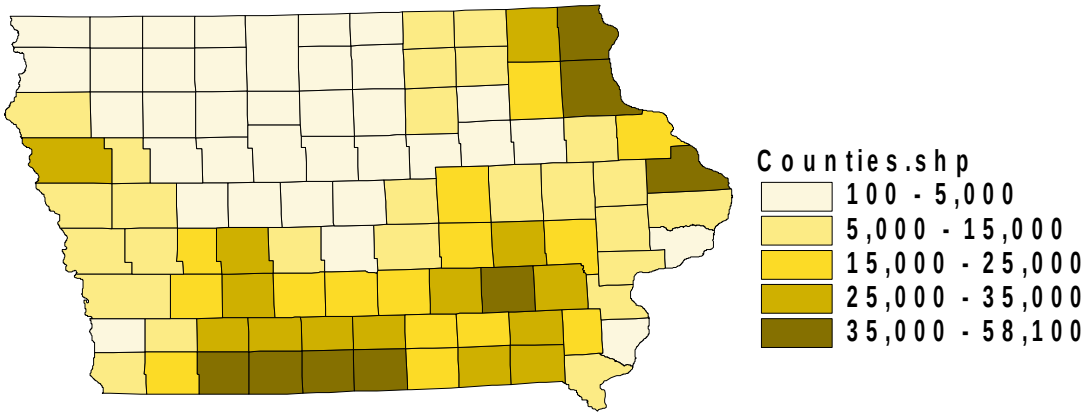


Table A.1. Grass waterway average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$2,152	Floyd	19067	$2,056	Monona	19133	$3,486
Adams	19003	$1,799	Franklin	19069	$1,938	Monroe	19135	$1,554
Allamakee	19005	$1,978	Fremont	19071	$3,383	Montgomery	19137	$2,144
Appanoose	19007	$1,014	Greene	19073	$2,287	Muscatine	19139	$2,096
Audubon	19009	$2,181	Grundy	19075	$2,191	O'Brien	19141	$2,051
Benton	19011	$2,612	Guthrie	19077	$2,537	Osceola	19143	$2,633
Black Hawk	19013	$1,828	Hamilton	19079	$1,325	Page	19145	$968
Boone	19015	$2,897	Hancock	19081	$4,654	Palo Alto	19147	$2,378
Bremer	19017	$1,646	Hardin	19083	$3,107	Plymouth	19149	$2,291
Buchanan	19019	$1,822	Harrison	19085	$2,845	Pocahontas	19151	$2,170
Buena Vista	19021	$1,924	Henry	19087	$1,016	Polk	19153	$3,454
Butler	19023	$2,284	Howard	19089	$1,685	Pottawattamie	19155	$2,386
Calhoun	19025	$1,233	Humboldt	19091	$3,400	Poweshiek	19157	$3,692
Carroll	19027	$821	Ida	19093	$1,671	Ringgold	19159	$1,642
Cass	19029	$2,836	Iowa	19095	$2,638	Sac	19161	$1,520
Cedar	19031	$2,352	Jackson	19097	$2,483	Scott	19163	$3,381
Cerro Gordo	19033	$1,977	Jasper	19099	$2,246	Shelby	19165	$1,987
Cherokee	19035	$2,263	Jefferson	19101	$1,418	Sioux	19167	$1,097
Chickasaw	19037	$1,654	Johnson	19103	$1,771	Story	19169	$2,745
Clarke	19039	$1,469	Jones	19105	$2,205	Tama	19171	$2,159
Clay	19041	$2,472	Keokuk	19107	$1,038	Taylor	19173	$1,150
Clayton	19043	$3,024	Kossuth	19109	$2,923	Union	19175	$2,369
Clinton	19045	$2,664	Lee	19111	$740	Van Buren	19177	$480
Crawford	19047	$1,540	Linn	19113	$2,279	Wapello	19179	$4,630
Dallas	19049	$2,913	Louisa	19115	$1,632	Warren	19181	$1,844
Davis	19051	$947	Lucas	19117	$2,206	Washington	19183	$1,543
Decatur	19053	$1,424	Lyon	19119	$1,455	Wayne	19185	$1,764
Delaware	19055	$1,724	Madison	19121	$3,449	Webster	19187	$4,607
Des Moines	19057	$2,089	Mahaska	19123	$823	Winnebago	19189	$2,411
Dickinson	19059	$1,687	Marion	19125	$2,033	Winneshiek	19191	$1,151
Dubuque	19061	$1,202	Marshall	19127	$3,764	Woodbury	19193	$1,846
Emmet	19063	$2,384	Mills	19129	$1,020	Worth	19195	$2,000
Fayette	19065	$2,384	Mitchell	19131	$1,843	Wright	19197	$1,657

Table A.2. Terrace average cost per foot.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$1.79	Floyd	19067	$3.31	Monona	19133	$1.21
Adams	19003	$3.53	Franklin	19069	$4.69	Monroe	19135	$3.92
Allamakee	19005	$3.08	Fremont	19071	$1.04	Montgomery	19137	$1.94
Appanoose	19007	$5.19	Greene	19073	$4.72	Muscatine	19139	$3.55
Audubon	19009	$2.63	Grundy	19075	$2.07	O'Brien	19141	$2.18
Benton	19011	$2.85	Guthrie	19077	$2.65	Osceola	19143	$2.26
Black Hawk	19013	$2.95	Hamilton	19079	$2.29	Page	19145	$1.92
Boone	19015	$4.53	Hancock	19081	$6.83	Palo Alto	19147	$5.55
Bremer	19017	$2.01	Hardin	19083	$4.56	Plymouth	19149	$1.00
Buchanan	19019	$2.97	Harrison	19085	$1.55	Pocahontas	19151	$4.33
Buena Vista	19021	$2.70	Henry	19087	$5.71	Polk	19153	$4.00
Butler	19023	$2.81	Howard	19089	$2.52	Pottawattamie	19155	$1.28
Calhoun	19025	$4.44	Humboldt	19091	$8.03	Poweshiek	19157	$4.02
Carroll	19027	$2.18	Ida	19093	$1.28	Ringgold	19159	$3.50
Cass	19029	$2.48	Iowa	19095	$4.09	Sac	19161	$2.97
Cedar	19031	$3.08	Jackson	19097	$4.48	Scott	19163	$4.90
Cerro Gordo	19033	$2.21	Jasper	19099	$3.97	Shelby	19165	$1.34
Cherokee	19035	$1.85	Jefferson	19101	$4.56	Sioux	19167	$1.05
Chickasaw	19037	$2.73	Johnson	19103	$3.32	Story	19169	$4.72
Clarke	19039	$3.67	Jones	19105	$3.41	Tama	19171	$3.21
Clay	19041	$2.05	Keokuk	19107	$5.09	Taylor	19173	$3.26
Clayton	19043	$2.78	Kossuth	19109	$3.73	Union	19175	$4.90
Clinton	19045	$5.00	Lee	19111	$5.16	Van Buren	19177	$4.42
Crawford	19047	$1.06	Linn	19113	$5.82	Wapello	19179	$4.99
Dallas	19049	$2.94	Louisa	19115	$5.81	Warren	19181	$3.93
Davis	19051	$4.82	Lucas	19117	$4.28	Washington	19183	$4.03
Decatur	19053	$3.56	Lyon	19119	$1.21	Wayne	19185	$4.23
Delaware	19055	$4.63	Madison	19121	$2.62	Webster	19187	$4.55
Des Moines	19057	$7.10	Mahaska	19123	$5.12	Winnebago	19189	$7.93
Dickinson	19059	$2.80	Marion	19125	$4.40	Winneshiek	19191	$3.29
Dubuque	19061	$4.63	Marshall	19127	$4.78	Woodbury	19193	$1.17
Emmet	19063	$5.00	Mills	19129	$1.36	Worth	19195	$5.00
Fayette	19065	$4.36	Mitchell	19131	$2.93	Wright	19197	$5.55

Table A.3. Water & sediment control basin average cost per structure.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$1,564	Floyd	19067	$4,851	Monona	19133	$1,689
Adams	19003	$1,975	Franklin	19069	$12,425	Monroe	19135	$1,798
Allamakee	19005	$3,803	Fremont	19071	$1,959	Montgomery	19137	$2,678
Appanoose	19007	$2,757	Greene	19073	$2,448	Muscatine	19139	$2,166
Audubon	19009	$1,947	Grundy	19075	$4,439	O'Brien	19141	$3,624
Benton	19011	$4,454	Guthrie	19077	$2,895	Osceola	19143	$38,350
Black Hawk	19013	$3,354	Hamilton	19079	$1,926	Page	19145	$2,613
Boone	19015	$20,677	Hancock	19081	$5,549	Palo Alto	19147	$6,519
Bremer	19017	$2,840	Hardin	19083	$2,401	Plymouth	19149	$1,879
Buchanan	19019	$2,120	Harrison	19085	$1,843	Pocahontas	19151	$14,538
Buena Vista	19021	$1,841	Henry	19087	$4,686	Polk	19153	$3,260
Butler	19023	$3,126	Howard	19089	$2,676	Pottawattamie	19155	$1,276
Calhoun	19025	$1,135	Humboldt	19091	$7,679	Poweshiek	19157	$1,577
Carroll	19027	$1,403	Ida	19093	$1,892	Ringgold	19159	$7,279
Cass	19029	$3,750	Iowa	19095	$2,055	Sac	19161	$1,982
Cedar	19031	$2,342	Jackson	19097	$2,773	Scott	19163	$2,165
Cerro Gordo	19033	$1,411	Jasper	19099	$1,846	Shelby	19165	$1,353
Cherokee	19035	$1,586	Jefferson	19101	$10,127	Sioux	19167	$9,572
Chickasaw	19037	$2,938	Johnson	19103	$1,661	Story	19169	$2,020
Clarke	19039	$1,564	Jones	19105	$8,617	Tama	19171	$2,710
Clay	19041	$2,017	Keokuk	19107	$1,686	Taylor	19173	$5,079
Clayton	19043	$1,849	Kossuth	19109	$8,584	Union	19175	$2,178
Clinton	19045	$2,074	Lee	19111	$1,789	Van Buren	19177	$2,365
Crawford	19047	$2,143	Linn	19113	$3,954	Wapello	19179	$2,155
Dallas	19049	$895	Louisa	19115	$4,542	Warren	19181	$1,469
Davis	19051	$10,234	Lucas	19117	$13,086	Washington	19183	$2,404
Decatur	19053	$1,787	Lyon	19119	$2,421	Wayne	19185	$3,529
Delaware	19055	$3,145	Madison	19121	$2,442	Webster	19187	$4,565
Des Moines	19057	$2,283	Mahaska	19123	$2,483	Winnebago	19189	$7,340
Dickinson	19059	$1,669	Marion	19125	$1,716	Winneshiek	19191	$2,909
Dubuque	19061	$2,285	Marshall	19127	$2,003	Woodbury	19193	$2,112
Emmet	19063	$11,371	Mills	19129	$1,838	Worth	19195	$2,451
Fayette	19065	$3,275	Mitchell	19131	$2,444	Wright	19197	$1,990

Table A.4. Grade stabilization structure average cost per structure.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$5,971	Floyd	19067	$9,471	Monona	19133	$73,092
Adams	19003	$9,917	Franklin	19069	$14,000	Monroe	19135	$26,168
Allamakee	19005	$6,857	Fremont	19071	$20,432	Montgomery	19137	$11,054
Appanoose	19007	$7,240	Greene	19073	$27,269	Muscatine	19139	$6,067
Audubon	19009	$9,966	Grundy	19075	$9,817	O'Brien	19141	$36,543
Benton	19011	$15,444	Guthrie	19077	$38,301	Osceola	19143	$16,684
Black Hawk	19013	$11,398	Hamilton	19079	$11,060	Page	19145	$7,439
Boone	19015	$8,637	Hancock	19081	$11,131	Palo Alto	19147	$12,628
Bremer	19017	$5,221	Hardin	19083	$12,942	Plymouth	19149	$67,944
Buchanan	19019	$3,685	Harrison	19085	$21,159	Pocahontas	19151	$12,501
Buena Vista	19021	$15,009	Henry	19087	$7,885	Polk	19153	$17,975
Butler	19023	$15,984	Howard	19089	$3,298	Pottawattamie	19155	$12,721
Calhoun	19025	$10,000	Humboldt	19091	$11,580	Poweshiek	19157	$10,711
Carroll	19027	$20,537	Ida	19093	$29,677	Ringgold	19159	$11,089
Cass	19029	$7,709	Iowa	19095	$8,206	Sac	19161	$19,875
Cedar	19031	$7,519	Jackson	19097	$9,334	Scott	19163	$13,324
Cerro Gordo	19033	$16,143	Jasper	19099	$11,868	Shelby	19165	$17,092
Cherokee	19035	$24,097	Jefferson	19101	$27,348	Sioux	19167	$32,570
Chickasaw	19037	$8,180	Johnson	19103	$11,868	Story	19169	$8,803
Clarke	19039	$13,953	Jones	19105	$6,651	Tama	19171	$16,771
Clay	19041	$23,083	Keokuk	19107	$20,103	Taylor	19173	$15,913
Clayton	19043	$8,529	Kossuth	19109	$11,295	Union	19175	$8,513
Clinton	19045	$7,901	Lee	19111	$1,497	Van Buren	19177	$10,319
Crawford	19047	$20,592	Linn	19113	$8,658	Wapello	19179	$21,761
Dallas	19049	$18,459	Louisa	19115	$5,447	Warren	19181	$9,891
Davis	19051	$6,525	Lucas	19117	$12,982	Washington	19183	$10,601
Decatur	19053	$9,561	Lyon	19119	$17,581	Wayne	19185	$7,421
Delaware	19055	$9,259	Madison	19121	$11,670	Webster	19187	$14,621
Des Moines	19057	$4,866	Mahaska	19123	$7,478	Winnebago	19189	$13,101
Dickinson	19059	$26,613	Marion	19125	$10,750	Winneshiek	19191	$7,588
Dubuque	19061	$10,921	Marshall	19127	$31,614	Woodbury	19193	$36,335
Emmet	19063	$11,295	Mills	19129	$38,882	Worth	19195	$13,835
Fayette	19065	$12,862	Mitchell	19131	$2,837	Wright	19197	$7,835

Table A.5. Filter strip average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$116	Floyd	19067	$74	Monona	19133	$114
Adams	19003	$92	Franklin	19069	$96	Monroe	19135	$292
Allamakee	19005	$84	Fremont	19071	$96	Montgomery	19137	$90
Appanoose	19007	$204	Greene	19073	$76	Muscatine	19139	$142
Audubon	19009	$98	Grundy	19075	$120	O'Brien	19141	$90
Benton	19011	$120	Guthrie	19077	$124	Osceola	19143	$30
Black Hawk	19013	$152	Hamilton	19079	$108	Page	19145	$80
Boone	19015	$122	Hancock	19081	$40	Palo Alto	19147	$62
Bremer	19017	$128	Hardin	19083	$158	Plymouth	19149	$174
Buchanan	19019	$118	Harrison	19085	$164	Pocahontas	19151	$168
Buena Vista	19021	$96	Henry	19087	$66	Polk	19153	$108
Butler	19023	$84	Howard	19089	$98	Pottawattamie	19155	$108
Calhoun	19025	$94	Humboldt	19091	$108	Poweshiek	19157	$114
Carroll	19027	$128	Ida	19093	$126	Ringgold	19159	$90
Cass	19029	$110	Iowa	19095	$96	Sac	19161	$124
Cedar	19031	$148	Jackson	19097	$120	Scott	19163	$148
Cerro Gordo	19033	$86	Jasper	19099	$178	Shelby	19165	$134
Cherokee	19035	$104	Jefferson	19101	$118	Sioux	19167	$126
Chickasaw	19037	$64	Johnson	19103	$86	Story	19169	$128
Clarke	19039	$92	Jones	19105	$84	Tama	19171	$86
Clay	19041	$116	Keokuk	19107	$78	Taylor	19173	$80
Clayton	19043	$112	Kossuth	19109	$70	Union	19175	$126
Clinton	19045	$178	Lee	19111	$172	Van Buren	19177	$202
Crawford	19047	$92	Linn	19113	$154	Wapello	19179	$88
Dallas	19049	$332	Louisa	19115	$118	Warren	19181	$116
Davis	19051	$270	Lucas	19117	$94	Washington	19183	$120
Decatur	19053	$82	Lyon	19119	$90	Wayne	19185	$102
Delaware	19055	$114	Madison	19121	$96	Webster	19187	$122
Des Moines	19057	$22	Mahaska	19123	$138	Winnebago	19189	$72
Dickinson	19059	$138	Marion	19125	$136	Winneshiek	19191	$88
Dubuque	19061	$104	Marshall	19127	$86	Woodbury	19193	$176
Emmet	19063	$60	Mills	19129	$168	Worth	19195	$72
Fayette	19065	$132	Mitchell	19131	$158	Wright	19197	$108

Table A.6. Contour buffer strip average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$106	Floyd	19067	$36	Monona	19133	$100
Adams	19003	$72	Franklin	19069	$48	Monroe	19135	$116
Allamakee	19005	$56	Fremont	19071	$50	Montgomery	19137	$48
Appanoose	19007	$104	Greene	19073	$32	Muscatine	19139	$104
Audubon	19009	$60	Grundy	19075	$118	O'Brien	19141	$96
Benton	19011	$66	Guthrie	19077	$84	Osceola	19143	$76
Black Hawk	19013	$64	Hamilton	19079	$70	Page	19145	$24
Boone	19015	$128	Hancock	19081	$12	Palo Alto	19147	$82
Bremer	19017	$86	Hardin	19083	$54	Plymouth	19149	$50
Buchanan	19019	$88	Harrison	19085	$102	Pocahontas	19151	$146
Buena Vista	19021	$96	Henry	19087	$12	Polk	19153	$34
Butler	19023	$40	Howard	19089	$56	Pottawattamie	19155	$70
Calhoun	19025	$92	Humboldt	19091	$104	Poweshiek	19157	$14
Carroll	19027	$88	Ida	19093	$66	Ringgold	19159	$76
Cass	19029	$72	Iowa	19095	$36	Sac	19161	$132
Cedar	19031	$90	Jackson	19097	$82	Scott	19163	$108
Cerro Gordo	19033	$8	Jasper	19099	$114	Shelby	19165	$64
Cherokee	19035	$80	Jefferson	19101	$122	Sioux	19167	$6
Chickasaw	19037	$38	Johnson	19103	$62	Story	19169	$90
Clarke	19039	$120	Jones	19105	$84	Tama	19171	$16
Clay	19041	$20	Keokuk	19107	$56	Taylor	19173	$70
Clayton	19043	$74	Kossuth	19109	$90	Union	19175	$50
Clinton	19045	$46	Lee	19111	$8	Van Buren	19177	$67
Crawford	19047	$74	Linn	19113	$102	Wapello	19179	$94
Dallas	19049	$474	Louisa	19115	$104	Warren	19181	$120
Davis	19051	$98	Lucas	19117	$100	Washington	19183	$62
Decatur	19053	$66	Lyon	19119	$22	Wayne	19185	$24
Delaware	19055	$106	Madison	19121	$120	Webster	19187	$70
Des Moines	19057	$41	Mahaska	19123	$142	Winnebago	19189	$92
Dickinson	19059	$34	Marion	19125	$58	Winneshiek	19191	$78
Dubuque	19061	$114	Marshall	19127	$38	Woodbury	19193	$76
Emmet	19063	$48	Mills	19129	$70	Worth	19195	$10
Fayette	19065	$68	Mitchell	19131	$294	Wright	19197	$74

Table A.7. Riparian buffer average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$586	Floyd	19067	$312	Monona	19133	$414
Adams	19003	$436	Franklin	19069	$498	Monroe	19135	$1,320
Allamakee	19005	$498	Fremont	19071	$676	Montgomery	19137	$550
Appanoose	19007	$1,116	Greene	19073	$396	Muscatine	19139	$542
Audubon	19009	$486	Grundy	19075	$480	O'Brien	19141	$398
Benton	19011	$516	Guthrie	19077	$408	Osceola	19143	$216
Black Hawk	19013	$206	Hamilton	19079	$450	Page	19145	$350
Boone	19015	$470	Hancock	19081	$463	Palo Alto	19147	$246
Bremer	19017	$432	Hardin	19083	$582	Plymouth	19149	$570
Buchanan	19019	$440	Harrison	19085	$766	Pocahontas	19151	$326
Buena Vista	19021	$230	Henry	19087	$182	Polk	19153	$376
Butler	19023	$458	Howard	19089	$226	Pottawattamie	19155	$376
Calhoun	19025	$430	Humboldt	19091	$522	Poweshiek	19157	$590
Carroll	19027	$384	Ida	19093	$680	Ringgold	19159	$714
Cass	19029	$296	Iowa	19095	$516	Sac	19161	$528
Cedar	19031	$450	Jackson	19097	$558	Scott	19163	$496
Cerro Gordo	19033	$432	Jasper	19099	$1,122	Shelby	19165	$558
Cherokee	19035	$410	Jefferson	19101	$520	Sioux	19167	$416
Chickasaw	19037	$344	Johnson	19103	$340	Story	19169	$464
Clarke	19039	$852	Jones	19105	$380	Tama	19171	$432
Clay	19041	$502	Keokuk	19107	$240	Taylor	19173	$166
Clayton	19043	$512	Kossuth	19109	$344	Union	19175	$1,090
Clinton	19045	$492	Lee	19111	$436	Van Buren	19177	$468
Crawford	19047	$584	Linn	19113	$462	Wapello	19179	$542
Dallas	19049	$402	Louisa	19115	$520	Warren	19181	$616
Davis	19051	$726	Lucas	19117	$460	Washington	19183	$400
Decatur	19053	$986	Lyon	19119	$452	Wayne	19185	$712
Delaware	19055	$424	Madison	19121	$346	Webster	19187	$540
Des Moines	19057	$160	Mahaska	19123	$388	Winnebago	19189	$292
Dickinson	19059	$198	Marion	19125	$660	Winneshiek	19191	$554
Dubuque	19061	$494	Marshall	19127	$570	Woodbury	19193	$562
Emmet	19063	$84	Mills	19129	$142	Worth	19195	$498
Fayette	19065	$518	Mitchell	19131	$454	Wright	19197	$656

Table A.8. Wetland restoration average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$52	Floyd	19067	$128	Monona	19133	$34
Adams	19003	$87	Franklin	19069	$254	Monroe	19135	$352
Allamakee	19005	$417	Fremont	19071	$244	Montgomery	19137	$210
Appanoose	19007	$232	Greene	19073	$118	Muscatine	19139	$288
Audubon	19009	$110	Grundy	19075	$684	O'Brien	19141	$8
Benton	19011	$144	Guthrie	19077	$126	Osceola	19143	$228
Black Hawk	19013	$224	Hamilton	19079	$902	Page	19145	$0
Boone	19015	$386	Hancock	19081	$24	Palo Alto	19147	$366
Bremer	19017	$158	Hardin	19083	$170	Plymouth	19149	$0
Buchanan	19019	$192	Harrison	19085	$150	Pocahontas	19151	$118
Buena Vista	19021	$164	Henry	19087	$34	Polk	19153	$148
Butler	19023	$412	Howard	19089	$370	Pottawattamie	19155	$262
Calhoun	19025	$180	Humboldt	19091	$190	Poweshiek	19157	$0
Carroll	19027	$152	Ida	19093	$97	Ringgold	19159	$78
Cass	19029	$163	Iowa	19095	$460	Sac	19161	$144
Cedar	19031	$242	Jackson	19097	$208	Scott	19163	$254
Cerro Gordo	19033	$448	Jasper	19099	$244	Shelby	19165	$188
Cherokee	19035	$90	Jefferson	19101	$490	Sioux	19167	$0
Chickasaw	19037	$152	Johnson	19103	$318	Story	19169	$294
Clarke	19039	$256	Jones	19105	$66	Tama	19171	$524
Clay	19041	$154	Keokuk	19107	$314	Taylor	19173	$105
Clayton	19043	$558	Kossuth	19109	$214	Union	19175	$293
Clinton	19045	$270	Lee	19111	$514	Van Buren	19177	$428
Crawford	19047	$107	Linn	19113	$124	Wapello	19179	$278
Dallas	19049	$776	Louisa	19115	$166	Warren	19181	$164
Davis	19051	$226	Lucas	19117	$192	Washington	19183	$324
Decatur	19053	$78	Lyon	19119	$79	Wayne	19185	$96
Delaware	19055	$24	Madison	19121	$750	Webster	19187	$330
Des Moines	19057	$4	Mahaska	19123	$128	Winnebago	19189	$80
Dickinson	19059	$92	Marion	19125	$342	Winneshiek	19191	$339
Dubuque	19061	$1,500	Marshall	19127	$388	Woodbury	19193	$54
Emmet	19063	$310	Mills	19129	$368	Worth	19195	$116
Fayette	19065	$276	Mitchell	19131	$508	Wright	19197	$140

*Note: see the wetland restoration section for a discussion on average cost estimates.

Table A.9. Nutrient management average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$4.35	Floyd	19067	$7.41	Monona	19133	$4.00
Adams	19003	$6.33	Franklin	19069	$2.00	Monroe	19135	$2.14
Allamakee	19005	$3.00	Fremont	19071	$3.26	Montgomery	19137	$3.96
Appanoose	19007	$2.00	Greene	19073	$3.00	Muscatine	19139	$2.33
Audubon	19009	$2.00	Grundy	19075	$3.00	O'Brien	19141	$5.00
Benton	19011	$5.77	Guthrie	19077	$2.13	Osceola	19143	$3.00
Black Hawk	19013	$3.00	Hamilton	19079	$4.00	Page	19145	$3.26
Boone	19015	$6.00	Hancock	19081	$6.00	Palo Alto	19147	$8.00
Bremer	19017	$7.00	Hardin	19083	$9.00	Plymouth	19149	$3.75
Buchanan	19019	$8.51	Harrison	19085	$2.00	Pocahontas	19151	$5.26
Buena Vista	19021	$3.16	Henry	19087	$4.55	Polk	19153	$8.00
Butler	19023	$3.03	Howard	19089	$5.00	Pottawattamie	19155	$3.61
Calhoun	19025	$8.43	Humboldt	19091	$3.03	Poweshiek	19157	$2.00
Carroll	19027	$2.00	Ida	19093	$3.00	Ringgold	19159	$5.00
Cass	19029	$5.00	Iowa	19095	$2.00	Sac	19161	$2.00
Cedar	19031	$7.69	Jackson	19097	$3.19	Scott	19163	$2.00
Cerro Gordo	19033	$3.00	Jasper	19099	$4.39	Shelby	19165	$2.00
Cherokee	19035	$5.00	Jefferson	19101	$2.41	Sioux	19167	$3.00
Chickasaw	19037	$2.00	Johnson	19103	$7.00	Story	19169	$8.08
Clarke	19039	$8.15	Jones	19105	$3.00	Tama	19171	$3.00
Clay	19041	$4.00	Keokuk	19107	$7.00	Taylor	19173	$7.00
Clayton	19043	$2.00	Kossuth	19109	$4.04	Union	19175	$9.00
Clinton	19045	$3.00	Lee	19111	$3.17	Van Buren	19177	$6.00
Crawford	19047	$2.71	Linn	19113	$4.00	Wapello	19179	$3.00
Dallas	19049	$4.00	Louisa	19115	$2.00	Warren	19181	$4.00
Davis	19051	$2.00	Lucas	19117	$1.00	Washington	19183	$3.00
Decatur	19053	$1.00	Lyon	19119	$3.00	Wayne	19185	$2.00
Delaware	19055	$3.75	Madison	19121	$4.00	Webster	19187	$4.00
Des Moines	19057	$2.41	Mahaska	19123	$2.00	Winnebago	19189	$7.00
Dickinson	19059	$8.00	Marion	19125	$3.00	Winneshiek	19191	$4.00
Dubuque	19061	$2.00	Marshall	19127	$5.00	Woodbury	19193	$4.71
Emmet	19063	$5.00	Mills	19129	$3.44	Worth	19195	$5.00
Fayette	19065	$2.00	Mitchell	19131	$3.00	Wright	19197	$5.00

Table A.10. No-till average cost per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$13.92	Floyd	19067	$29.19	Monona	19133	$11.03
Adams	19003	$6.56	Franklin	19069	$12.63	Monroe	19135	$13.22
Allamakee	19005	$12.51	Fremont	19071	$10.61	Montgomery	19137	$16.60
Appanoose	19007	$16.26	Greene	19073	$49.83	Muscatine	19139	$6.71
Audubon	19009	$8.60	Grundy	19075	$17.49	O'Brien	19141	$30.78
Benton	19011	$23.47	Guthrie	19077	$28.31	Osceola	19143	$14.68
Black Hawk	19013	$14.18	Hamilton	19079	$19.75	Page	19145	$15.70
Boone	19015	$10.44	Hancock	19081	$6.83	Palo Alto	19147	$21.37
Bremer	19017	$27.97	Hardin	19083	$17.71	Plymouth	19149	$20.29
Buchanan	19019	$17.44	Harrison	19085	$10.70	Pocahontas	19151	$3.93
Buena Vista	19021	$22.45	Henry	19087	$22.37	Polk	19153	$31.85
Butler	19023	$70.90	Howard	19089	$24.74	Pottawattamie	19155	$3.78
Calhoun	19025	$25.66	Humboldt	19091	$22.58	Poweshiek	19157	$10.06
Carroll	19027	$17.38	Ida	19093	$17.24	Ringgold	19159	$6.69
Cass	19029	$13.44	Iowa	19095	$41.23	Sac	19161	$32.52
Cedar	19031	$14.63	Jackson	19097	$4.33	Scott	19163	$7.31
Cerro Gordo	19033	$12.98	Jasper	19099	$6.49	Shelby	19165	$15.33
Cherokee	19035	$9.27	Jefferson	19101	$5.99	Sioux	19167	$18.06
Chickasaw	19037	$61.53	Johnson	19103	$10.59	Story	19169	$25.42
Clarke	19039	$15.60	Jones	19105	$5.96	Tama	19171	$5.22
Clay	19041	$24.62	Keokuk	19107	$22.79	Taylor	19173	$0.00
Clayton	19043	$6.50	Kossuth	19109	$27.54	Union	19175	$34.11
Clinton	19045	$16.38	Lee	19111	$8.56	Van Buren	19177	$7.51
Crawford	19047	$10.69	Linn	19113	$18.72	Wapello	19179	$24.37
Dallas	19049	$22.12	Louisa	19115	$7.82	Warren	19181	$30.34
Davis	19051	$6.51	Lucas	19117	$6.23	Washington	19183	$5.23
Decatur	19053	$13.70	Lyon	19119	$11.13	Wayne	19185	$10.68
Delaware	19055	$16.09	Madison	19121	$35.55	Webster	19187	$25.44
Des Moines	19057	$46.35	Mahaska	19123	$4.49	Winnebago	19189	$24.40
Dickinson	19059	$25.12	Marion	19125	$8.84	Winneshiek	19191	$7.68
Dubuque	19061	$12.14	Marshall	19127	$13.40	Woodbury	19193	$12.40
Emmet	19063	$16.03	Mills	19129	$17.53	Worth	19195	$30.08
Fayette	19065	$16.14	Mitchell	19131	$28.34	Wright	19197	$29.91

Table A.11. Continuous CRP average annual rental payment per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$127	Floyd	19067	$135	Monona	19133	$115
Adams	19003	$128	Franklin	19069	$154	Monroe	19135	$95
Allamakee	19005	$136	Fremont	19071	$129	Montgomery	19137	$129
Appanoose	19007	$91	Greene	19073	$156	Muscatine	19139	$146
Audubon	19009	$153	Grundy	19075	$170	O'Brien	19141	$147
Benton	19011	$157	Guthrie	19077	$150	Osceola	19143	$139
Black Hawk	19013	$162	Hamilton	19079	$170	Page	19145	$123
Boone	19015	$165	Hancock	19081	$160	Palo Alto	19147	$146
Bremer	19017	$160	Hardin	19083	$159	Plymouth	19149	$141
Buchanan	19019	$156	Harrison	19085	$129	Pocahontas	19151	$162
Buena Vista	19021	$164	Henry	19087	$128	Polk	19153	$166
Butler	19023	$159	Howard	19089	$131	Pottawattamie	19155	$146
Calhoun	19025	$168	Humboldt	19091	$166	Poweshiek	19157	$138
Carroll	19027	$154	Ida	19093	$151	Ringgold	19159	$103
Cass	19029	$145	Iowa	19095	$150	Sac	19161	$164
Cedar	19031	$180	Jackson	19097	$132	Scott	19163	$165
Cerro Gordo	19033	$155	Jasper	19099	$148	Shelby	19165	$146
Cherokee	19035	$160	Jefferson	19101	$125	Sioux	19167	$146
Chickasaw	19037	$133	Johnson	19103	$147	Story	19169	$170
Clarke	19039	$89	Jones	19105	$140	Tama	19171	$136
Clay	19041	$147	Keokuk	19107	$138	Taylor	19173	$121
Clayton	19043	$133	Kossuth	19109	$161	Union	19175	$113
Clinton	19045	$141	Lee	19111	$141	Van Buren	19177	$122
Crawford	19047	$158	Linn	19113	$151	Wapello	19179	$129
Dallas	19049	$160	Louisa	19115	$145	Warren	19181	$130
Davis	19051	$97	Lucas	19117	$102	Washington	19183	$146
Decatur	19053	$99	Lyon	19119	$125	Wayne	19185	$92
Delaware	19055	$164	Madison	19121	$114	Webster	19187	$176
Des Moines	19057	$145	Mahaska	19123	$141	Winnebago	19189	$151
Dickinson	19059	$138	Marion	19125	$118	Winneshiek	19191	$127
Dubuque	19061	$136	Marshall	19127	$154	Woodbury	19193	$130
Emmet	19063	$146	Mills	19129	$138	Worth	19195	$149
Fayette	19065	$158	Mitchell	19131	$127	Wright	19197	$169

Table A.12. General CRP average annual rental payment per acre.

County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost	County Name	FIP Code	Average Cost
Adair	19001	$90	Floyd	19067	$97	Monona	19133	$82
Adams	19003	$88	Franklin	19069	$109	Monroe	19135	$72
Allamakee	19005	$104	Fremont	19071	$90	Montgomery	19137	$87
Appanoose	19007	$70	Greene	19073	$107	Muscatine	19139	$106
Audubon	19009	$100	Grundy	19075	$122	O'Brien	19141	$95
Benton	19011	$102	Guthrie	19077	$95	Osceola	19143	$95
Black Hawk	19013	$100	Hamilton	19079	$114	Page	19145	$83
Boone	19015	$107	Hancock	19081	$103	Palo Alto	19147	$92
Bremer	19017	$94	Hardin	19083	$120	Plymouth	19149	$86
Buchanan	19019	$89	Harrison	19085	$94	Pocahontas	19151	$108
Buena Vista	19021	$110	Henry	19087	$96	Polk	19153	$112
Butler	19023	$106	Howard	19089	$99	Pottawattamie	19155	$97
Calhoun	19025	$117	Humboldt	19091	$101	Poweshiek	19157	$99
Carroll	19027	$99	Ida	19093	$99	Ringgold	19159	$68
Cass	19029	$97	Iowa	19095	$99	Sac	19161	$103
Cedar	19031	$122	Jackson	19097	$105	Scott	19163	$120
Cerro Gordo	19033	$104	Jasper	19099	$101	Shelby	19165	$96
Cherokee	19035	$104	Jefferson	19101	$92	Sioux	19167	$87
Chickasaw	19037	$97	Johnson	19103	$106	Story	19169	$116
Clarke	19039	$68	Jones	19105	$107	Tama	19171	$101
Clay	19041	$97	Keokuk	19107	$100	Taylor	19173	$78
Clayton	19043	$101	Kossuth	19109	$101	Union	19175	$81
Clinton	19045	$107	Lee	19111	$97	Van Buren	19177	$77
Crawford	19047	$104	Linn	19113	$105	Wapello	19179	$86
Dallas	19049	$106	Louisa	19115	$111	Warren	19181	$86
Davis	19051	$68	Lucas	19117	$72	Washington	19183	$113
Decatur	19053	$63	Lyon	19119	$84	Wayne	19185	$68
Delaware	19055	$105	Madison	19121	$80	Webster	19187	$122
Des Moines	19057	$102	Mahaska	19123	$105	Winnebago	19189	$99
Dickinson	19059	$101	Marion	19125	$85	Winneshiek	19191	$101
Dubuque	19061	$112	Marshall	19127	$101	Woodbury	19193	$90
Emmet	19063	$95	Mills	19129	$85	Worth	19195	$98
Fayette	19065	$110	Mitchell	19131	$95	Wright	19197	$108

Table A.13. Statewide average cost.

Practice	Statewide Average Cost
Grass Waterway	$2,127/acre
Terrace	$3.57/ft
Water & Sediment Control Basin	$3,989/structure
Grade Stabilization Structure	$15,018/structure
Filter Strip	$116.83/acre
Contour Buffer Strip	$78/acre
Riparian Forest Buffer	$486/acre
Wetland Restoration	$245/acre
Nutrient Management	$4.09/acre
Contour Farming*	$6/acre
No Till	$17.94/acre
Continuous CRP**	$142/acre
General CRP**	$97/acre

* Estimated cost of $6/acre only applies to locations where contour farming is practical.
** Values reported are average annual rental payment per acre.

Appendix B: SWAT model, calibration and validation

B.1 The Soil and Water Assessment Tool (SWAT)

SWAT is a hydrologic and water quality model developed by the U.S. Department of Agriculture (USDA) Agricultural Research Service (ARS). It is a long-term continuous watershed scale simulation model that operates on a daily time step and is designed to assess the impact of different management practices on water, sediment, and agricultural chemical yields. The model is physically based, computationally efficient, and capable of simulating a high level of spatial detail. Major model components include weather, hydrology, soil temperature, crop growth, nutrients, pesticides, and land management. In SWAT, a watershed is divided into multiple subwatersheds, which are further subdivided into unique soil/land use characteristics called hydrologic response units (HRUs). The water balance of each HRU is represented by four storage volumes: snow, soil profile, shallow aquifer, and deep aquifer. Flow generation, sediment yield, and pollutant loadings are summed across all HRUs in a subwatershed, and the resulting loads are then routed through channels, ponds, and/or reservoirs to the watershed outlet.

Surface runoff from daily rainfall is estimated with the modified SCS curve number method (Mishra and Singh, 2003), which estimates the amount of runoff based on local land use, soil type, and antecedent moisture condition. The Green-Ampt method (Green and Ampt, 1911) of estimating infiltration is an alternative option of estimating surface runoff and infiltration that requires sub-daily weather data. Melted snow is treated the same as rainfall for estimating runoff and percolation. Channel routing is simulated using either the variable-storage method or the Muskingum method; both methods are variations of the kinematic wave model (Chow et al., 1988). Three methods of estimating

potential evapotranspiration are available: Priestley-Taylor (Priestley and Taylor, 1972), Hargreaves (Hargreaves and Samani, 1985), and Penman-Monteith (Allen et al., 1989). Figure B.1 depicts a complete SWAT hydrologic picture, adapted from Arnold et al., (1998).

Erosion and sediment yield are estimated for each HRU with the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1995). The channel sediment routing equation uses a modification of Bagnold's sediment transport equation (Bagnold, 1977), which estimates the transport concentration capacity as a function of velocity. The model either deposits excess sediment or re-entrains sediment through channel erosion depending on the sediment load entering the channel.

A generic crop growth submodel used in SWAT is a simplified version of the crop growth functions developed for the Environmental Impact Policy Climate (EPIC) model (Arnold and Forher, 2005; Gassman et al., 2007). A wide range of crop rotations can be simulated in the model, as well as different grassland and forest systems. Yields and/or biomass output are estimated at the HRU level in SWAT. SWAT simulates the complete nutrient cycle for nitrogen and phosphorus. The nitrogen cycle is simulated using five different pools; two are inorganic forms (ammonium and nitrate) while the other three are organic forms: fresh, stable, and active (Figure B.2). Similarly, SWAT monitors six different pools of phosphorus in soil; three are inorganic forms and the rest are organic forms (Figure B.3). Mineralization, decomposition, and immobilization are important parts in both cycles. These processes are allowed to occur only when the temperature of the soil layer exceeds 0ºC.

Nitrate export from runoff, lateral flow, and percolation are estimated as products of the volume of water and the average concentration of nitrate in the soil layer. Organic N and Organic P transport with sediment is calculated with a loading function developed by McElroy et al. (1976) and modified by Williams and Hann (1978) for application to individual runoff events. The loading function estimates daily Org N and P runoff loss based on the concentrations of constituents in the top soil layer, the sediment yield, and an enrichment ratio. The amount of soluble P removed in runoff is predicted using labile P concentration in the top 10 mm of the soil, the runoff volume, and a phosphorus soil partitioning coefficient. In-stream nutrient dynamics are simulated in SWAT using the kinetic routines from the QUAL2E in-stream water quality model (Brown and Barnwell, 1987).

A detailed theoretical description of SWAT and its major components can be found in Neitsch et al. (2002). SWAT has been widely validated across the U.S. and in other regions of the world for a variety of applications, including hydrologic, pollutant loss, and climate change studies. An extensive set of SWAT applications are documented in Gassman et al. (2005; 2007).

B.2 Calibration and validation: Hydrology and streamflow

Calibration and validation of water quality models are typically performed with data collected at the outlet of a watershed. Daily streamflow data were collected from the U.S. Geological Survey (USGS) website (http://www.waterdata.usgs.gov/usa/nwis/discharge). Table B.1 lists all USGS gauging stations, which were used for the calibration and validation of the SWAT model for streamflow.

The calibration process was initiated by calibrating the water balance and streamflow for average annual conditions. Once the water balance and annual streamflow were considered correctly calibrated, the monthly calibration process was performed. Baseflow is an important component of the streamflow and had to be calibrated before the model was fully calibrated for streamflow and other components. An automated digital filter technique (Arnold and Allen, 1999) was used to separate baseflow from the measured streamflow. This approach estimated the baseflow to be centered on 60% for most of the watersheds except for Nodaway and Skunk where it is around 50% of the streamflow on an average annual basis for the period 1986 to 2005. SWAT was then executed for a total simulation period of 20 years, which includes 1986-1995 as a calibration period and 1996-2005 as a validation period. Parameter adjustment was performed only during the calibration period; the validation process was performed by simply executing the model for the different time period using the previously calibrated input parameters. The streamflow calibration process varied several SWAT hydrologic calibration parameters within their acceptable ranges to match the model predicted baseflow fraction, average annual streamflow, and monthly streamflow time series with corresponding measured values. These parameters include the curve number (CN2), soil available water capacity (SOL_AWC), evaporation compensation coefficient (ESCO), groundwater delay (GW_DELAY), groundwater recession coefficient (GW_ALPHA), surface runoff lag coefficient (SURLAG), and snow parameters. A model was also attempted to calibrate for the daily streamflow.

The model predictions were evaluated for both the calibration and validation periods using two statistical measures: coefficient of determination (R^2) and Nash-

Sutcliffe simulation efficiency (E). The R^2 value is an indicator of strength of relationship between the measured and simulated values. The E value measures how well the simulated values agree with the measured values. The model prediction is considered unacceptable if the R^2 values are close to zero and the E values are less than or close to zero. If the values equal one, the model predictions are considered perfect. Generally, R^2 and E values greater than 0.5 are considered acceptable; however, explicit standards have not been specified for assessing model predictions using these statistics. Statistical evaluation of the streamflow simulation underscore that SWAT accurately replicated the streamflows for each watershed in both the calibration and validation periods. Results of the calibration and validation of the SWAT model for streamflow for all 13 watersheds are presented at the end of this appendix.

B.3 Calibration and validation: Water quality

Water quality data such as nitrate, Org N, Org P, and Min P were collected from the Environmental Protection Agency (EPA) database called STORET (STOrage and RETrieval) (http://www.igsb.uiowa.edu/storet). Iowa's STORET database is managed by the water monitoring section of the Iowa Geological Survey Bureau. These water quality samples have been collected under the Enhanced Ambient Surface Water Monitoring program from 2000 on a monthly basis. Table B.2 lists STORET water quality measurement sites that were used in this study for the calibration and validation of the SWAT model for water quality parameters for all 13 Iowa watersheds. All STORET stations may not necessarily be at the watershed outlet all the time. So, the regression equations were developed at stations that are closed to the watershed outlets. Then, these

equations were used in conjunction with the streamflow data at the watershed outlet to estimate water quality data at the watershed outlet and were used in the model verification.

These monthly samples of water quality data were extrapolated into continuous monthly data using the U.S. Geological Survey (USGS) Load Estimator (LOADEST) regression model (Runkel et al., 2004). LOADEST estimates constituent loads in streams and rivers by developing a regression model, given a time series of streamflow, constituent concentration, and additional data inputs. LOADEST is based on two previous models: LOADEST2 (Crawford, 1996) and ESTIMATOR (Cohn et al., 1989). The model is well documented in scientific publications and is accepted as a valid means of calculating annual solute load from a limited number of water quality measurements. However, the load estimation process of the model is complicated by retransformation bias, data censoring, and non-normality. Similar uncertainties are also inherent in other approaches. For example, Ferguson (1986) reported that the rating curve estimates of instantaneous load are biased and may underestimate the true load by as much as 50%.

There are a lot of uncertainties associated with the measured water quality data in addition to the error associated with the measurement process. First of all, measurement data were not available at the watershed outlet and so needed to be extrapolated. Furthermore, once-a-month samples were used to generate continuous monthly and then annual water quality data. Therefore, this study did not attempt to calibrate and validate the SWAT model based on the measured water quality data, but attempted to verify the model prediction with seasonal trends and annual totals. Nutrient calibration parameters were adjusted to bring annual totals of the simulated values into close agreement with the measured data. Model parameters used in the calibration were initial soil nutrient

concentrations, biological mixing efficiencies, nitrogen and phosphorus percolation coefficients, phosphorus soil partitioning coefficient, residue decomposition factor, and in-stream nutrient transformation parameters.

Table B.1. USGS gauging stations used in the SWAT streamflow calibration.

Watershed	USGS station #	USGS station name	Latitude	Longitude	Drainage Area (km2)
Boyer	6609500	Boyer River at Logan, IA	41.6425	-95.7828	2,256
Des Moines	5490500	Des Moines River at Keosauqua, IA	40.7278	-91.9596	36,358
Floyd	6600500	Floyd River at James, IA	42.5767	-96.3114	2,295
Iowa	5465500	Iowa River at Wapello, IA	41.1781	-91.1821	32,375
Little Sioux	6607500	Little Sioux River near Turin, IA	41.9644	-95.9728	9,132
Maquoketa	5418500	Maquoketa River near Maquoketa, IA	42.0834	-90.6329	4,022
Monona	6602400	Monona-Harrison Ditch near Turin, IA	41.9644	-95.992	2,331
Nishnabotna	6810000	Nishnabotna River above Hamburg, IA	40.6325	-95.6256	7,268
Nodawy	6817000	Nodaway River at Clarinda, IA	40.7394	-95.013	1,974
Skunk	5474000	Skunk River at Augusta, IA	40.7537	-91.2761	11,168
Turkey	5412500	Turkey River at Garber, IA	42.74	-91.2618	4,002
Upper Iowa	5388250	Upper Iowa River near Dorchester, IA	43.4211	-91.5088	1,994
Wapsipinicon	5422000	Wapsipinicon River near De Witt, IA	41.767	-90.5349	6,050

Table B.2. STORET water quality measurement stations points used in this study.

Watershed	STORET ID #	STORET station name
Boyer	10430001	Boyer River near Missouri Valley
Des Moines	10560001	Des Moines River near Keokuk
Floyd	10750001	Floyd River near Sioux City
Iowa	10580001	Iowa River at Columbus Junction
Little Sioux	10970001	Little Sioux River near Smithland
Maquoketa	10490002	Maquoketa River near Maquoketa
Monona	10670001	Monona-Harrison Ditch
Nishnabotna	10360001	East Nishnabotna River near Shenandoah
Nodaway	10730001	West Nodaway River near Shambaugh
Skunk	10620001	South Skunk River near Oskaloosa
Turkey	10220001	Turkey River near Garber
Upper Iowa	10030001	Upper Iowa River near Dorchester
Wapsipinicon	10820001	Wapsipinicon River at De Witt

Figure B.1. Hydrologic flow chart of SWAT model.

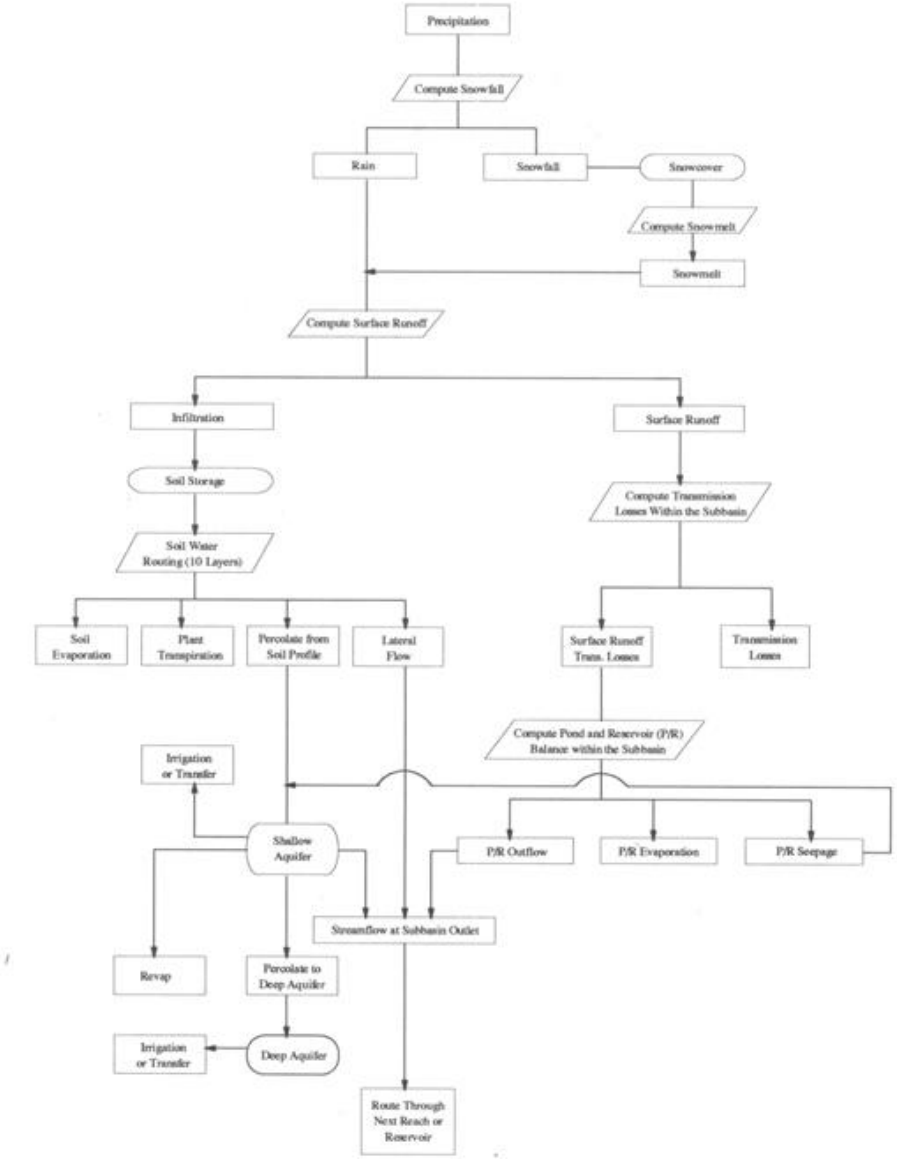


Figure B.2. Nitrogen cycle as simulated in SWAT (adapted from SWAT Theoretical Document).

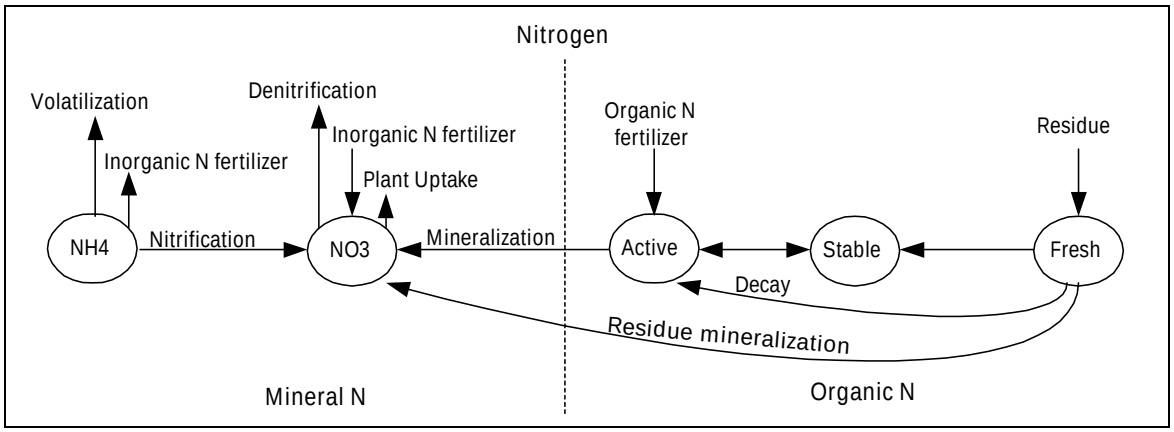
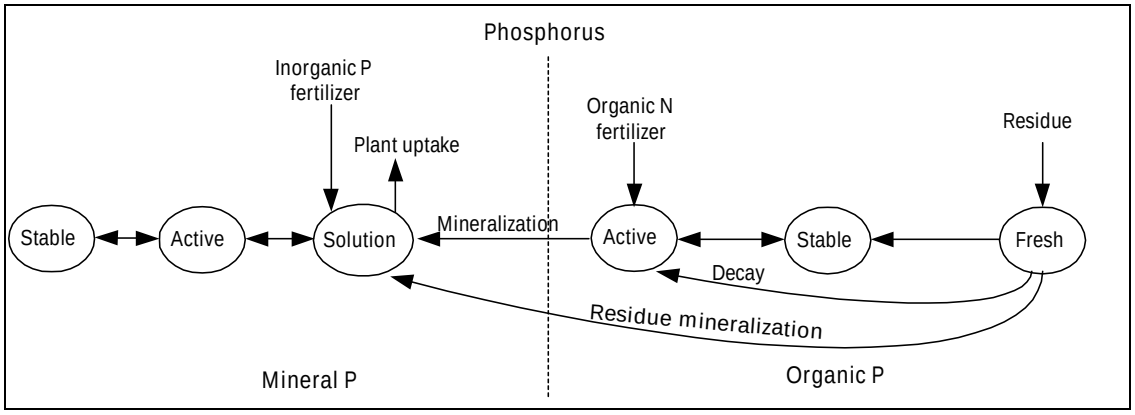


Figure B.3. Phosphorus cycle as simulated in SWAT (adapted from SWAT Theoretical Document).

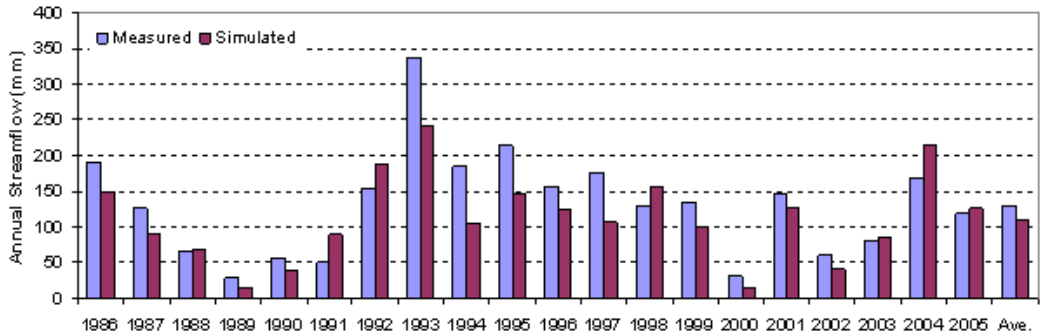


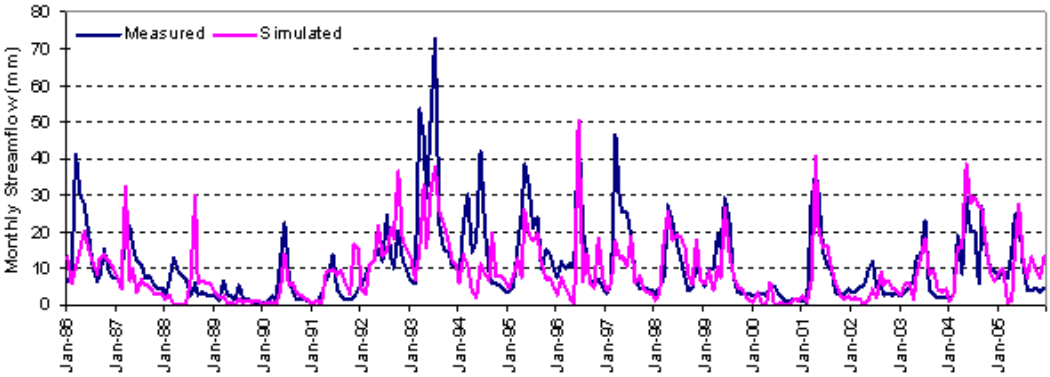
SWAT2005 calibration (1986-1995) and validation (1996-2005) results for all 13 Iowa watersheds.

Table B.3. Statistical evaluation of the SWAT2005 streamflow calibration and validation results.

	Statistical Evaluation							
	Annual				Monthly			
Iowa Watersheds	Calibration (1986-1995)		Validation (1996-2005)		Calibration (1986-1995)		Validation (1996-2005)	
	R^2	E	R^2	E	R^2	E	R^2	E
Boyer	0.89	0.84	0.8	0.78	0.68	0.66	0.75	0.75
Des Moines	0.98	0.92	0.78	0.65	0.81	0.78	0.67	0.65
Floyd	0.8	0.68	0.64	0.46	0.45	0.41	0.59	0.55
Iowa	0.98	0.97	0.63	0.88	0.84	0.83	0.69	0.74
Little Sioux	0.9	0.88	0.71	0.46	0.72	0.69	0.75	0.59
Maquoketa	0.91	0.89	0.83	0.74	0.79	0.79	0.77	0.76
Monona	0.86	0.83	0.49	0.52	0.55	0.51	0.52	0.4
Nishnabotna	0.95	0.94	0.88	0.84	0.73	0.72	0.84	0.83
Nodaway	0.9	0.9	0.9	0.88	0.8	0.79	0.84	0.82
Skunk	0.99	0.98	0.98	0.95	0.93	0.93	0.87	0.87
Turkey	0.95	0.92	0.88	0.8	0.8	0.79	0.73	0.71
Upper Iowa	0.88	0.83	0.65	0.52	0.81	0.79	0.7	0.59
Wapsipinicon	0.96	0.95	0.65	0.92	0.87	0.86	0.89	0.88

1. Floyd





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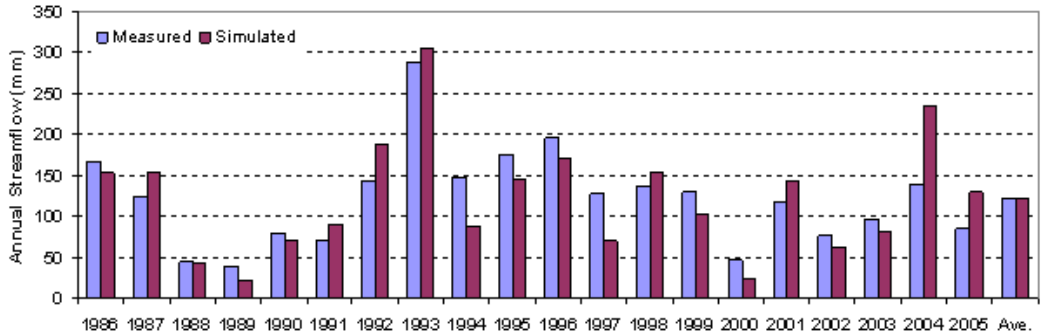

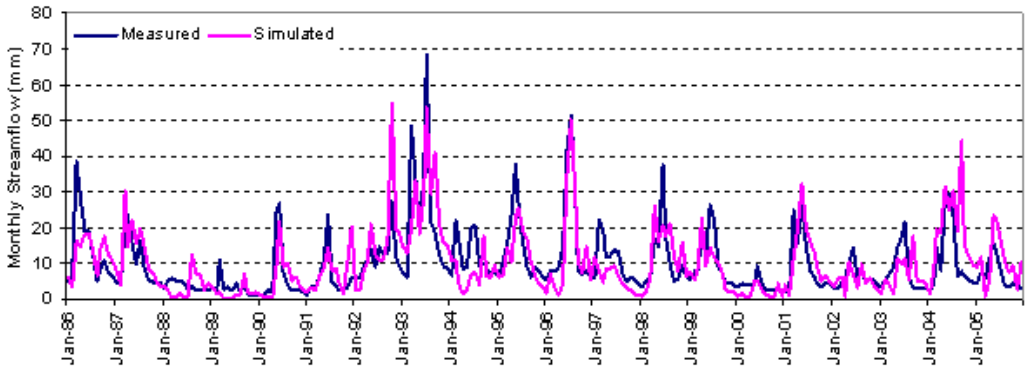

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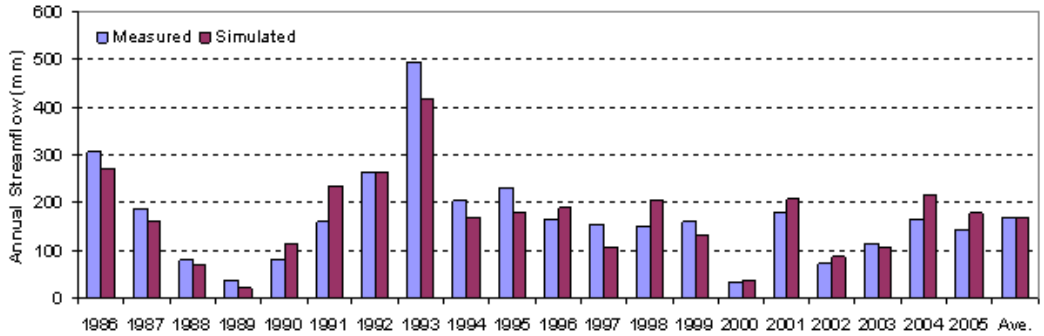
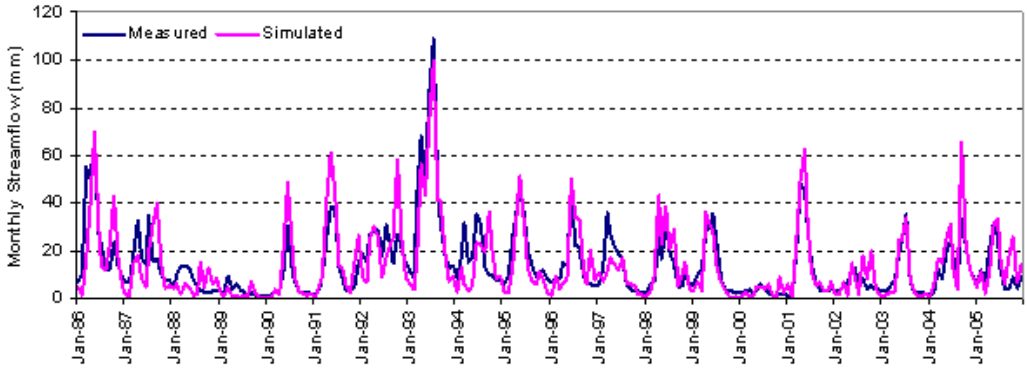
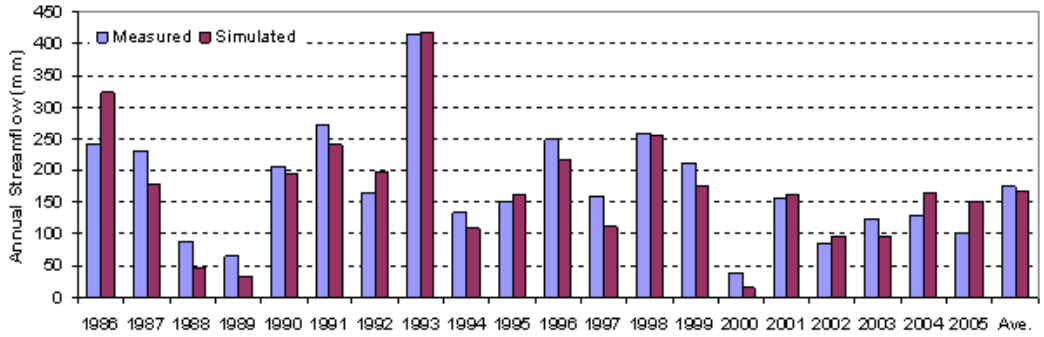
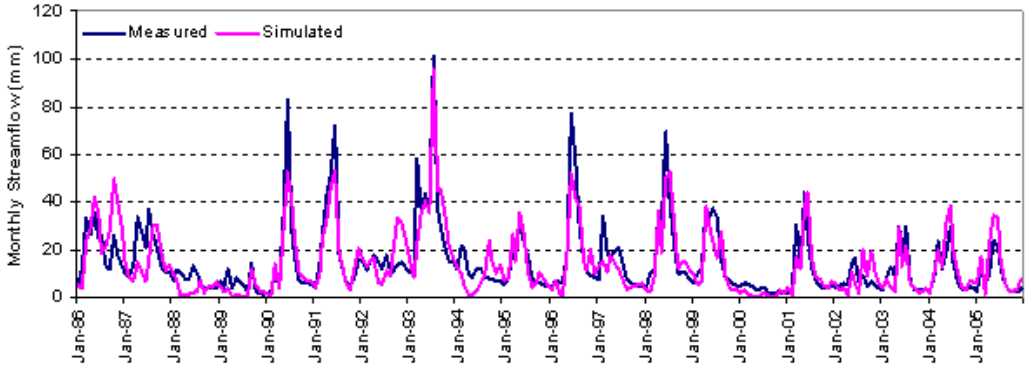


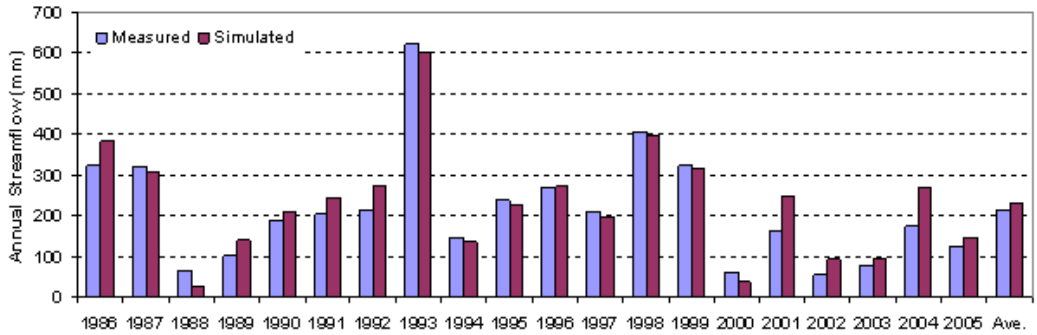


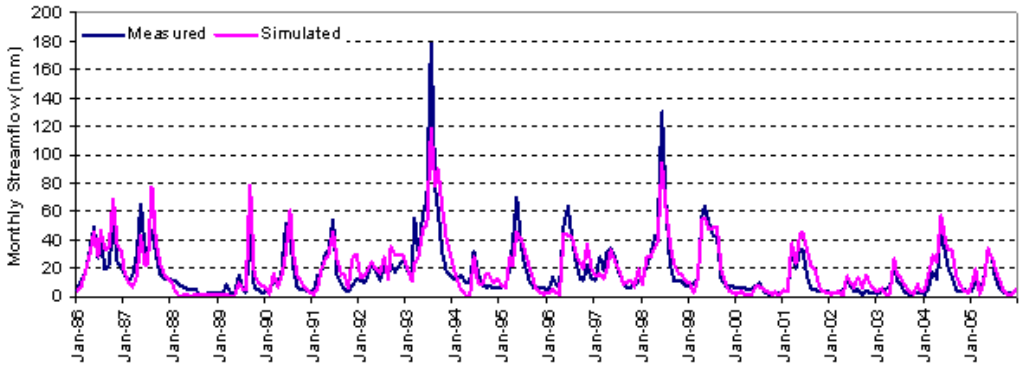
4. Boyer



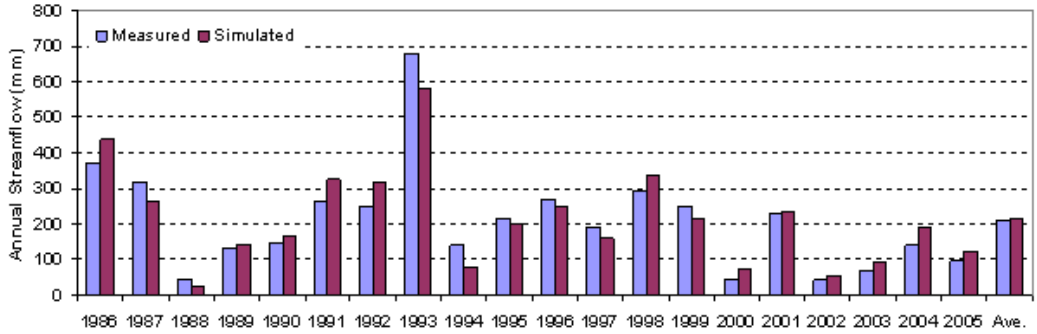


5. Nishnabotna




Measured
Simulated
Monthly Streamflow (mm)
200
180
160
140
120
100
80
60
40
20
0
Jan-86
Jan-87
Jan-88
Jan-89
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
Jan-02
Jan-03
Jan-04
Jan-05

6. Nodaway


Measured
Simulated
Annual Streamflow (mm)
800
700
600
500
400
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200
100
0
1986
1987
1988
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1991
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1993
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2000
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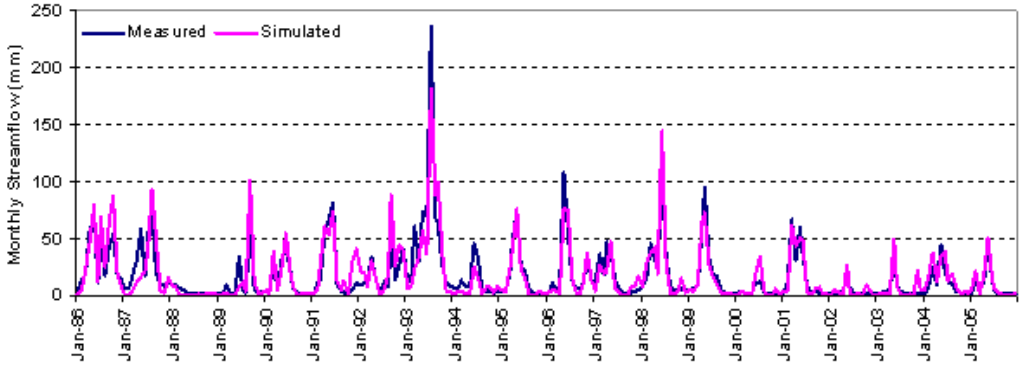
2004
2005
Ave.


Measured
Simulated
Monthly Streamflow (mm)
250
200
150
100
50
0
Jan-86
Jan-87
Jan-88
Jan-89
Jan-90
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Jan-94
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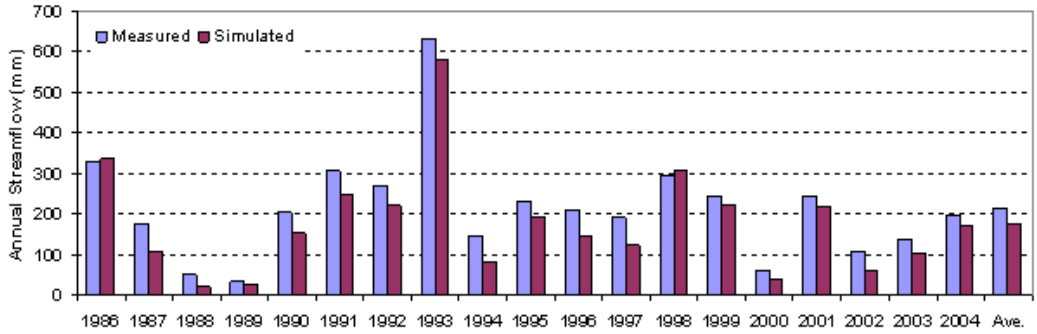
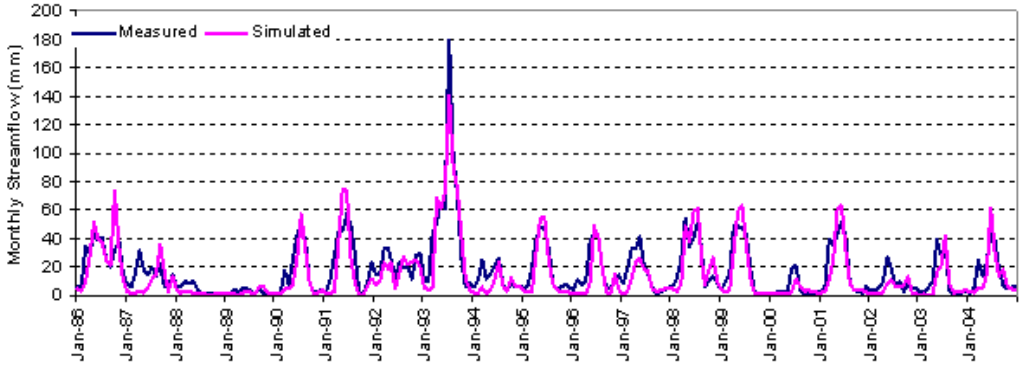
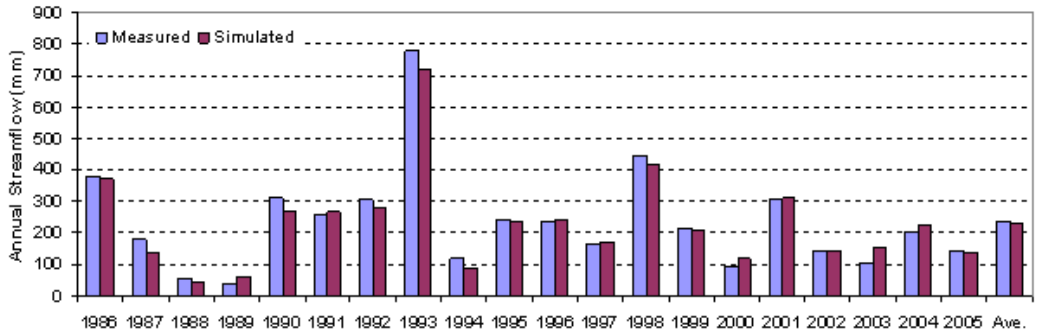
Jan-03
Jan-04
Jan-05

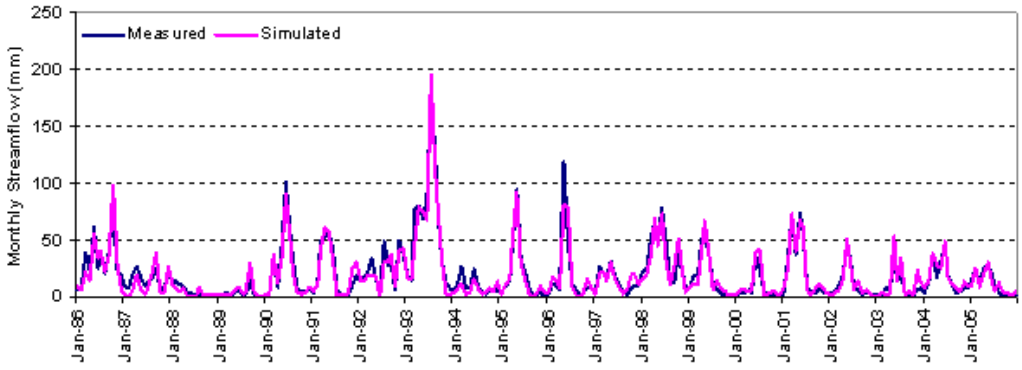
7. Des Moines



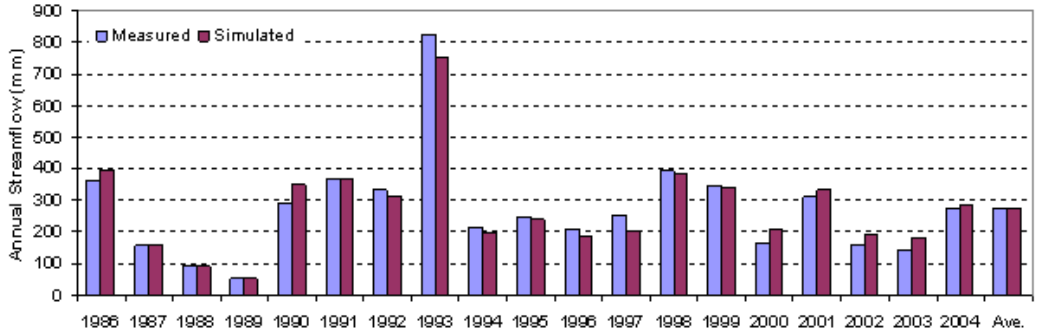


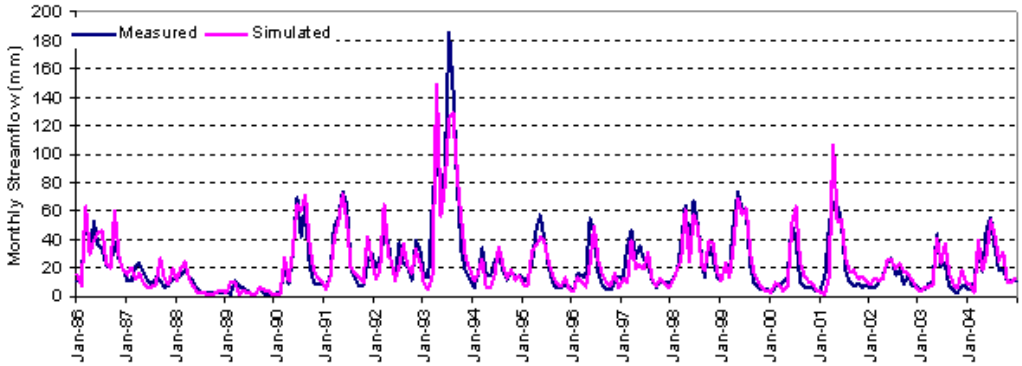
8. Skunk



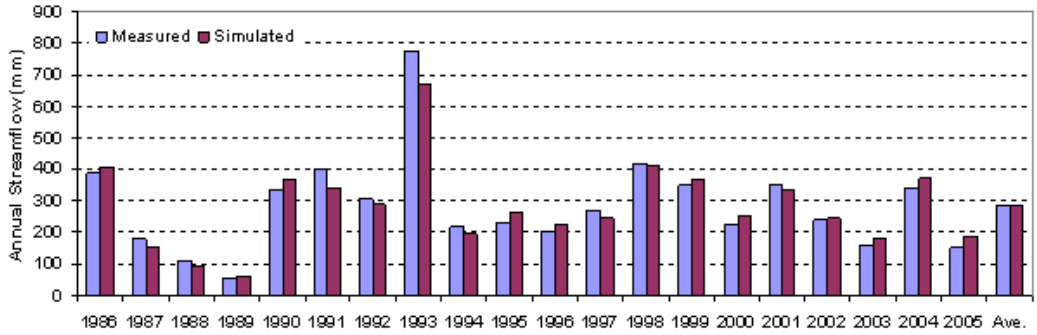


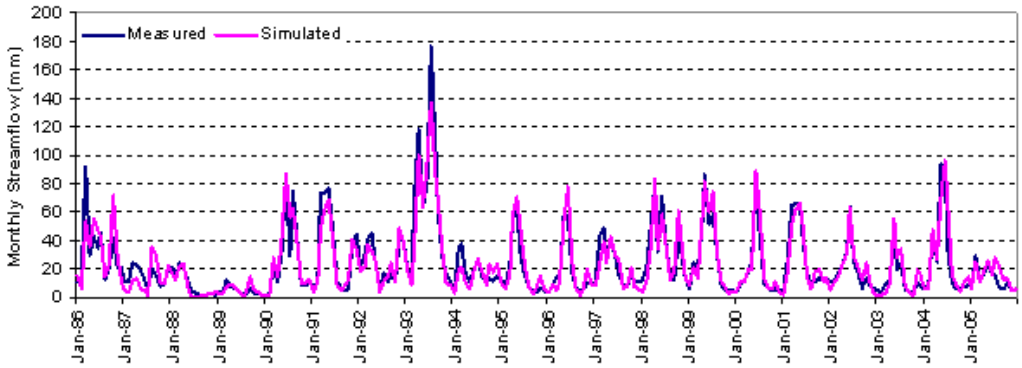
9. Iowa



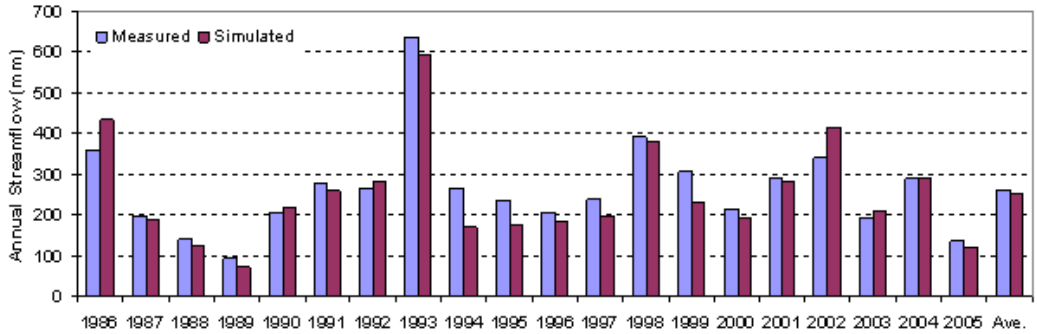


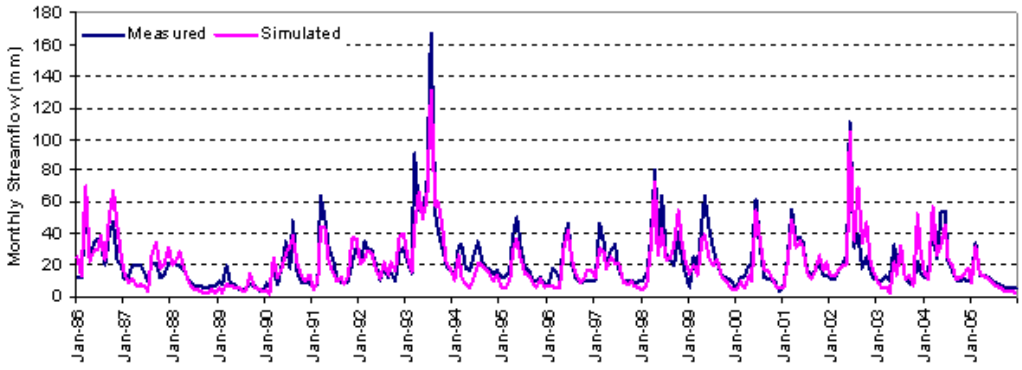
10. Wapsipinicon



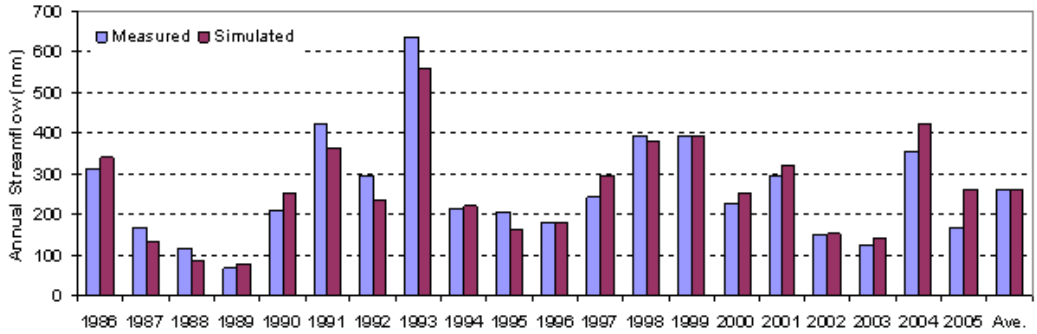


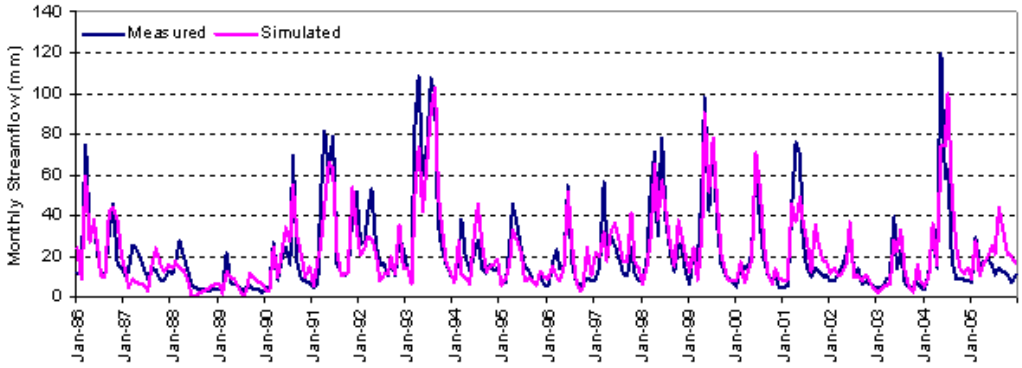
11. Maquoketa



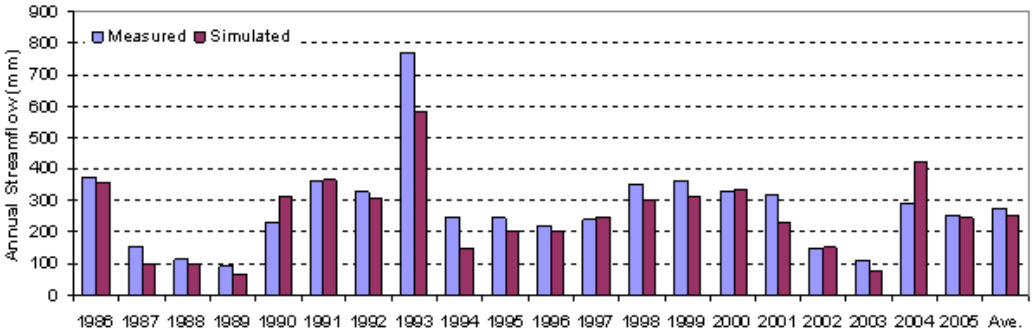


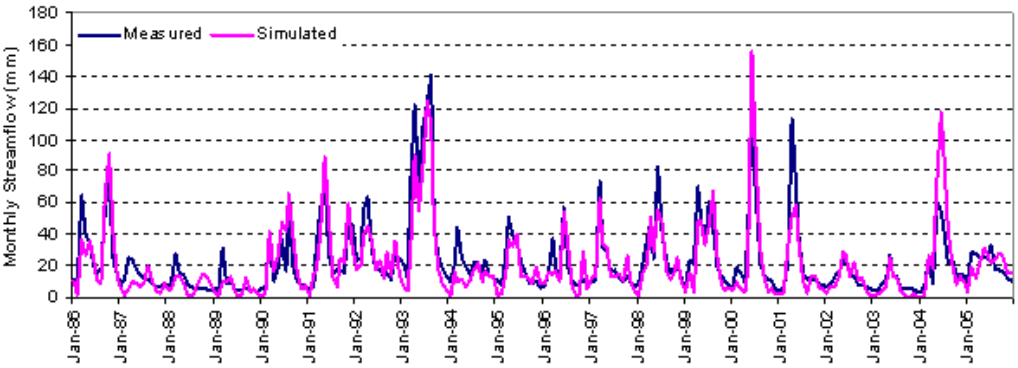
12. Turkey





13. Upper Iowa


Measured
Simulated
Annual Streamflow (mm)
900
800
700
600
500
400
300
200
100
0
1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 Ave.


Measured
Simulated
Monthly Streamflow (mm)
180
160
140
120
100
80
60
40
20
0
Jan-86 Jan-87 Jan-88 Jan-89 Jan-90 Jan-91 Jan-92 Jan-93 Jan-94 Jan-95 Jan-96 Jan-97 Jan-98 Jan-99 Jan-00 Jan-01 Jan-02 Jan-03 Jan-04 Jan-05

Appendix C: More description on the evolutionary algorithm

Beginning in 1950s and 1960s computer scientists came to a realization that the theory of biological evolution can be used as an optimization tool for engineering problems. Since the field of evolutionary computation owes its origins to observations of biological evolution, the terminology used has its analogs in biology, although typically the entities used to describe an optimization problem are much simpler than the real biological entities bearing the same name. A *genome* (or a *chromosome*) refers to a complete collection of *genes* and fully describes an *individual* (typically, a candidate solution in an optimization problem). A set of possible values that any gene can take is referred to as an *allele set*, or *alphabet.* Often, a genome representing a candidate solution is a one-dimensional array, or vector. A gene then is an element of this array and encodes a particular element of a candidate solution. A value of a gene comes from its allele set, also a vector. Analogous to haploid organisms in real biology, *offspring* is created from two parent individuals. During sexual reproduction, *recombination* (*crossover*) occurs: the offspring's genome consists of portions of each of the two parents' genomes. As in biological evolution, offspring are subject to *mutation:* a random substitution of a gene's value with a value from its allele set.

In many applications of evolutionary algorithms to spatial optimization (including this one), a genome is a vector of length F, where F is the number of spatial decision-making units (fields). Each element of the vector (gene) represents a field, with its value coming from the allele set A, and encoding a particular land use option. The allele set is typically the same for all genes. Figure C.1 presents a schematic representation of a particular genome, or individual.

Finally, as in biological evolution, individuals at every *generation* form *populations*, and are characterized by their *fitness*—a score which measures how well each individual is solving the optimization problem at hand (for example, a value of an objective function). Individuals possessing higher fitness scores are more likely to be selected for reproduction and therefore are more likely to pass along the characteristics associated with the candidate solutions they represent.

While there are many variations of evolutionary algorithms, most that can be called "genetic algorithms" have the following elements in common: populations of individual solutions, selection for reproduction according to fitness levels, crossover to produce new solutions (offspring), and random mutation of new offspring.

There is no strict theoretical guidance as to what are the optimization problems that evolutionary algorithms can attempt to solve; however, most researchers agree that the following characteristics of a problem make it a good candidate for evolutionary-based solution techniques: a) a large search space, which is not smooth or unimodal (or is not well understood), and b) acceptability of sufficiently good approximations (i.e., not needing to find the global solution exactly) (based on Mitchell, 1996). A problem of cost-efficient watershed management appears to fit the criteria outlined. The combinatorial nature of the spatial problem makes for a very large search space, and, given the complexity of the problem, a good approximation to the solution is in itself a worthwhile goal.

One of the earlier applications of genetic algorithms to watershed management is one by Srivastava et al. (2002). The authors use a genetic algorithm to allocate 45 fields to 15 mutually exclusive best management practices (BMPs), combine water pollution and

agricultural net returns into the fitness score, and discover a spatial allocation that reduced pollutant loads by 56% relative to the baseline of the worst-case scenario, while simultaneously increasing net returns by 109%.

Veith, Wolfe, and Heatwole (2003) minimize costs subject to sediment reduction target by proceeding lexicographically—first, minimize pollution; then, when pollution target is reached, minimize costs. Cost minimization is done under an additional constraint of "equitable" distribution of control costs over farms. In a later study, Veith, Wolfe, and Heatwole (2004) compare solutions obtained using a genetic algorithm to solutions obtained by targeting land based on slope and find that optimization reduces costs of sediment reduction from $42 per kg/ha to $36 per kg/ha. Such findings emphasize the fact that for any watershed problem, the returns to using a systematic search technique such as a genetic algorithm are likely to be significant.

One particular class of search algorithms appears to be particularly useful for identifying Pareto-optimal frontiers for competing objectives. Multiobjective optimization evolutionary algorithms (MOEAs) provide a particularly useful way to search for entire sets of cost-efficient nonpoint source pollution reduction strategies.

While most applications of evolutionary algorithms to the problem of watershed management have been limited to finding single cost-efficient pollution reduction solutions, recently some researchers have also utilized multi-objective methods. Muleta and Nicklow (2002) combine a previous version of the MOEA used in this study, SPEA, with a hydrologic model to look for Pareto-optimal frontiers for each spatial decision-making unit in the watershed. In a later study, Muleta and Nicklow (2005) subsequently focus more on the watershed scale and develop an approximation a genetic algorithm to

identify the spatial units that would maximize the benefit-to-cost ratio (where benefits are measured as sediment reductions), subject to an exogenously specified constraint of only 10% of land in the watershed being allocated for sediment reduction. Lant, Kraft, Beaulieu, Bennett, Loftus, and Nicklow (2005) model a watershed as a complex adaptive human ecosystem and incorporate an evolutionary algorithm to provide an approximation to the optimal set of trade-offs between an index of ecosystem services and returns from agricultural production for a small watershed in Illinois by considering land retirement as an option at farm scale. The current work differs from these studies in several respects. First, it searches explicitly for a watershed-scale Pareto-frontier, considering multiple options at the individual spatial decision-making unit.[1] Also, the geographic scale analyzed in this paper is significantly larger than any of the previous attempts. Second, this paper presents a first application of MOEAs to considering potentially conflicting environmental criteria in addition to the pollution control cost criterion.

The following section describes the logic of a multiobjective optimization problem and a particular MOEA used in this paper.

A general multiobjective optimization problem can be described as a vector function f that maps a tuple of m parameters (decision variables) to a tuple of n objectives (Zitzler and Thiele, 1999). Framing the problem as one of minimization (keeping in mind the application to "bads" such as cost or pollution), a typical multiobjective optimization problem is to minimize

(0.1) $$\mathbf{y} = f(\mathbf{x}) = \left(f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_n(\mathbf{x}) \right)$$

[1] J. Whittaker of USDA-ARS in Oregon and coauthors are working on a multiobjective optimization model on a watershed scale using an MOEA called NSGA-II. However, details of their study are not available at this time.

subject to

(0.2) $$\mathbf{x} = (x_1, x_2, \ldots, x_m) \in X$$

(0.3) $$\mathbf{y} = (y_1, y_2, \ldots, y_m) \in Y,$$

where $\mathbf{x}$ is called the *decision vector,* X is the *parameter space,* $\mathbf{y}$ is the *objective vector,* and Y is the *objective space.* The set of solutions to the multiobjective optimization problem consists of all decision vectors that are Pareto-optimal. A decision vector $\mathbf{a}$ is Pareto-optimal if there is no $\tilde{\mathbf{a}} \in X$ such that $f_i(\tilde{\mathbf{a}}) \leq f_i(\mathbf{a})$, $\forall i \in \{1, 2, \ldots, n\}$, and $\exists j \in \{1, 2, \ldots, n\}: f_j(\tilde{\mathbf{a}}) < f_j(\mathbf{a})$. The decision vectors that are nondominated within the entire search space constitute the Pareto-optimal set, or frontier. Over the last decade, several MOEAs have been suggested (see, e.g., Deb et al., 2000). One advantage of all MOEAs is that they are capable of searching for multiple Pareto-efficient solutions in a single optimization run.

In this paper, we use a modification of the Strength Pareto Evolutionary Algorithm 2 (SPEA2), proposed by Zitzler and Thiele (2002). As in genetic algorithms (GA), the search process starts with a population of candidate solutions from which a new population is created by the process of selection, crossover, and mutation. Unlike in the GA, the fitness score of each individual $\mathbf{i}$ in the population is now a function of how many other individuals in the population $\mathbf{i}$ dominates (in the sense of Pareto) and by how many individuals are dominated by $\mathbf{i}$. Furthermore, the algorithm takes into account the degree of "crowding" around $\mathbf{i}$ in order to preserve the diversity in the population and to cover as much as possible with the resulting Pareto-optimal frontier. The following discussion is framed in terms of fitness score minimization, following Zitzler and Thiele (2002).

To be specific, an individual $\mathbf{i}$ is assigned a strength value $S(\mathbf{i})$ which equals the number of solutions it dominates:

(0.4) $$S(\mathbf{i}) = \left|\{\mathbf{j} \mid \mathbf{j} \in \mathbf{P}_t \cup \overline{\mathbf{P}}_t \wedge \mathbf{i} \succ \mathbf{j}\}\right|,$$

where $\overline{\mathbf{P}}_t$ is the original population at generation t, $\mathbf{P}_t$ is the temporary population created, $|\cdot|$ denotes the cardinality of a set, and $\succ$ corresponds to the Pareto dominance relation. On the basis of this definition of strength values, the raw fitness for individual $\mathbf{i}$ is calculated:

(0.5) $$R(\mathbf{i}) = \sum_{\mathbf{j} \in \mathbf{P}_t \cup \overline{\mathbf{P}}_t, \mathbf{j} \succ \mathbf{i}} S(\mathbf{j}).$$

Thus, the raw fitness of an individual is determined by the strength of the dominators (individuals that dominate $\mathbf{i}$). Then, the raw fitness value of $R(\mathbf{i}) = 0$ corresponds to a nondominated individual, while a high raw fitness value corresponds to an individual that is dominated by many other individuals (which in turn dominate other individuals). In light of this interpretation, fitness minimization used in the formulation of the algorithm makes intuitive sense. Figure C.2 demonstrates the fitness assignment process and highlights the fact that individuals that are located in the "crowded" areas of the objective space get a higher raw fitness value and therefore are less likely to be selected into a future generation. For instance, point F dominates points B, C, and A, and therefore gets a strength value of 3. Since point F is nondominated, its raw fitness is zero. Point D, on the other hand, dominates only A and thus gets the strength value of one but is dominated by point G, which itself dominates 3 points. Thus, point D gets the raw fitness value of 3. Point A is the "worst" point in the objective space, as it is associated with the highest cost and pollution levels. It itself does not dominate any other points but is dominated by points F, G (with a strength value of 3), H (with a strength value of 2), D (with a strength

value of 1), and E (with a strength value of 1). Therefore, the raw fitness value for point A is 3+3+2+1+1=10. Recalling that in this algorithm, individuals with the lower fitness scores are considered "more fit," it is clear that individual A is far less likely to survive into the next generation than, for example, point F.

Such assignment of raw fitness scores also takes into account the relative "isolatedness" of candidate solutions in the objective space. Conceptually, we would like the resulting Pareto-optimal frontier to span a large portion of the objective space. Therefore, candidate solutions on the interior of the frontier are somewhat less preferred than those close to the edges. In the figure, for example, while both points B and C are dominated, point C is dominated by both points F and G by virtue of its "interior" location in the objective space; whereas point B is dominated only by point F and not by point G: its pollution level is lower than that of G. As a result, point B has a raw fitness score of 3 as opposed to the score of 6 for C, and its "genetic makeup" is therefore less likely to be eliminated in the subsequent generations.

Finally, while the raw fitness score assignment outlined above incorporates some information on the location of the solutions in the solution space, additional density information is also incorporated into the calculation of a fitness score. A density estimation technique is used to further differentiate between individuals that are located in the "crowded" areas of the objective space (less preferred) from those located in the relatively sparse areas of the objective space (more preferred). The density estimation technique used in SPEA2 is an adaptation of the k-th nearest neighbor method, where the density at any point is a decreasing function of the distance to the k-th nearest data point. For each individual $\mathbf{i}$, we calculate the distances (in objective space) to all the individuals

in the population and the temporary population and store them in a list. After sorting the list in an increasing order, the k-th element yields the distance, denoted as $\sigma_{\mathbf{i}}^{k}$. k is chosen to equal the square root of the sum of the population size and the size of the temporary population. The density is computed as

(0.6) $$D(i) = \frac{1}{\sigma_{\mathbf{i}}^{k} + 2},$$

where 2 is added to the denominator to ensure that the value of the density is greater than zero and less than one.

Given the raw fitness score and the estimated density, the fitness of an individual $\mathbf{i}$ is calculated as

(0.7) $$F(\mathbf{i}) = R(\mathbf{i}) + D(\mathbf{i}).$$

This is the fitness score used for selecting individuals in the algorithm implemented.[2]

[2] Actually, in order to preserve the logic of the original GA library, which was set up for fitness score maximization, we use K-fitness score as the actual fitness score in the code, where K=100000.

Figure C.1 A candidate solution (genome) and its relationship to the allele set.

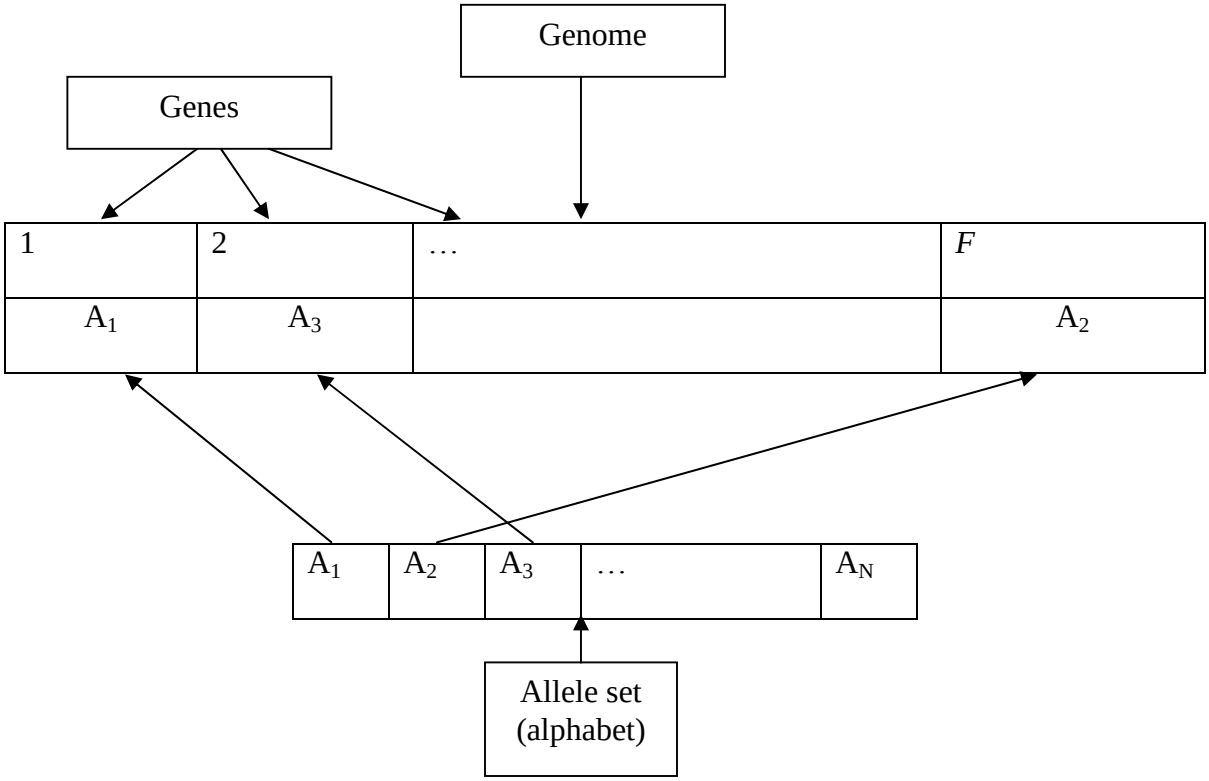
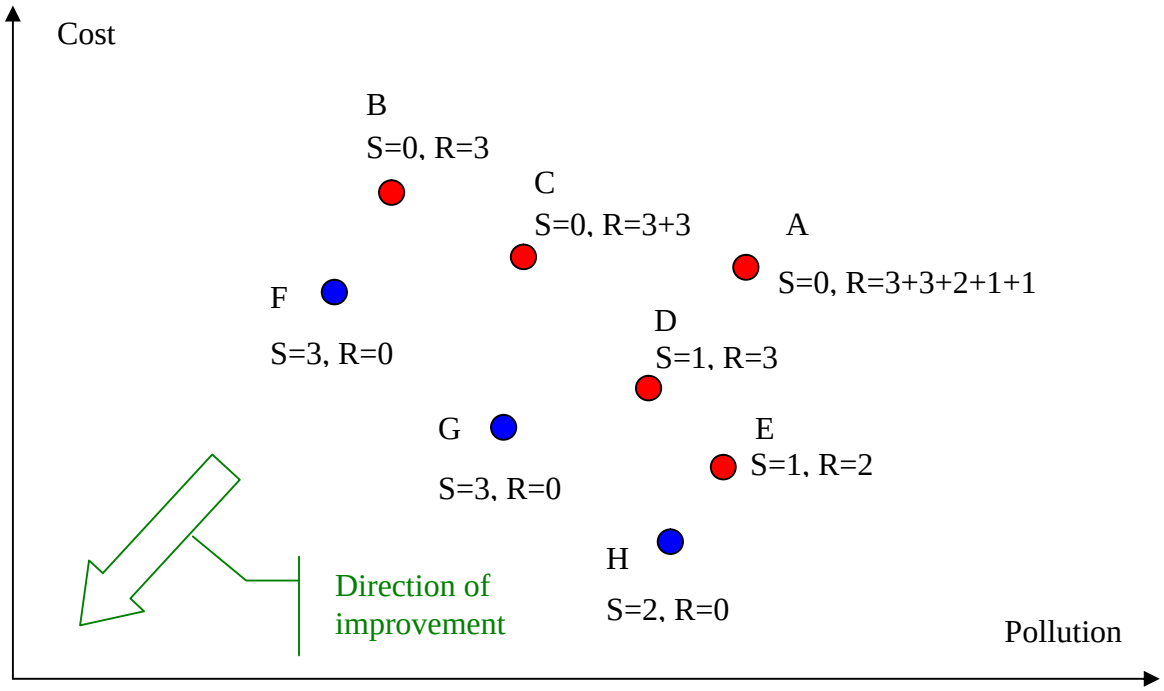


Figure C.2. Raw fitness assignment in SPEA2.



Appendix D. Results for the 13 watersheds

(Charts of watersheds follow these descriptions in Appendix E)

Boyer

The Boyer Watershed is located in western Iowa and is composed of five subbasins. The watershed is bordered by Des Moines Watershed to the east, Nishnabotna to the south, and Little Sioux to the north. Boyer is the ninth-largest watershed among the 13 watersheds in terms of drainage area at 2,820 km^2. Land within the watershed is primarily in cropland (68% of watershed) or grassland (13%), while only a small percentage is in forest (4%) or urban (2%) land use. In comparison to other watersheds, the percentage land allocation to any of these uses is not particularly extreme. According to the National Assessment Database for 2002, reporting on assessed water bodies in the watershed, no rivers, streams, creeks, or wetlands are listed as impaired (by nutrients); however, 24 acres of lakes, ponds, and reservoirs are impaired. Boyer's baseline nutrient concentrations rank them 10th highest in nitrate concentration (3.78 mg/L) and first in phosphorus concentration (1.22 mg/L) among the 13 watersheds. Counties located in the watershed include Buena Vista, Carroll, Crawford, Harrison, Ida, Monona, Pottawattamie, Sac, and Shelby.

Under N-targeting, nitrate loadings decline 24.8%; however, phosphorus loadings increase by 12.2%. The gross cost under this scenario is approximately $7.8 million annually, with net cost showing a reduction of $2.4 million annually. Under P-N-targeting, both phosphorus and nitrate loadings fall, with phosphorus reduced by 40.3% and nitrate reduced by 33.8%. In this case, annual gross cost and net cost are $15 million and $4.7

million, respectively. These results are not uncommon among the watersheds, with phosphorus loadings increasing in eight of the watersheds and cost relative to baseline decreasing in nine watersheds under N-targeting. Our results for Boyer under P-N-targeting are also not unusual, with nitrate and phosphorus loadings declining in all watersheds but cost relative to baseline increasing for all but two watersheds.

As with most watersheds, Boyer's five subbasins use a mix of practices under P-N-targeting. However, under N targeting, only subbasins 1 and 2 use a mix of practices while subbasins 3, 4, and 5 use almost all corn-soybean rotation/conventional tillage. Baseline figures show that all subbasins in the watershed employ a mix of corn-soybean rotation/conventional tillage, no-till, terracing, and contouring. The usage of a mix of practices is similar to results found under optimization with P-N-targeting but differs from optimization with N-targeting for subbasins 3, 4, and 5, as they rely much more heavily on corn-soybean rotation/conventional tillage.

Des Moines

Please see the description in the main report.

Floyd

The Floyd Watershed is located in northwestern Iowa, with Little Sioux Watershed bordering to the east and Monona to the south. Floyd is composed of five subbasins and is the 12th largest watershed, with a drainage area of 2,820 km^2. It also has the second-largest percentage of watershed area allocated to cropland (84%). The National Assessment Database reported 38 miles of rivers, streams, and creeks as impaired by

nutrients while no lakes, ponds, reservoirs, or wetlands were reported as impaired by nutrients. Floyd's baseline nutrient concentrations rank it second in nitrate concentration (6.55 mg/L) and third in phosphorus concentration (0.92 mg/L). Counties located in the watershed include Cherokee, O'Brien, Osceola, Plymouth, Sioux, and Woodbury.

For the five subbasins in the watershed, practice selection differs under both N and P targeting. While subbasin 2 utilizes a larger portion of corn-soybean rotation/conventional tillage under P-N-targeting than under N-targeting, subbasin 4 uses a smaller portion. Overall, subbasin 1 and 4 receive the largest assignment of conservation practices. These subbasins do not border each other for the most part, illustrating the lack of clustering that may possibly occur in practice assignment. This also shows that the assignment of conservation practices to subbasin 5 has been reduced relative to subbasins 1 and 4 under either targeting optimization. However, this is a relative shift and it is perhaps more accurate to suggest that since the total practice area for subbasin 5 is similar under baseline and targeting optimization, the relative assignment of practices to subbasins 1 and 4 has increased. The baseline also shows a mix of no-till, terracing, and contouring being largely used among all subbasins in the watershed; this differs from results under N or P-N-targeting for several subbasins in which corn-soybean rotation/conventional tillage is heavily selected.

Nitrate and phosphorus loadings both decrease under N-targeting by 51% and 15%, respectively. Annual gross cost is $5.7 million and annual net cost is $427,000. With P-N-targeting, phosphorus declines by 47.8%, nitrate declines by 35.8%, and annual gross cost and net cost (cost under optimization less cost under baseline) are $8 million and $2.8 million, respectively.

Iowa

The Iowa Watershed ranges from southern Minnesota to southeastern Iowa and is composed of nine subbasins. The watershed is bordered primarily by Des Moines to the west, Skunk to the southwest, and Wapsipinicon to the east. At 32,796 km^2, the watershed has the second-largest drainage area. It is distinct in that it has the largest percentage (8%) of watershed area classified as urban among all 13 watersheds. The watershed is also particularly interesting because of the difference in slope and erodibility index within the watershed, with the slope and erodibility index measures in the northern half of the watershed consistently lower than in the southern half. The National Assessment Database reports 52 miles of rivers, streams, and creeks, 1,539 acres of lakes, ponds, and reservoirs, and 3,742 acres of wetlands within the watershed as impaired by nutrients. Iowa's baseline nutrient concentrations rank this watershed first in nitrate concentration (7.96 mg/L) and ninth in phosphorus concentration (0.28 mg/L). The watershed includes approximately 30 counties throughout the state.

Under N-targeting, nitrate loadings and phosphorus loadings are reduced 24.8% and 16%, respectively. The gross cost under this scenario is $164 million annually while net cost is $80.5 million annually. Under P-N-targeting, phosphorus is reduced by 32.9% and nitrate by 24.8%; annual gross cost and net cost are $193.6 million and $110 million, respectively.

Among the nine subbasins in the Iowa Watershed, the practice selection under both N-targeting and P-N-targeting is similar among subbasins 3 through 9; these subbasins use a mix primarily of N fertilizer reduction, no-till, terracing, and contouring. For subbasins 1 and 2, a practice mix similar to subbasins 3 through 9 is selected under P-N-targeting;

however, usage of these four practices is reduced under N-targeting as corn-soybean rotation/conventional tillage is primarily selected. In comparison to the baseline, less land is assigned to no-till under both N-targeting and P-N-targeting.

Little Sioux

The Little Sioux Watershed is located in northwestern Iowa and consists of 10 subbasins. Floyd and Monona border to the west while Des Moines and Boyer are to the east and southeast. The watershed is the fourth largest in terms of drainage area (9,203 km^2) and ranks first in percentage of watershed in cropland at 86%. No rivers, streams, or creeks are reported as impaired by nutrients in the National Assessment Database but nutrient impairments are reported for 14,566 acres of lakes, ponds, and reservoirs, and 1,700 acres of wetlands. Little Sioux's baseline nutrient concentrations rank it seventh in nitrate concentration (5.02 mg/L) and sixth in phosphorus concentration (0.73 mg/L). Counties located in the watershed include Buena Vista, Cherokee, Clay, Dickinson, Emmet, Harrison, Ida, Monona, O'Brien, Osceola, Palo Alto, Plymouth, and Woodbury.

Nitrate loadings under N-targeting decrease by 28.3% while phosphorus loadings decrease by 11.5%. Annual gross cost under N-targeting is $14.3 million with annual net cost at a negative $6.9 million. Under P-N-targeting, phosphorus and nitrate decrease by 42.5% and 35.8%, while annual gross cost and net cost are $33.1 million and $11.9 million, respectively.

Generally, significantly more corn-soybean rotation/conventional tillage is used under N-targeting than under P-targeting in the watershed. In most subbasins, corn-soybean rotation/conventional tillage is the primary practice utilized under N-targeting;

however, under P-targeting there is a greater mix of practice selection. In this respect, P-targeting is more similar to the baseline; however, the baseline for Little Sioux's subbasins shows much greater usage of no-till than under either targeting scenarios.

Maquoketa

The Maquoketa Watershed, composed of 10 subbasins, is located in eastern Iowa and bordered by Wapsipinicon to the southwest and Turkey to the north. It is particularly interesting in terms of land allocation, as the watershed has one of the smallest area percentages devoted to cropland, one of the highest percentages in grassland and forest, and is about average in percentage urban. At seventh overall, Maquoketa is around the median in terms of watershed rank by drainage area (4,827 km^2). The National Assessment Database reports 167 miles of rivers, streams, and creeks and 59 acres of lakes, ponds, and reservoirs as impaired by nutrients while no wetlands are reported as nutrient impaired. Maquoketa's baseline nutrient concentrations rank it 5th in nitrate concentration (5.77 mg/L) and 12th in phosphorus concentration (0.19 mg/L). Counties located in the watershed include Buchanan, Clayton, Clinton, Delaware, Dubuque, Fayette, Jackson, Jones, and Linn.

Under N-targeting, nitrate loadings decrease by 43.8% while phosphorus loadings increase by 62.8%. The gross cost under this scenario is $569,000 annually, resulting in net cost at a negative $17.4 million annually. The drastic decrease in cost makes sense, as a shift from non-zero cost practices in no-till and contouring to a zero cost practice in corn-soybean rotation/conventional tillage should result in drastic cost reductions; however, particular caution should be taken in interpreting these results, as an increase of

62.8% in phosphorus loadings also follows from this scenario. Under the other scenario, P-N-targeting, phosphorus is reduced by 60.2% and nitrate by 39.4%. This scenario results in annual gross cost of $2.2 million and annual net cost of a negative $15.8 million; negative net cost occurs in only 2 of the 13 watersheds, and of these Maquoketa's is by far the largest in magnitude.

The Maquoketa Watershed follows the general pattern of the other watersheds in terms of direction of change in practice usage from baseline to optimization with N or P-N-targeting. However, it is interesting to note that the magnitude of change does differ from other watersheds with significantly more land area utilizing corn-soybean rotation/conventional tillage and significantly less land utilizing no-till and contouring under both targeting scenarios. All subbasins in Maquoketa, with the exception of subbasin 10 (the outlet subbasin) under P-targeting, almost exclusively use corn-soybean rotation/conventional tillage under both N and P-N-targeting. This is in contrast to the baseline, which shows almost no corn-soybean rotation/conventional tillage usage but significant usage of no-till and contouring within each subbasin. Because of the difference, from baseline to targeting in the magnitude of practice selection of this watershed in contrast to other watersheds, it is particularly interesting that the land uses as percentages of watershed are also somewhat different in Maquoketa from most other watersheds.

Monona

The Monona Watershed, bordered by Floyd and Little Sioux, is located in northwestern Iowa. It is composed of five subbasins and, at 2,452 km^2, is the 11th largest watershed in terms of drainage area. The watershed has no reported nutrient impairments

on the three major water body types according to the National Assessment Database. However, Monona's baseline nutrient concentrations rank third in nitrate concentration (6.2 mg/L) and fourth in phosphorus concentration (0.8 mg/L) among watersheds. Counties located in the watershed include Cherokee, Harrison, Monona, Plymouth, and Woodbury.

Under N-targeting, nitrate loadings and phosphorus loadings are reduced 40.8% and 16.7%, respectively. The gross cost under this scenario is $5.8 million annually while net cost is a negative $3.4 million annually. Under P-N-targeting, phosphorus is reduced by 39.7% and nitrate by 44.9%; annual gross cost and net cost are $7.8 million and negative $1.5 million, respectively.

Under both N and P-targeting, none of the subbasins has a practice mix that is composed almost entirely of any one practice; this is also true of the baseline. However, under the baseline, almost no corn-soybean rotation/conventional tillage is used by any subbasin, differing from results under N and P-targeting.

Nishnabotna

The Nishnabotna Watershed is located in southwestern Iowa and is bordered by Boyer to the north, Des Moines to the east, and Nodaway to the southeast. The watershed consists of 11 subbasins, has the fifth-largest drainage area (7,718 km^2), and is second-largest in terms of percentage of watershed in cropland (84%). While no rivers, streams, creeks, or wetlands are reported as nutrient impaired, 506 acres of lakes, ponds, and reservoirs are listed by the National Assessment Database as impaired. Nishnabotna's baseline nutrient concentrations rank ninth in nitrate concentration (3.86 mg/L) and

second in phosphorus concentration (0.98 mg/L) among watersheds. Counties located in the watershed include Adair, Audubon, Carroll, Cass, Crawford, Fremont, Guthrie, Mills, Montgomery, Page, Pottawattamie, and Shelby.

Nitrate loadings decrease under N-targeting by 24.7% while phosphorus loadings increase by 27.2%. Annual gross cost is $23.7 million and annual net cost is negative $6.2 million. With P-N-targeting, phosphorus declines by 32.7%, nitrate declines by 34.9%, and annual gross and net cost are $43.6 million and $13.7 million, respectively.

Most subbasins in the watershed follow the general pattern of less corn-soybean rotation/conventional tillage usage under P-N-targeting in comparison to N-targeting. However, the difference in corn-soybean rotation/conventional tillage under P-N and N-targeting in subbasins 4, 5, and 7 is minimal, as levels of corn-soybean rotation/conventional tillage under N-targeting are already low.

Nodaway

Please see the description in the main report.

Skunk

The Skunk Watershed ranges from central to southeastern Iowa and is bordered by Des Moines to the southwest and Iowa Watershed to the northeast. It is composed of 12 subbasins and, at 11,246 km^2, has the third-largest drainage area. The National Assessment Database reports 35 miles of rivers, streams, and creeks and 1,747 acres of lakes, ponds, and reservoirs as nutrient impaired; no wetlands are reported as nutrient impaired. The Skunk's baseline nutrient concentrations rank it 11th in nitrate

concentration (3.70 mg/L) and 5th in phosphorus concentration (0.80 mg/L). Counties located in the watershed include Boone, Des Moines, Hamilton, Hardin, Henry, Jasper, Jefferson, Keokuk, Lee, Louisa, Mahaska, Marion, Marshall, Polk, Poweshiek, Story, Van Buren, Wapello, Washington, and Webster.

Under N-targeting, nitrate loadings decrease by 24.9% while phosphorus loadings slightly increase by 0.1%. The gross cost under this scenario is $37.5 million annually while net cost is $16.3 million annually; Skunk is the only watershed in which net cost is positive while phosphorus loadings increase under N-targeting. Under P-N-targeting, phosphorus is reduced by 36.4% and nitrate by 24.8%; annual gross cost and net cost are $50.4 million and negative $29.2 million, respectively.

Interestingly, practice usage is relatively similar under N-targeting and P-N-targeting for subbasins 1 through 8, with these subbasins selecting a mix of practices. However, a stark difference exists in practice usage in subbasins 9 through 12, as corn-soybean rotation/conventional tillage is the primary practice selected under N-targeting, whereas a mix of practices is used under P-N-targeting. In comparison to baseline, far less no-till is used relative to other practices under either targeting scenario for all subbasins.

Turkey

The Turkey Watershed is located in northeastern Iowa and bordered by Upper Iowa to the north, Wapsipinicon to the west, and Maquoketa to the south. It is composed of 9 subbasins and has the eighth-largest drainage area at 4,400 km^2. Turkey has one of the lowest percentages of watershed area in cropland (56%) and the second-largest percentage of watershed area in forestland (16%). No rivers, streams, creeks, or wetlands

are listed as nutrient impaired by the National Assessment Database; however, 37 acres of lakes, ponds, and reservoirs are listed as impaired. Turkey's baseline nutrient concentrations rank eighth in both nitrate concentration (4.30 mg/L) and phosphorus concentration (0.54 mg/L) among watersheds. Counties located in the watershed include Allamakee, Chickasaw, Clayton, Delaware, Dubuque, Fayette, Howard, and Winneshiek.

Nitrate loadings decrease under N-targeting by 25% while phosphorus loadings increase by 20.2%. Annual gross cost is $10.2 million and annual net cost is negative $5.1 million. With P-N-targeting, phosphorus declines by 28.7%, nitrate declines by 26%, and annual gross and net cost are $17.1 million and $1.7 million, respectively.

Subbasins 1 through 3 differ significantly from the other subbasins under N-targeting. Under N-targeting, these three subbasins employ almost no corn-soybean rotation/conventional tillage while it is the primary practice in the other subbasins. However, all subbasins in the Turkey Watershed are similar in employing a mix of conservation practices under P-targeting. Under baseline, most subbasins are similar, having a greater emphasis on no-till than any other practice while also using a mix of other practices.

Upper Iowa

The Upper Iowa Watershed is located in northeastern Iowa. The watershed is bordered mainly by Turkey to the south but Wapsipinicon and Iowa watersheds also border to the west. It is composed of 7 subbasins and has the 10th-largest drainage area (2,569 km^2). Upper Iowa also has the lowest percentage of watershed in cropland (51%) and the highest percentage in forest (19%). The National Assessment Database reports 55

miles of rivers, streams, and creeks listed as nutrient impaired; no lakes, ponds, reservoirs, or wetlands are listed as nutrient impaired. Upper Iowa's baseline nutrient concentrations show it to have both the lowest nitrate concentration (2.32 mg/L) and phosphorus concentration (0.16 mg/L) among the 13 watersheds. Counties located in the watershed include Allamakee, Howard, Mitchell, and Winneshiek.

The N-targeting scenario results in a decline of nitrate loadings of 25.7% while phosphorus loadings increase by 29.5%. The gross cost under this scenario is $7.2 million annually while net cost is negative $71,000 annually. Under P-N-targeting, phosphorus is reduced by 39.5% and nitrate by 24.2%; annual gross cost and net cost are $11 million and $3.7 million, respectively.

Overall, Upper Iowa's subbasins are similar under P-targeting, as they all employ a mix of practices. However, under N-targeting, subbasins 4 through 7 use corn-soybean rotation/conventional tillage almost exclusively while subbasin 3 uses some corn-soybean rotation/conventional tillage along with a mix of other practices. Subbasins 1 and 2 use almost no corn-soybean rotation/conventional tillage under N-targeting.

Wapsipinicon

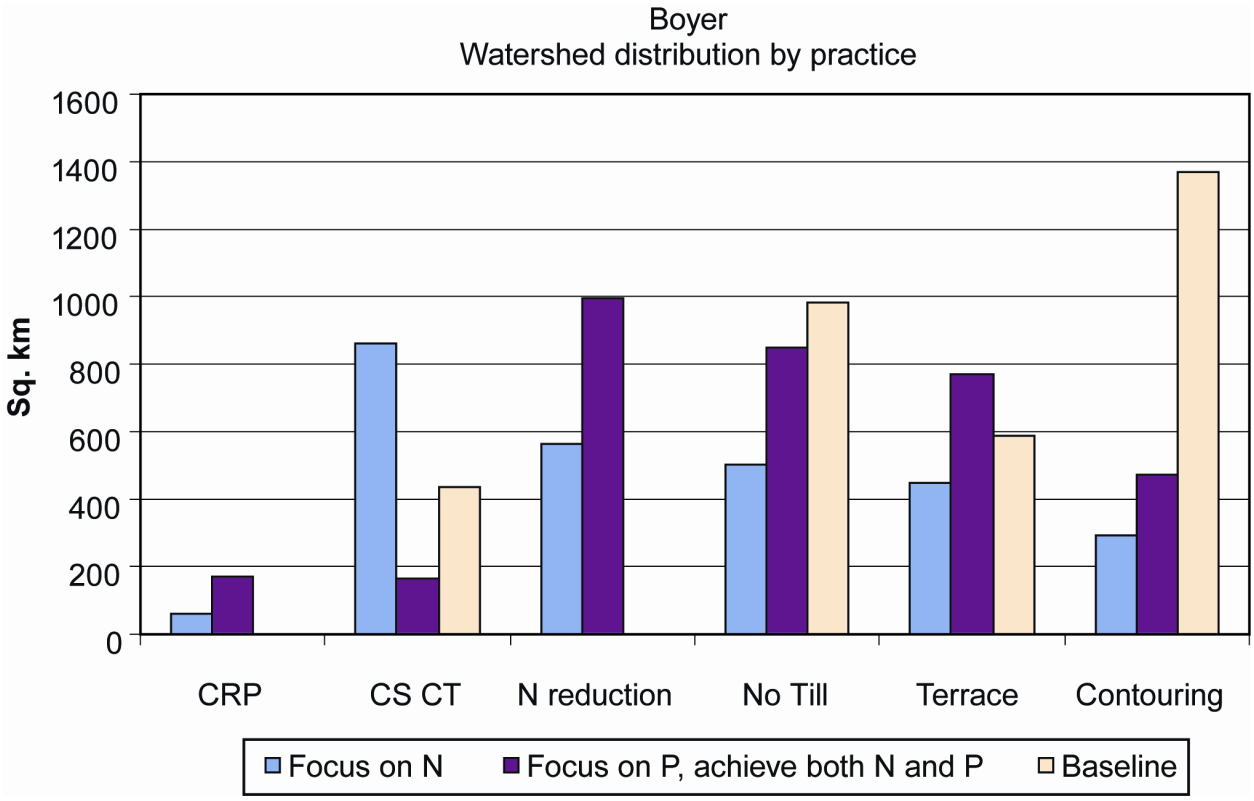
The Wapsipinicon Watershed is located in northeastern Iowa and is bordered by Iowa Watershed to the southwest and Upper Iowa, Turkey, and Maquoketa watersheds to the northeast. It is composed of 9 subbasins and has the sixth-largest drainage area at 6,582 km^2. No wetlands are reported as nutrient impaired by the National Assessment Database; however, 90 miles of rivers, streams, and creeks, along with 40 acres of lakes, ponds, and reservoirs, are listed as nutrient impaired. Wapsipinicon's baseline nutrient

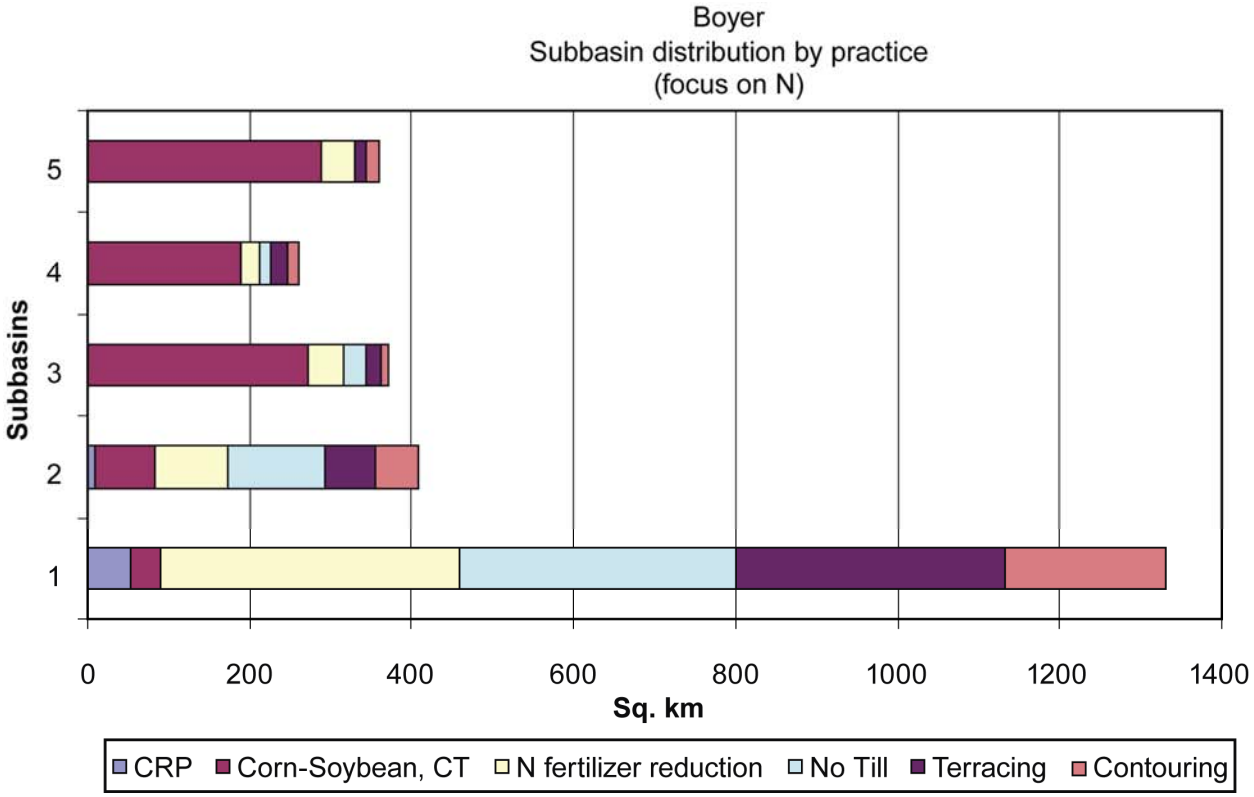
concentrations rank 6th in nitrate concentration (5.7 mg/L) and 11th in phosphorus concentration (0.20 mg/L) among watersheds. Counties located in the watershed include Black Hawk, Bremer, Buchanan, Cedar, Chickasaw, Clinton, Delaware, Fayette, Floyd, Howard, Jones, Linn, Mitchell, and Scott.

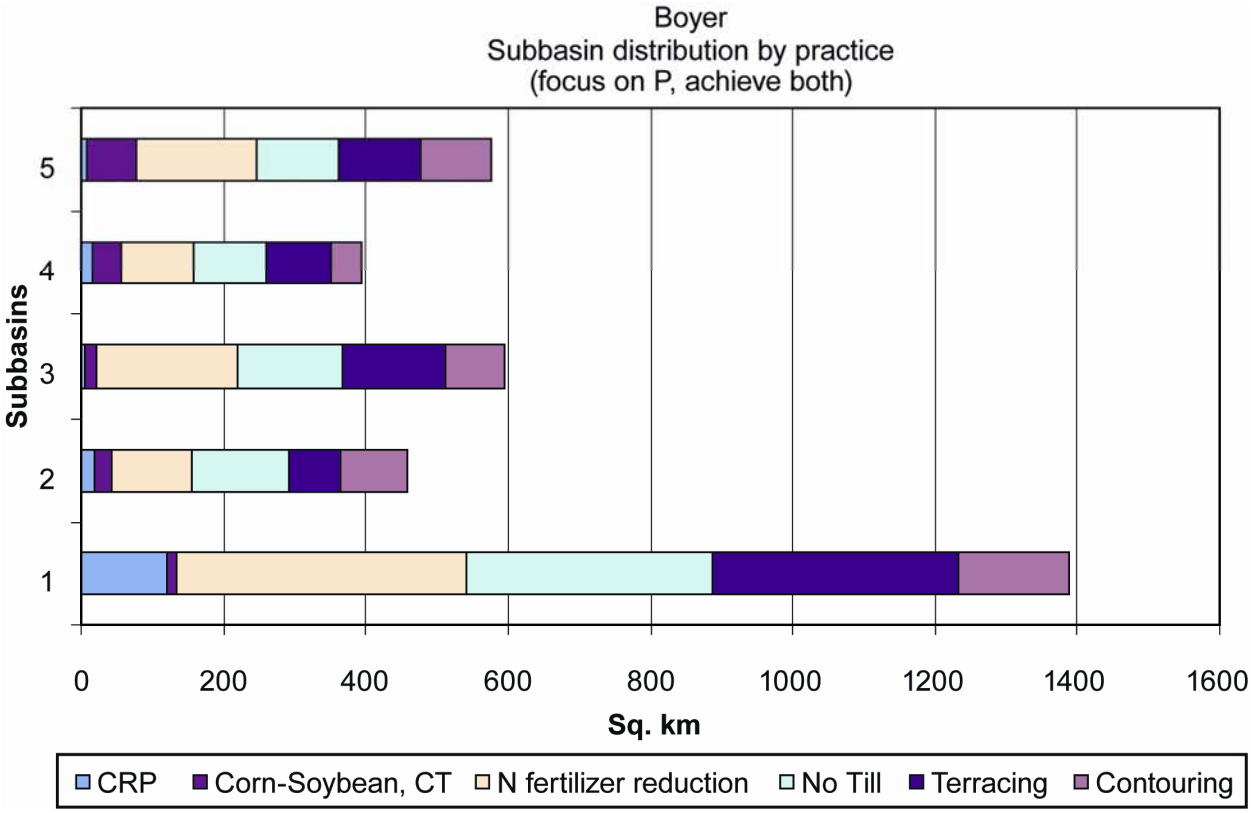
Nitrate loadings decrease under N-targeting by 24.5%, while the 67.9% increase in phosphorus loadings is the largest among all watersheds under N-targeting. Annual gross cost is $8.3 million and annual net cost is negative $12.6 million. With P-N-targeting, phosphorus declines by 32.4%, nitrate declines by 30%, and annual gross and net cost are $33 million and $12.1 million, respectively.

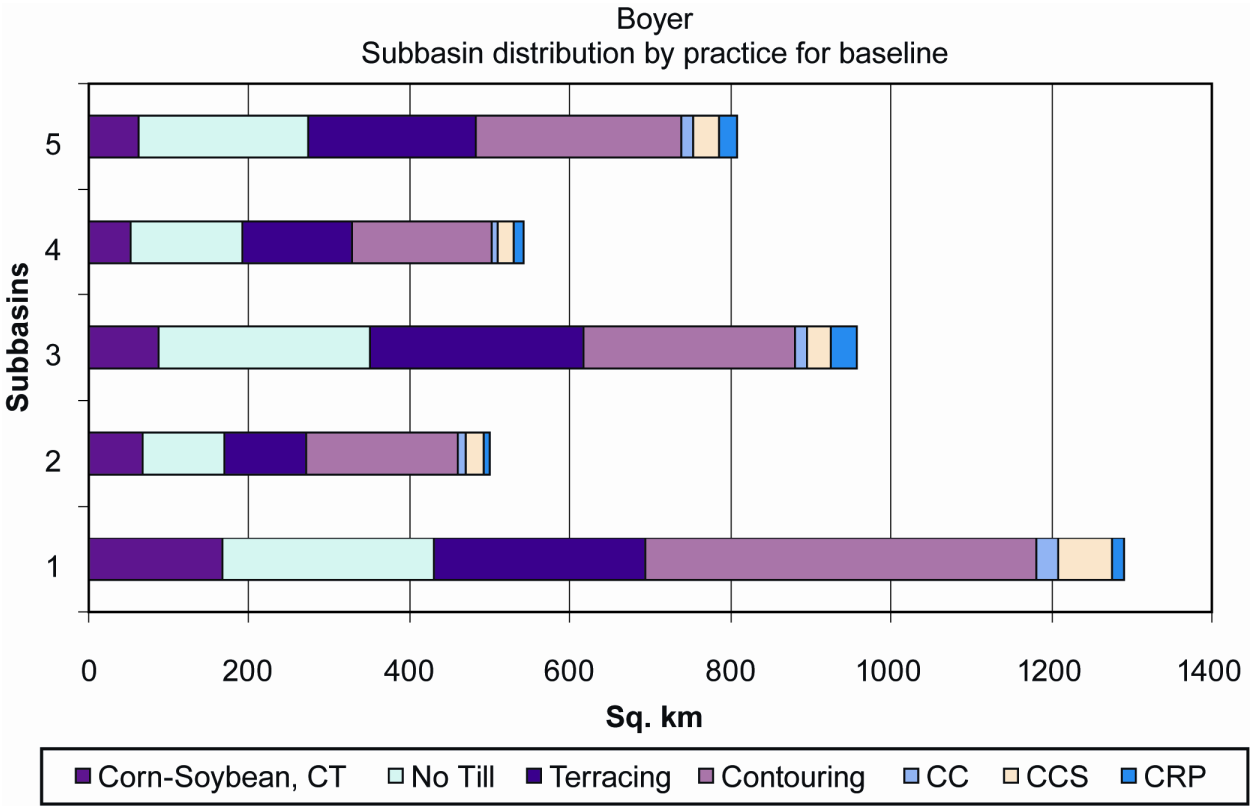
While Wapsipinicon's subbasins differ in practice mix from N to P-N-targeting, they do employ a relatively similar mix of conservation practices for a given targeting scenario. The exception to this is the northern-most subbasin, subbasin 1, which uses a practice mix with far less corn-soybean rotation/conventional tillage under N-targeting than the other subbasins. Comparison of subbasins under baseline shows similarity, as no-till is heavily used among all.

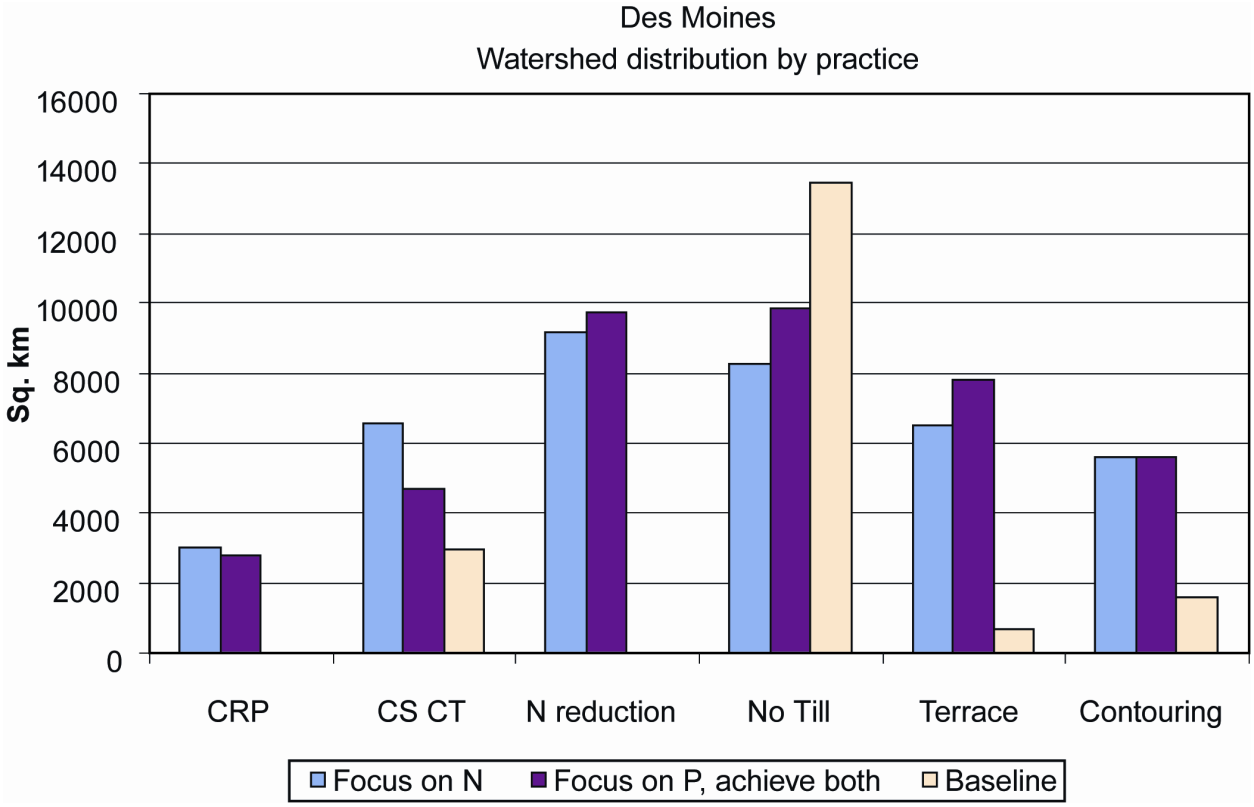
Appendix E

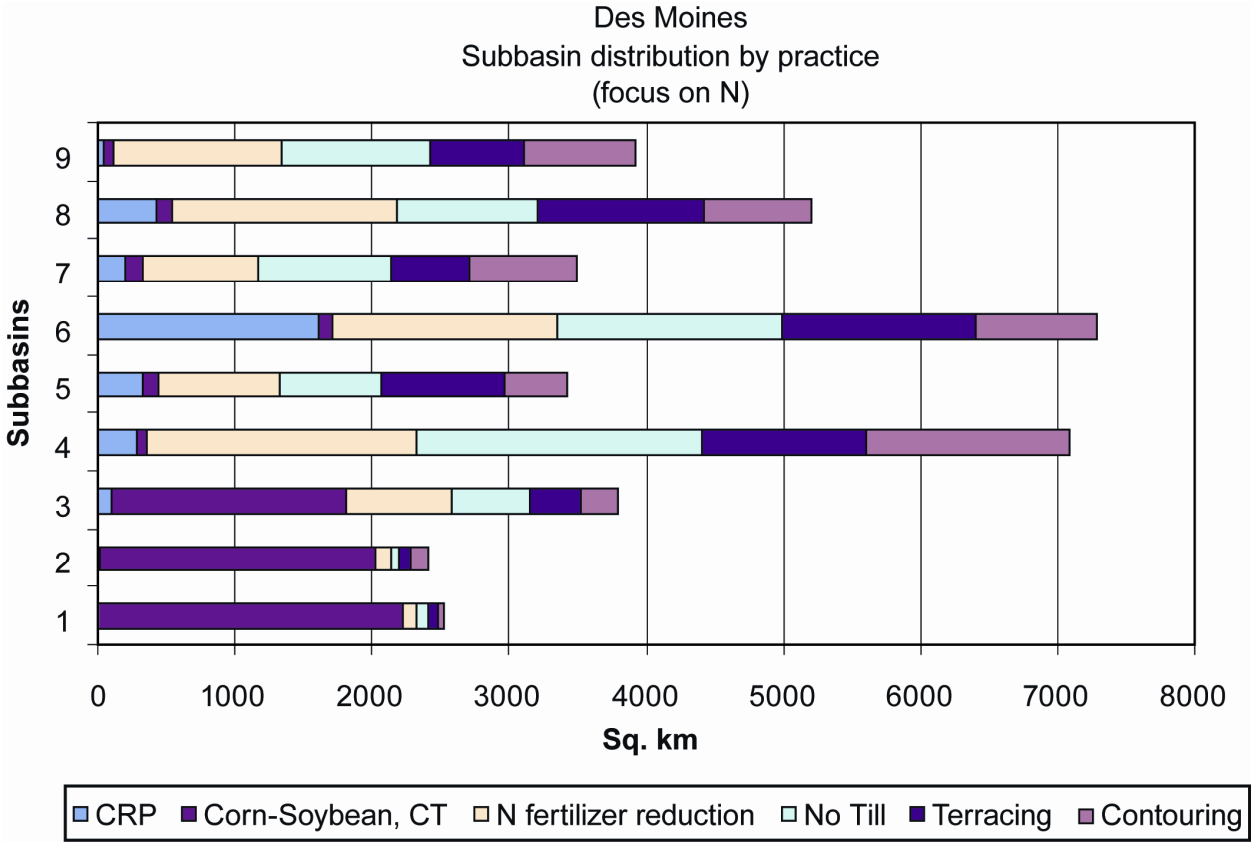

Boyer
Watershed distribution by practice
Sq. km
1600
1400
1200
1000
800
600
400
200
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

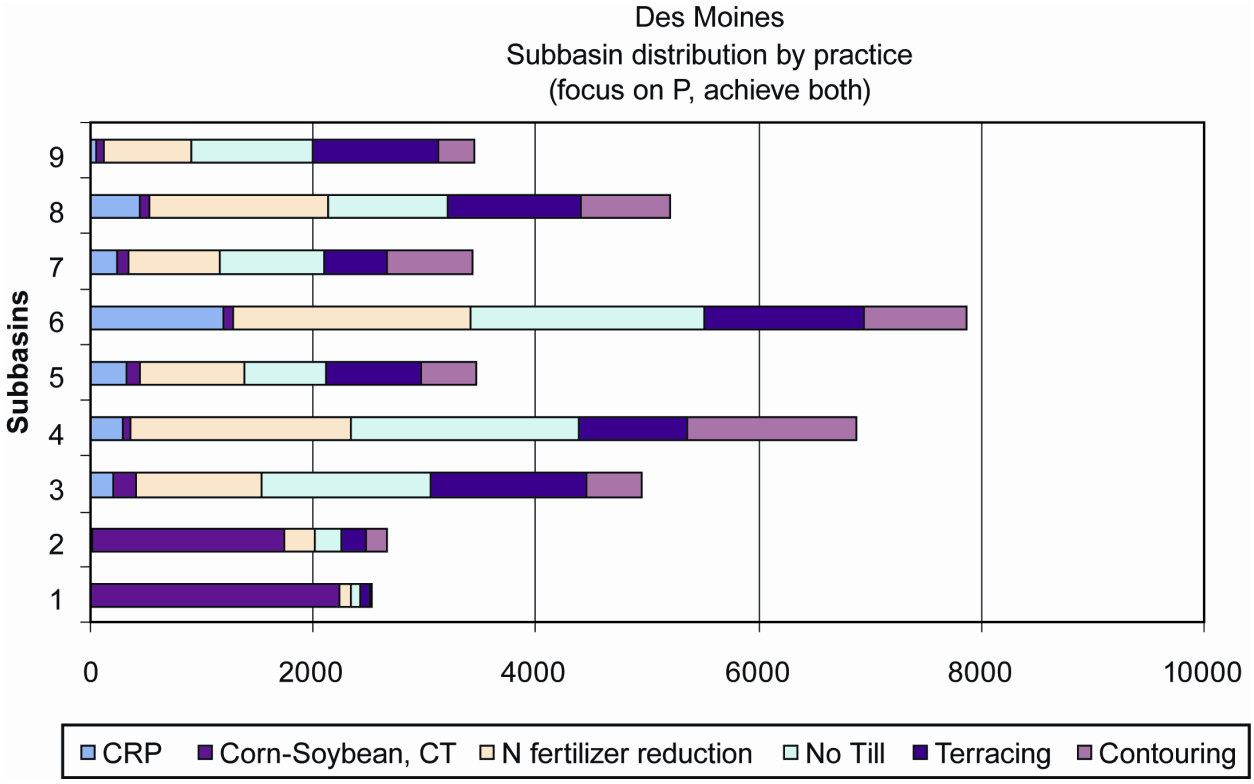

Boyer
Subbasin distribution by practice
(focus on N)
Subbasins
5
4
3
2
1
0
200
400
600
800
1000
1200
1400
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

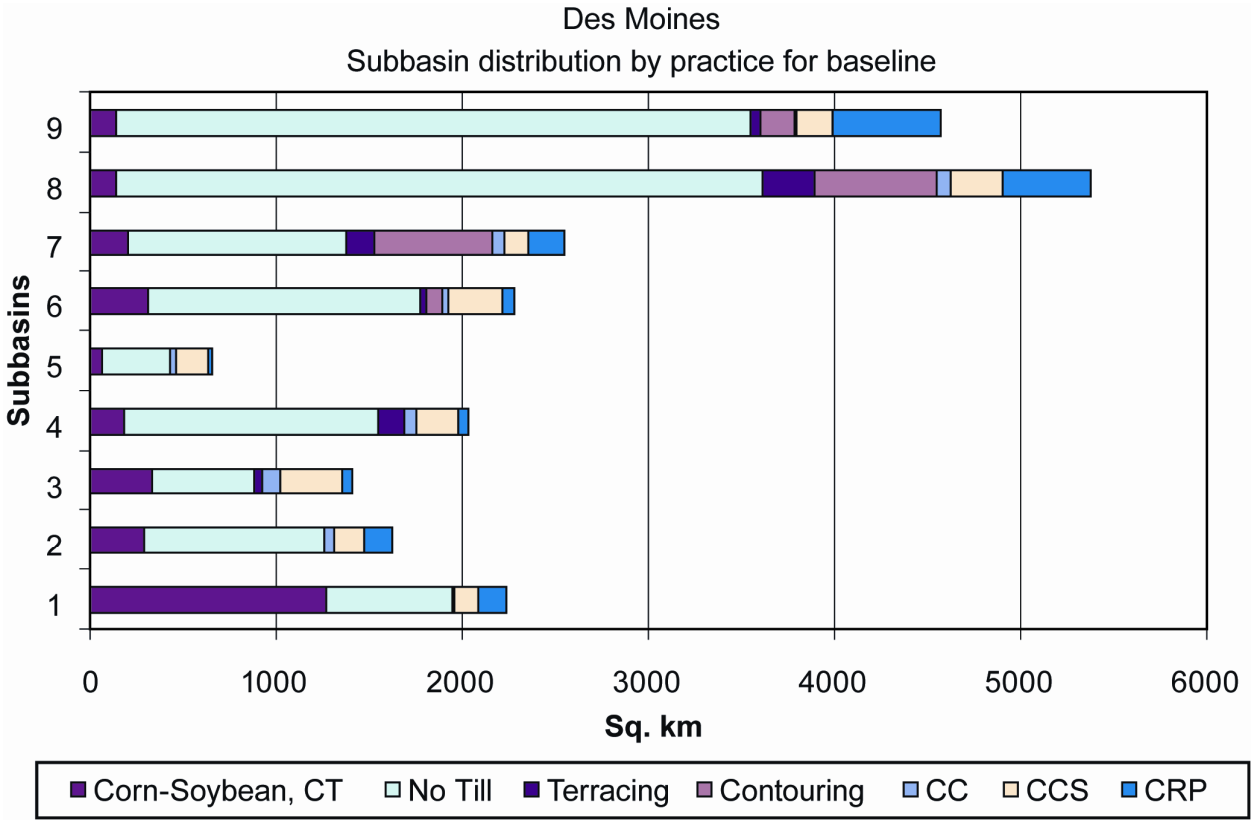

Boyer
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
5
4
3
2
1
0
200
400
600
800
1000
1200
1400
1600
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

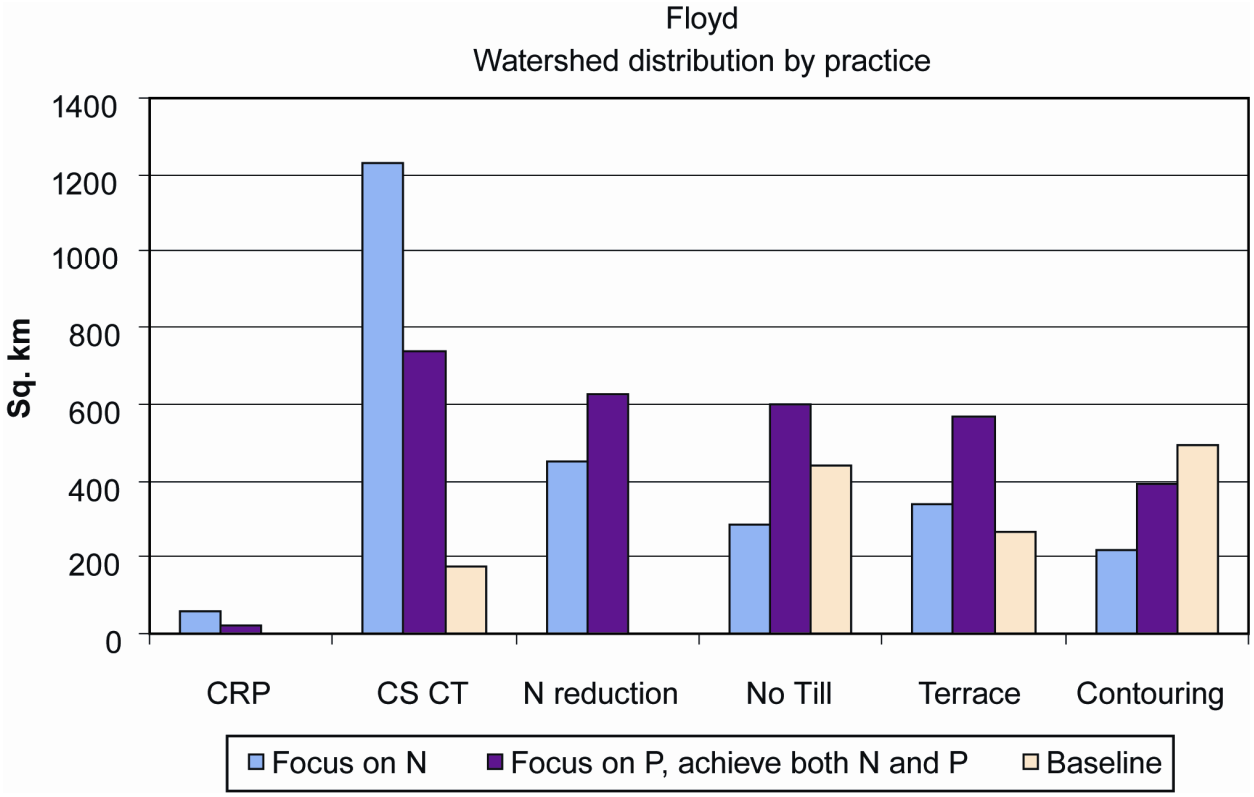

Boyer
Subbasin distribution by practice for baseline
Subbasins
5
4
3
2
1
0
200
400
600
800
1000
1200
1400
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

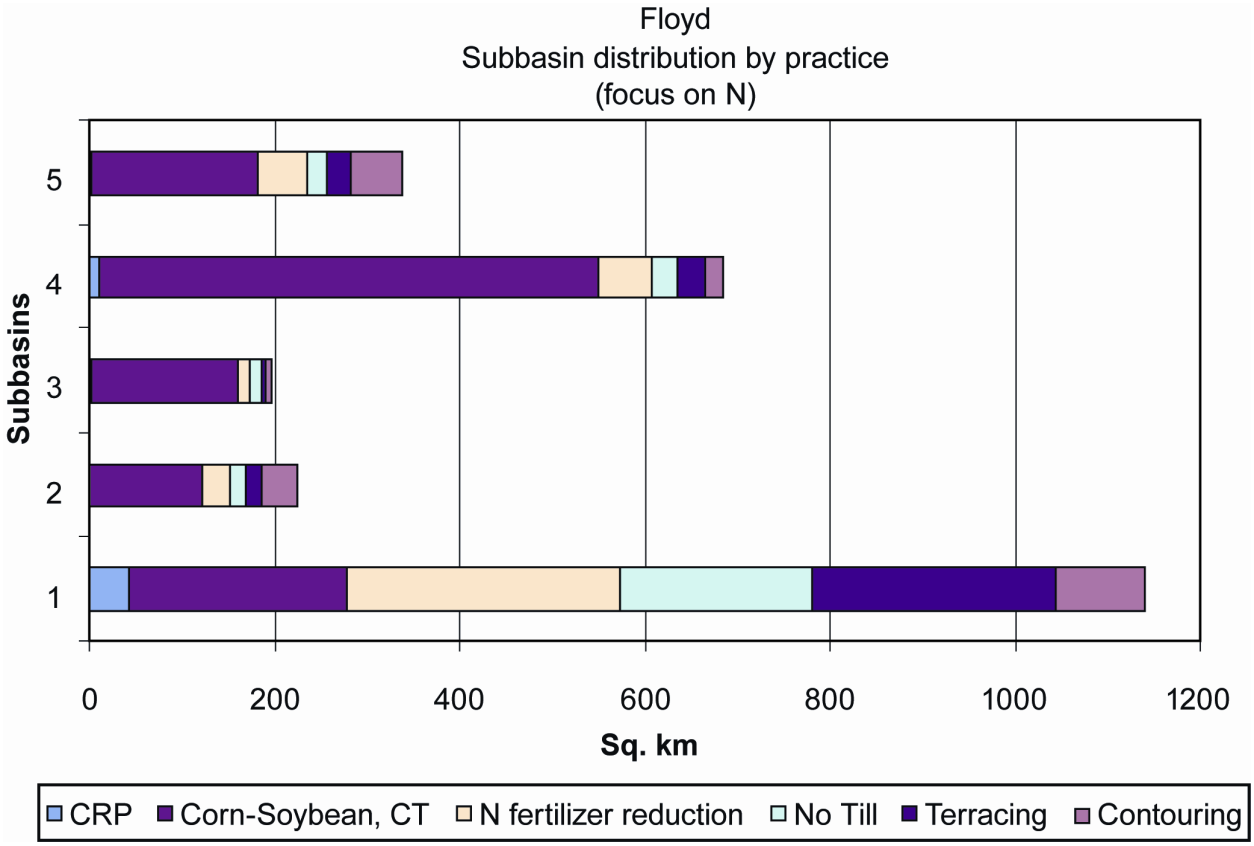

Des Moines
Watershed distribution by practice
Sq. km
16000
14000
12000
10000
8000
6000
4000
2000
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both
Baseline

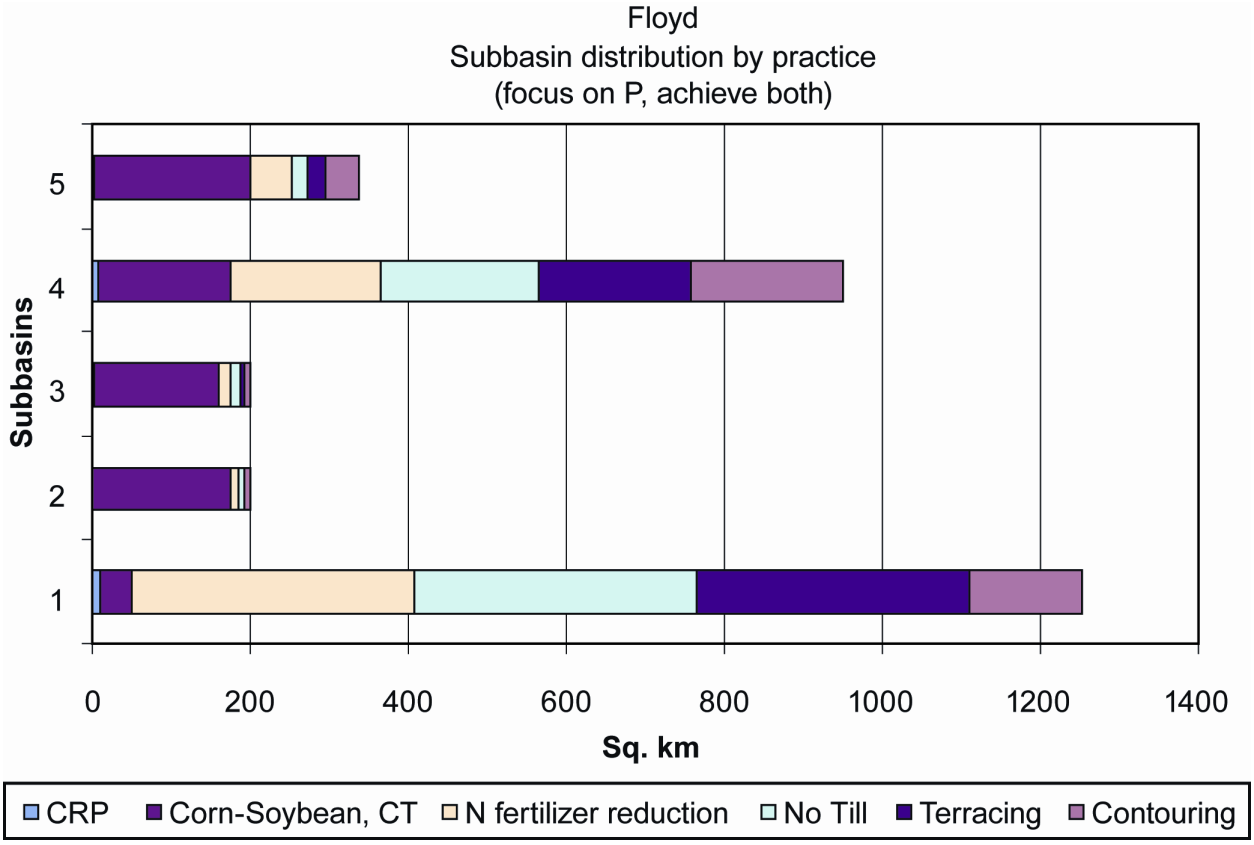

Des Moines
Subbasin distribution by practice
(focus on N)
Subbasins
9
8
7
6
5
4
3
2
1
0
1000
2000
3000
4000
5000
6000
7000
8000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

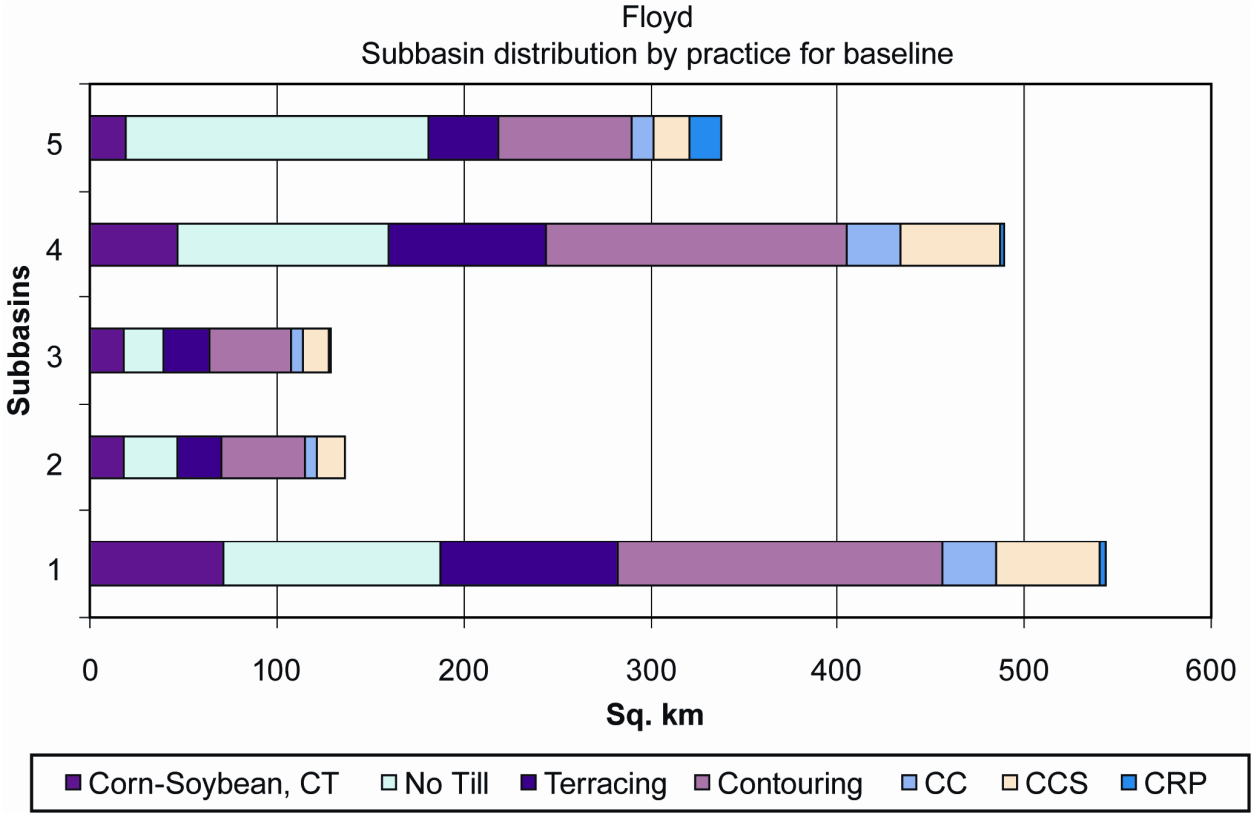

Des Moines
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
9
8
7
6
5
4
3
2
1
0
2000
4000
6000
8000
10000
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

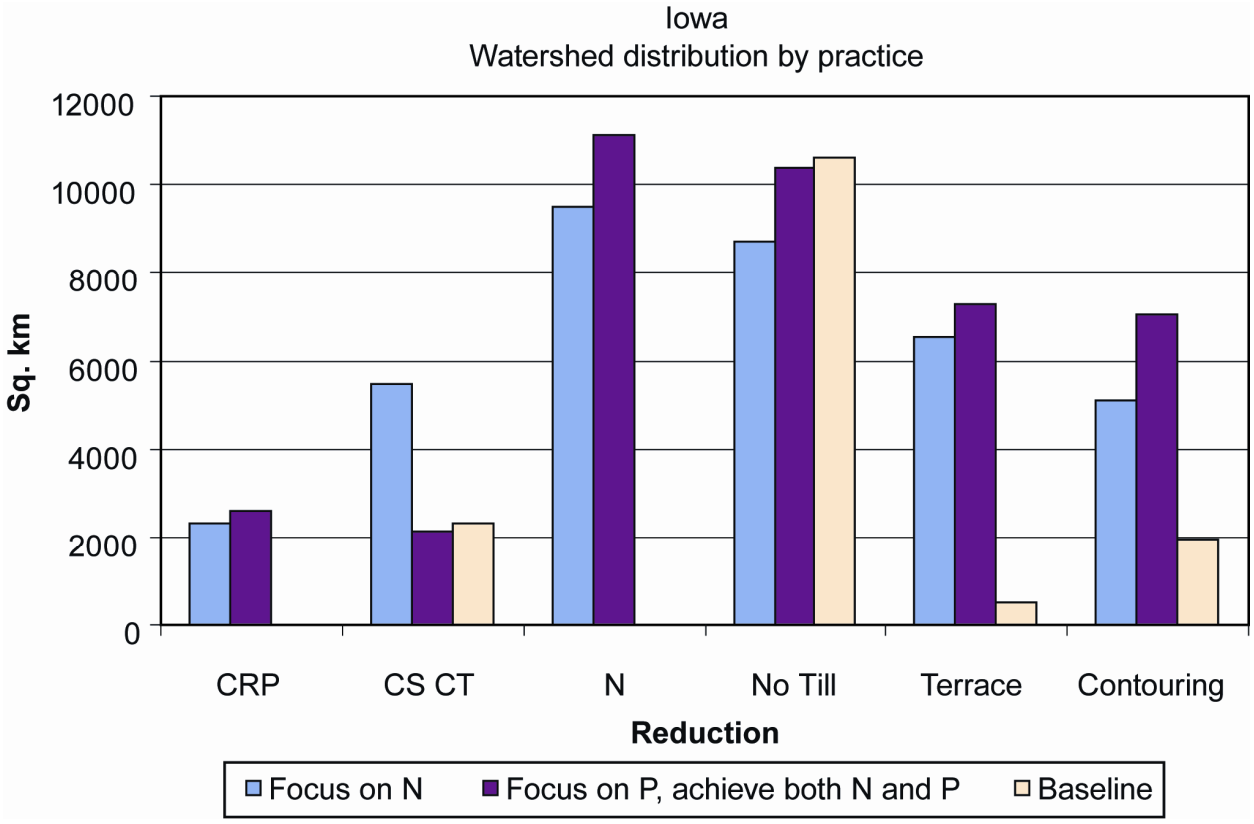

Des Moines
Subbasin distribution by practice for baseline
Subbasins
9
8
7
6
5
4
3
2
1
0
1000
2000
3000
4000
5000
6000
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

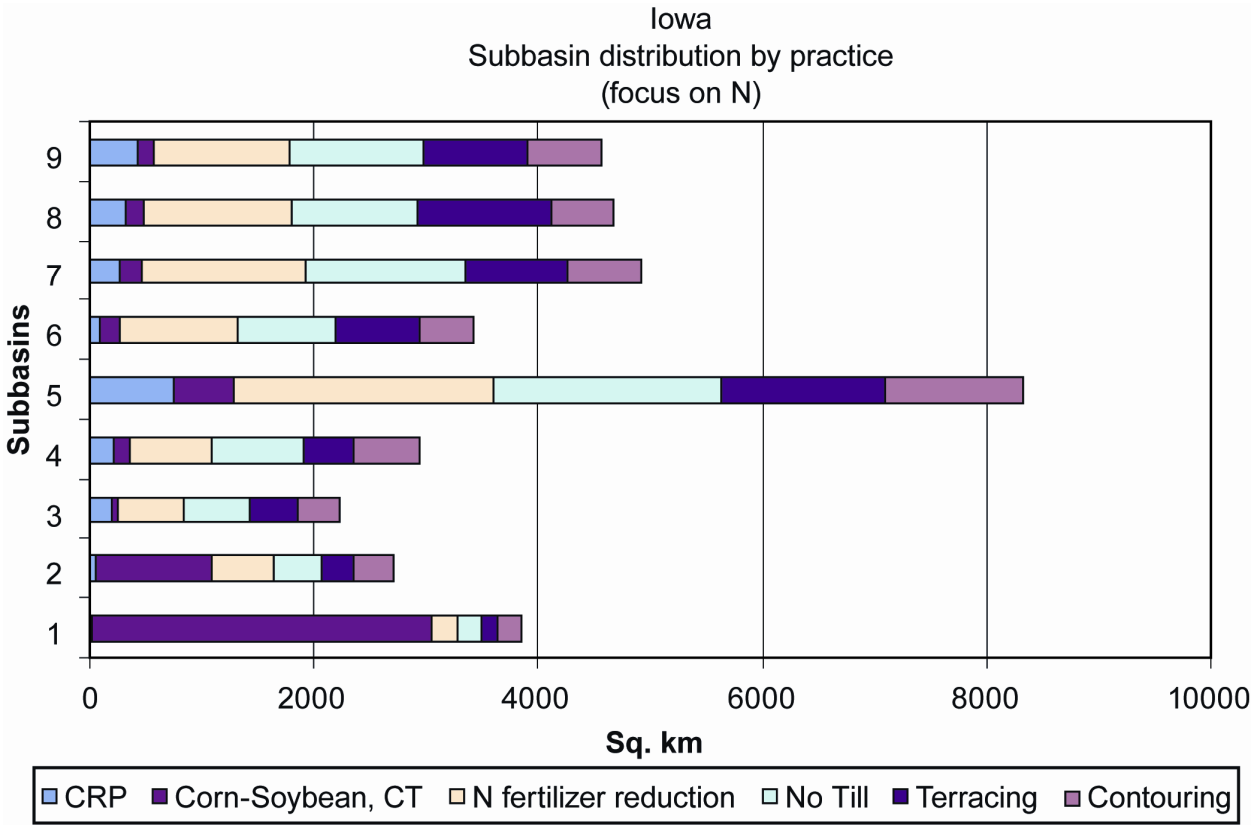

Floyd
Watershed distribution by practice
Sq. km
1400
1200
1000
800
600
400
200
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

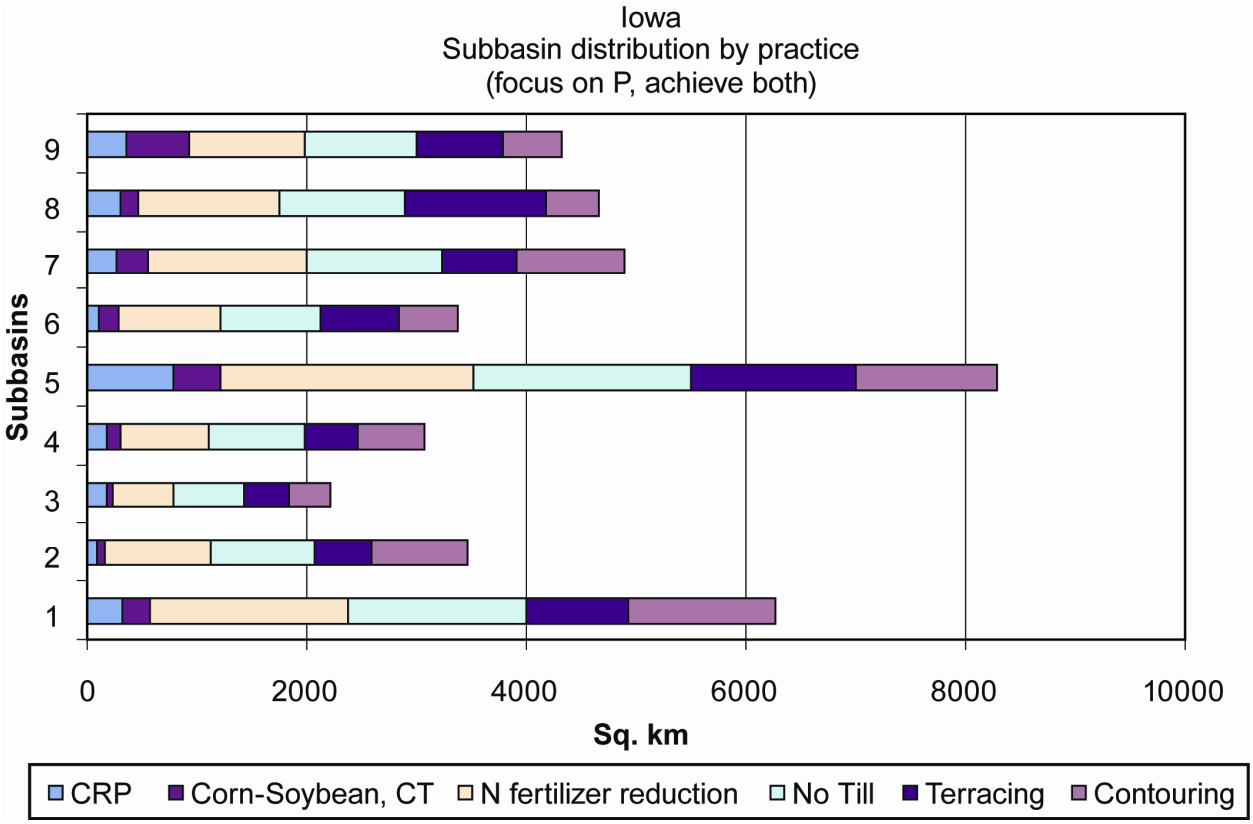

Floyd
Subbasin distribution by practice
(focus on N)
Subbasins
5
4
3
2
1
0
200
400
600
800
1000
1200
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

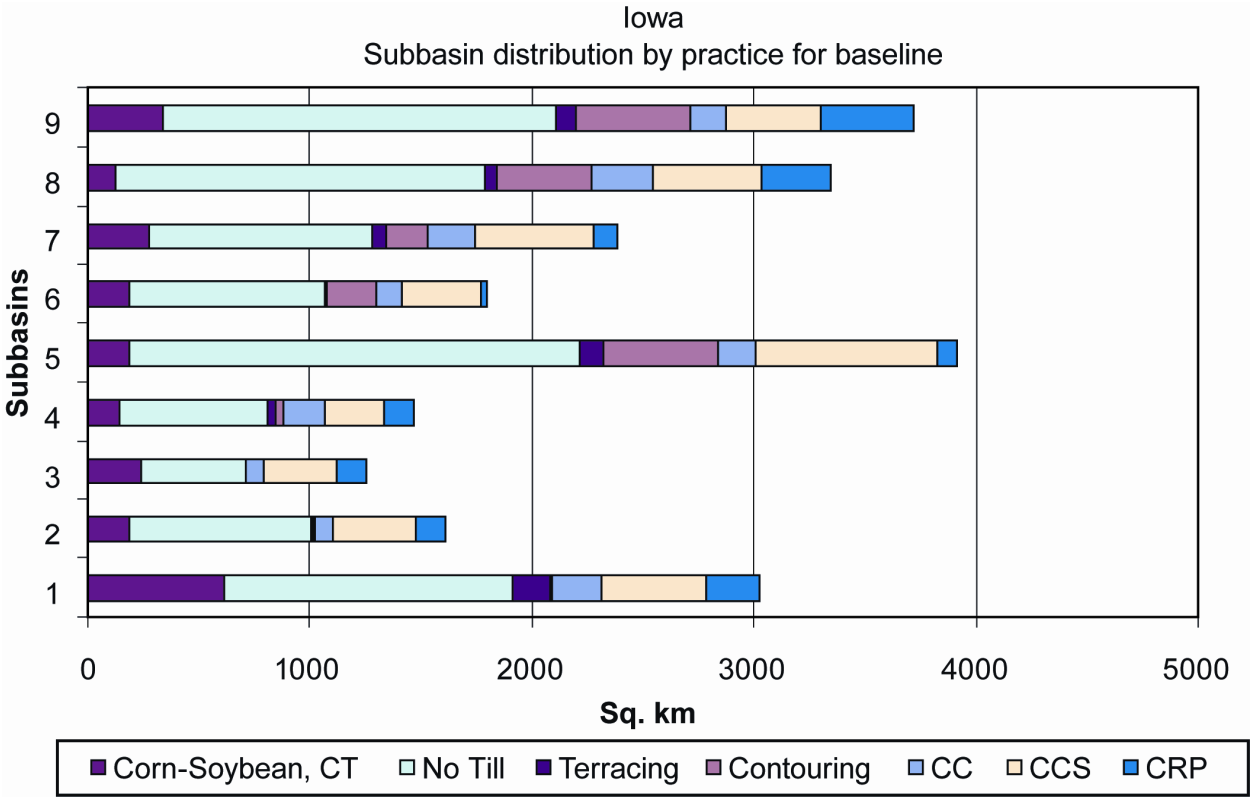

Floyd
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
5
4
3
2
1
0
200
400
600
800
1000
1200
1400
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

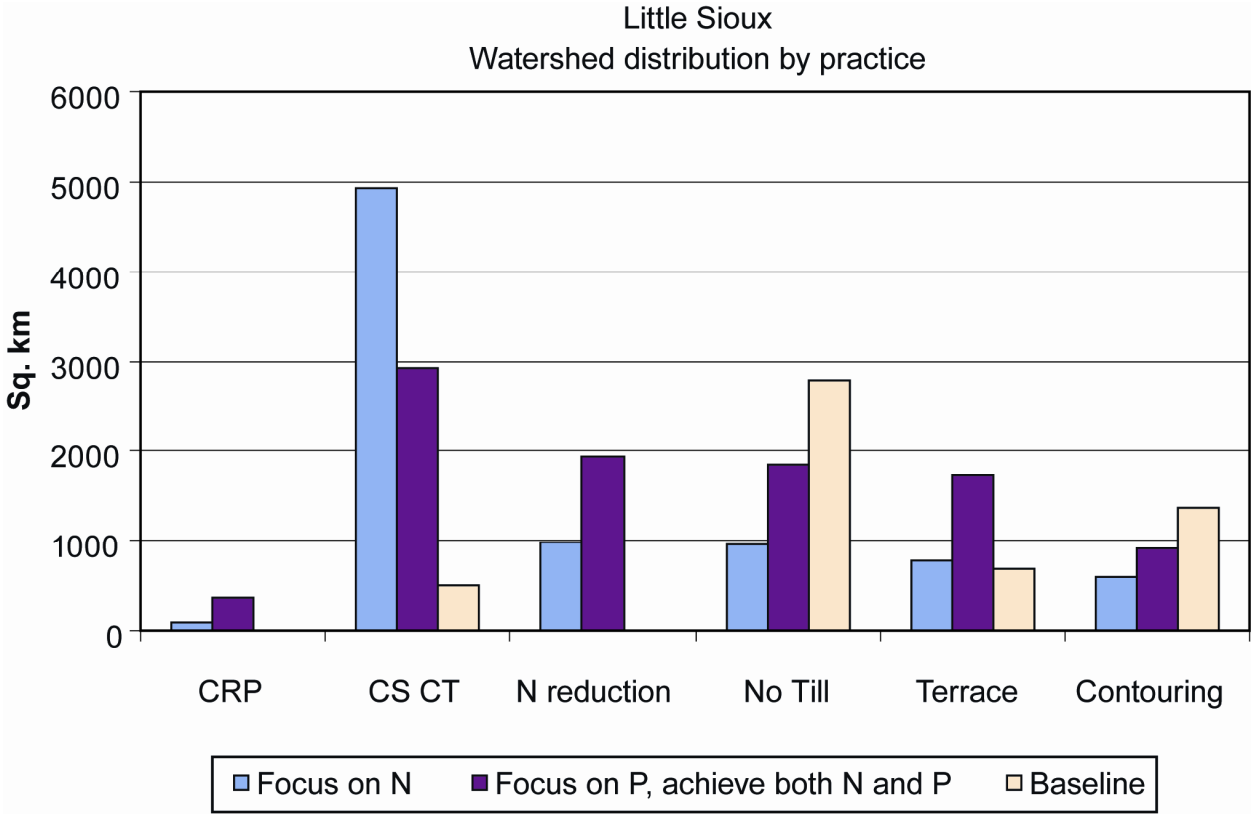

Floyd
Subbasin distribution by practice for baseline
Subbasins
5
4
3
2
1
0
100
200
300
400
500
600
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

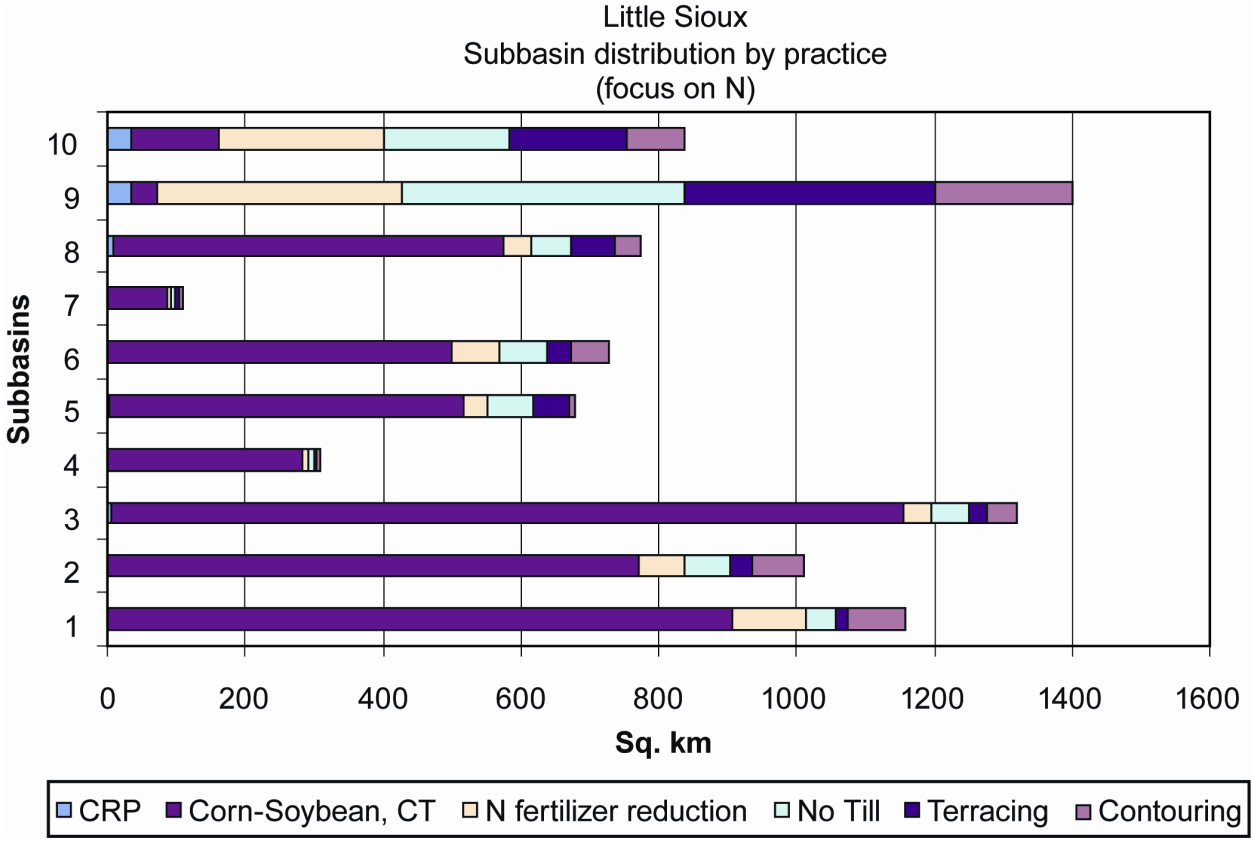

Iowa
Watershed distribution by practice
12000
10000
8000
6000
4000
2000
0
Sq. km
CRP
CS CT
N
No Till
Terrace
Contouring
Reduction
Focus on N
Focus on P, achieve both N and P
Baseline

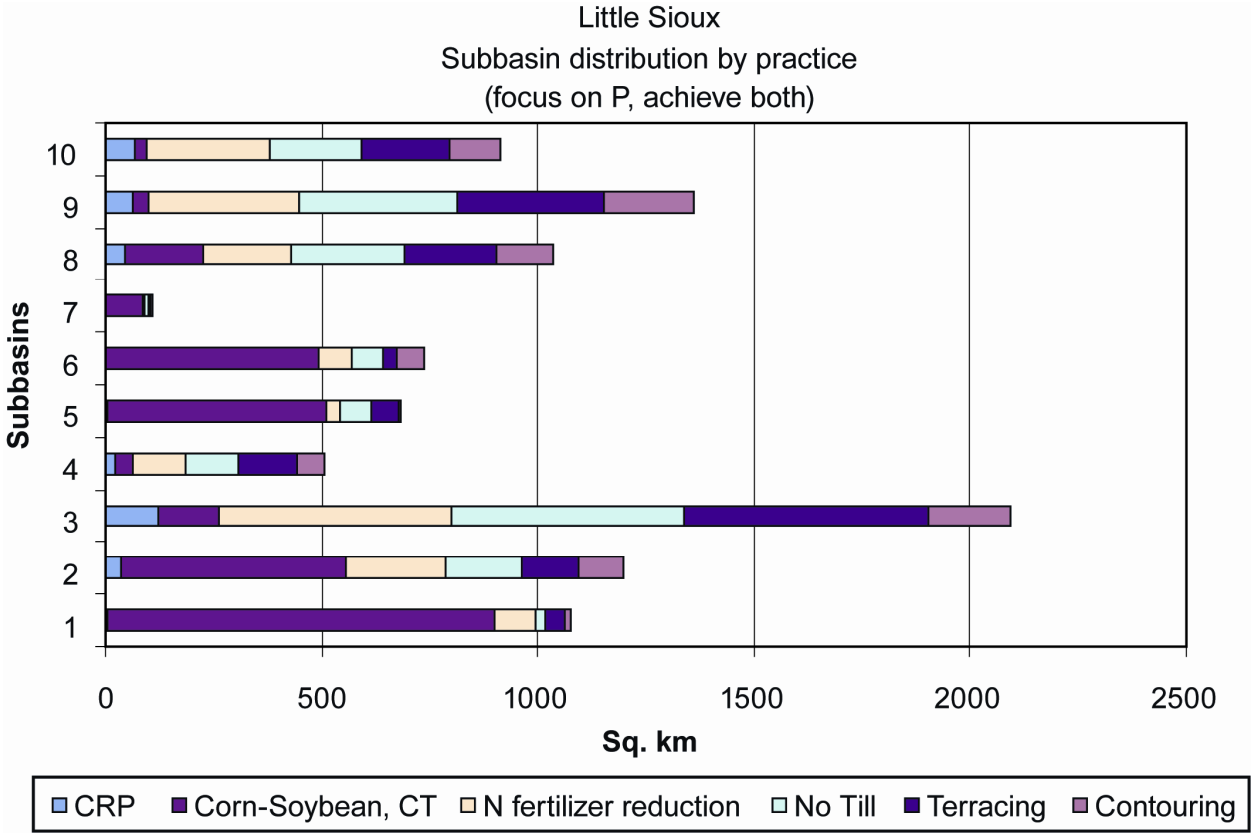

Iowa
Subbasin distribution by practice
(focus on N)
Subbasins
9
8
7
6
5
4
3
2
1
0
2000
4000
6000
8000
10000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

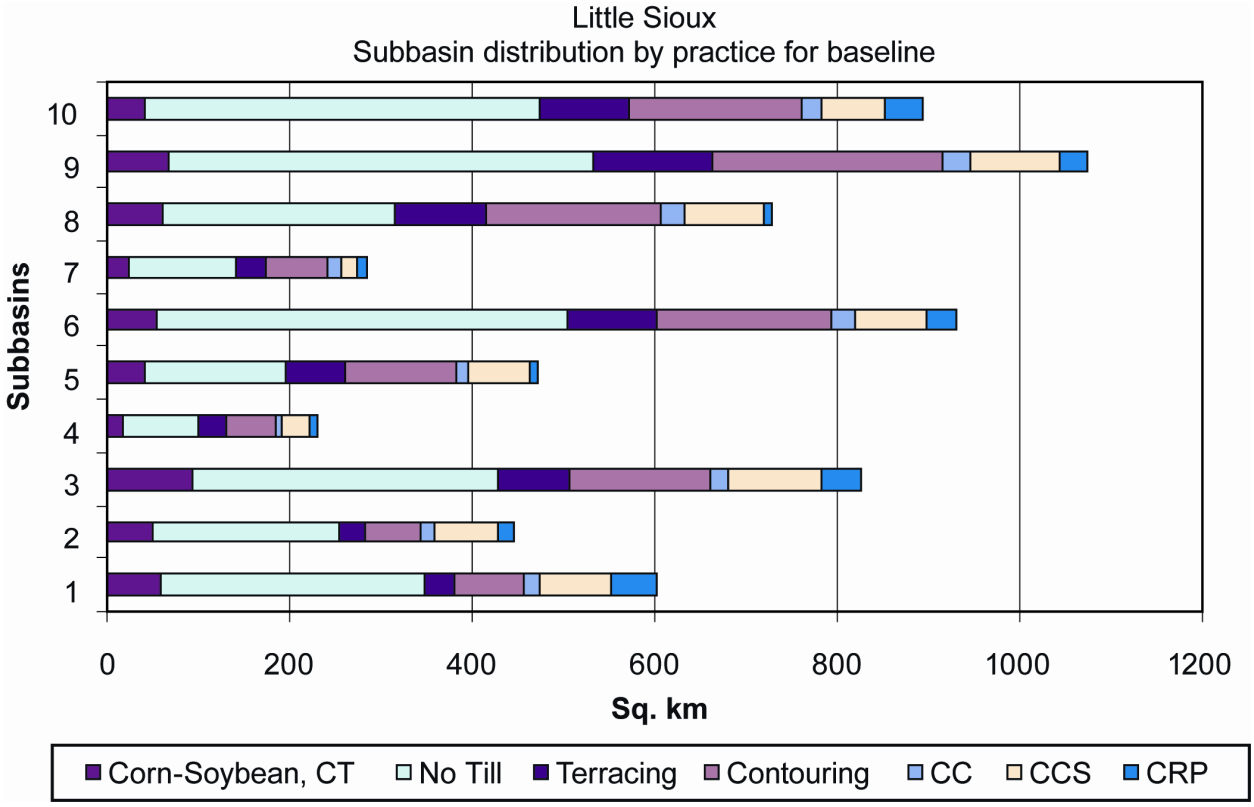

Iowa
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
9
8
7
6
5
4
3
2
1
0
2000
4000
6000
8000
10000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

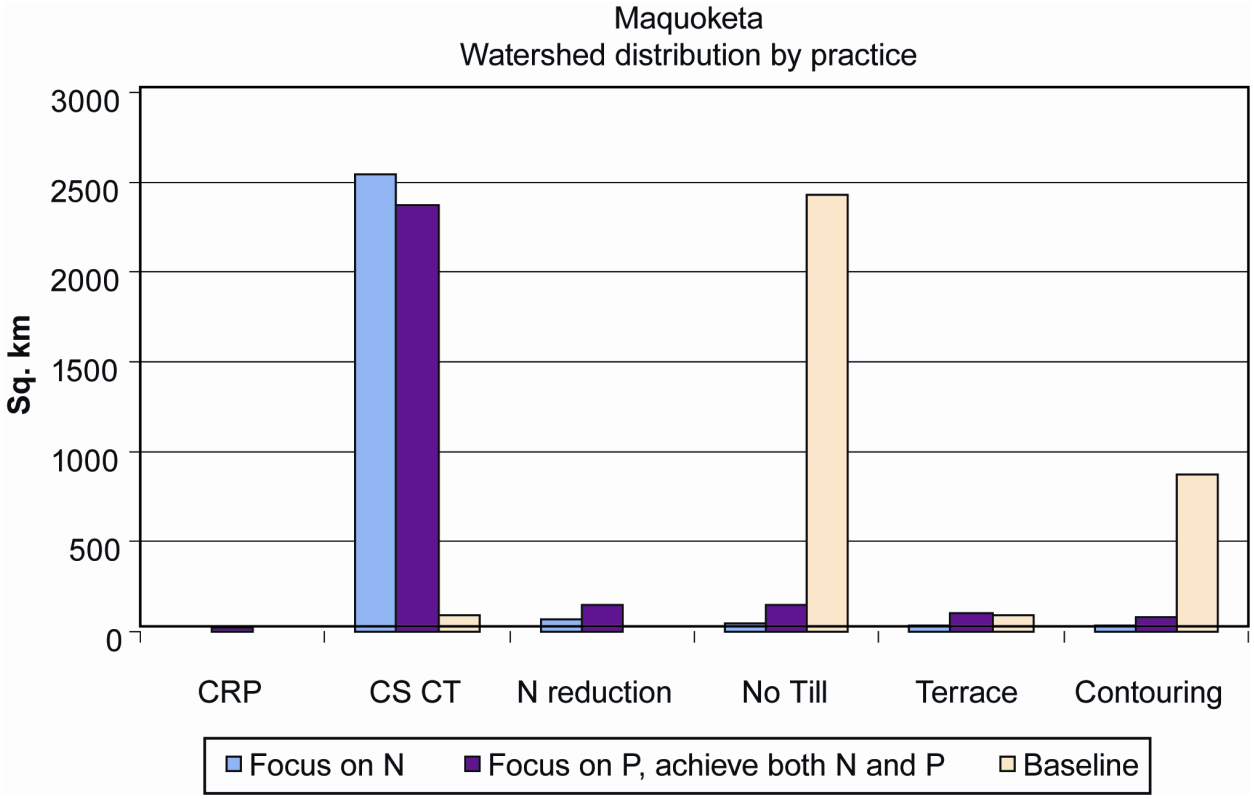

Iowa
Subbasin distribution by practice for baseline
Subbasins
9
8
7
6
5
4
3
2
1
0
1000
2000
3000
4000
5000
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

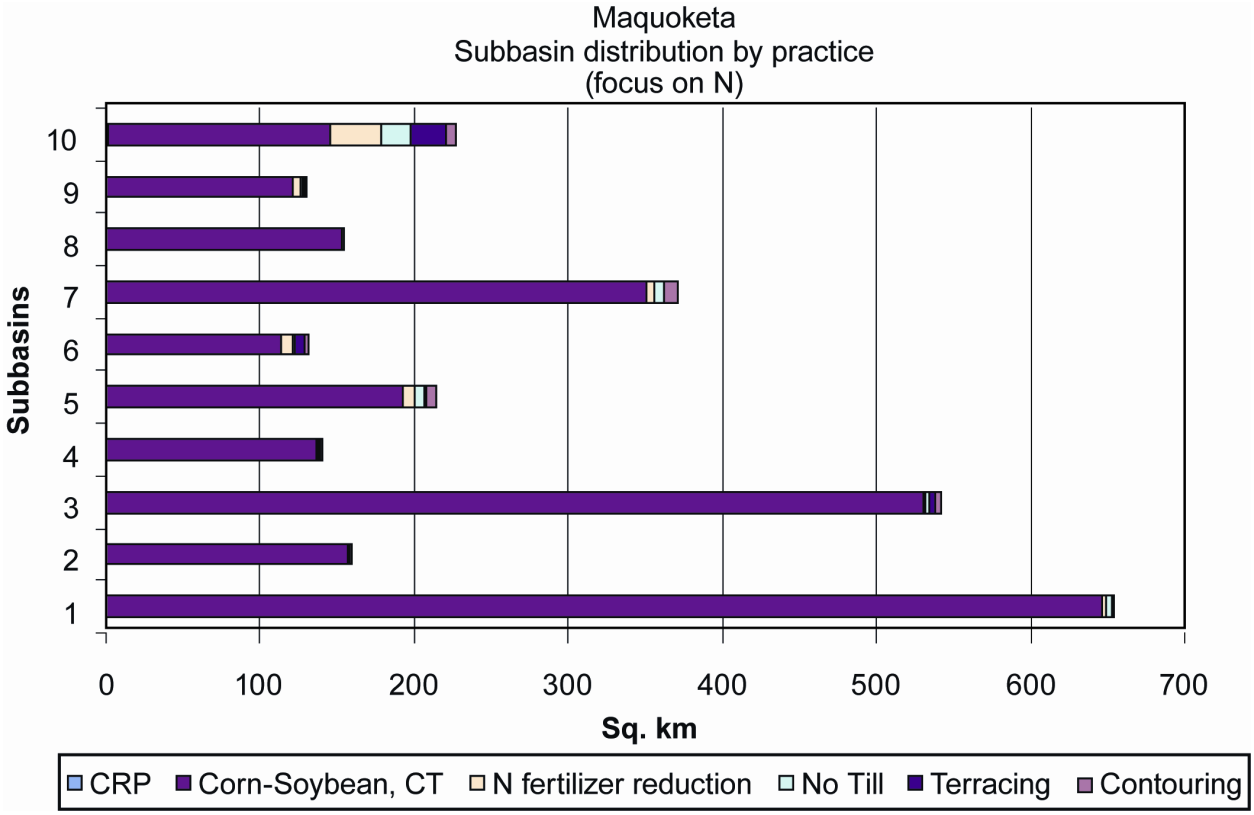

Little Sioux
Watershed distribution by practice
Sq. km
6000
5000
4000
3000
2000
1000
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

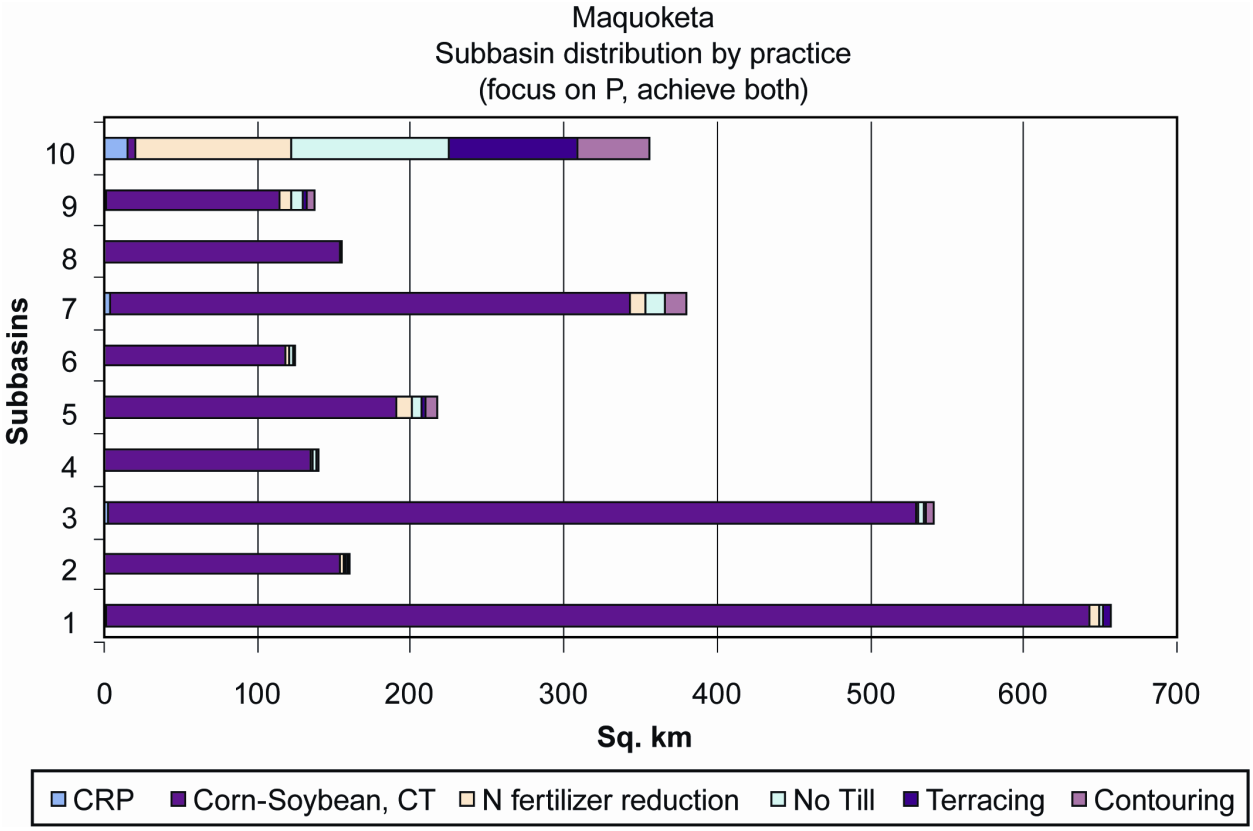

Little Sioux
Subbasin distribution by practice
(focus on N)
Subbasins
10
9
8
7
6
5
4
3
2
1
0
200
400
600
800
1000
1200
1400
1600
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

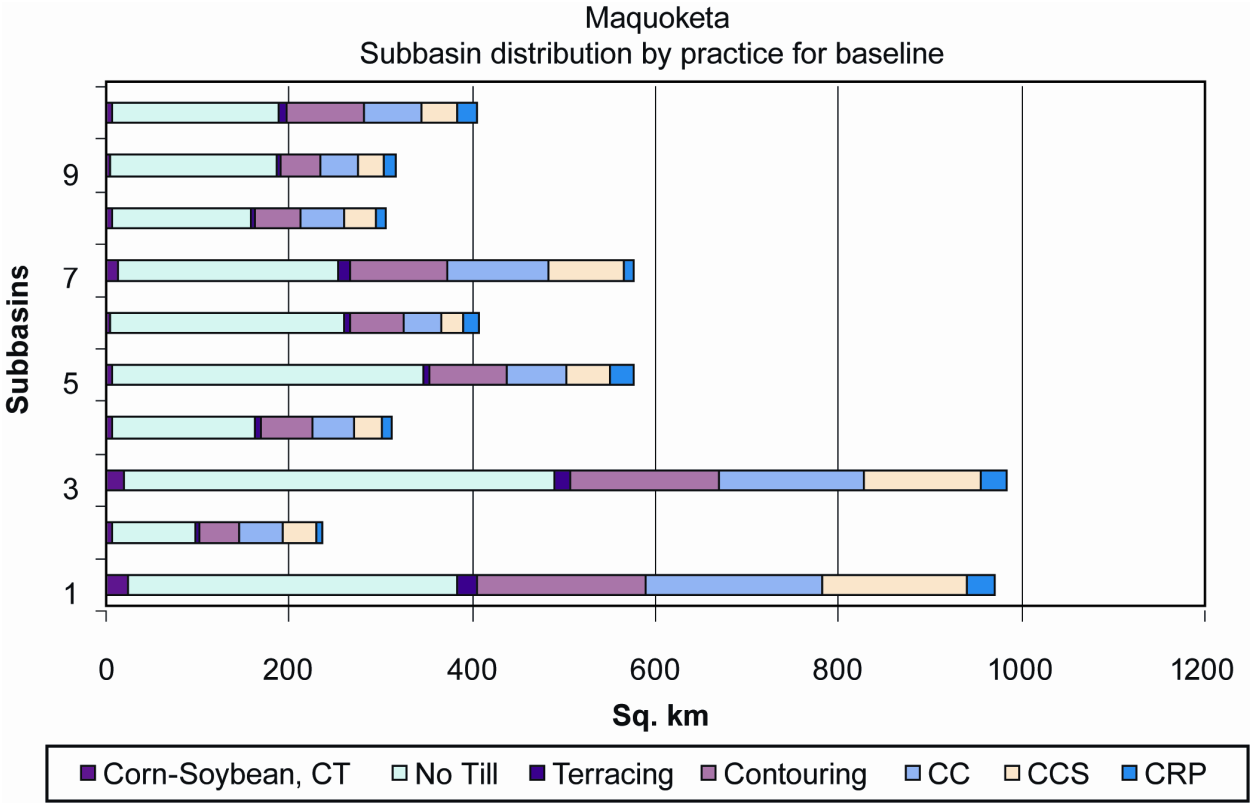

Little Sioux
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
10
9
8
7
6
5
4
3
2
1
0
500
1000
1500
2000
2500
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

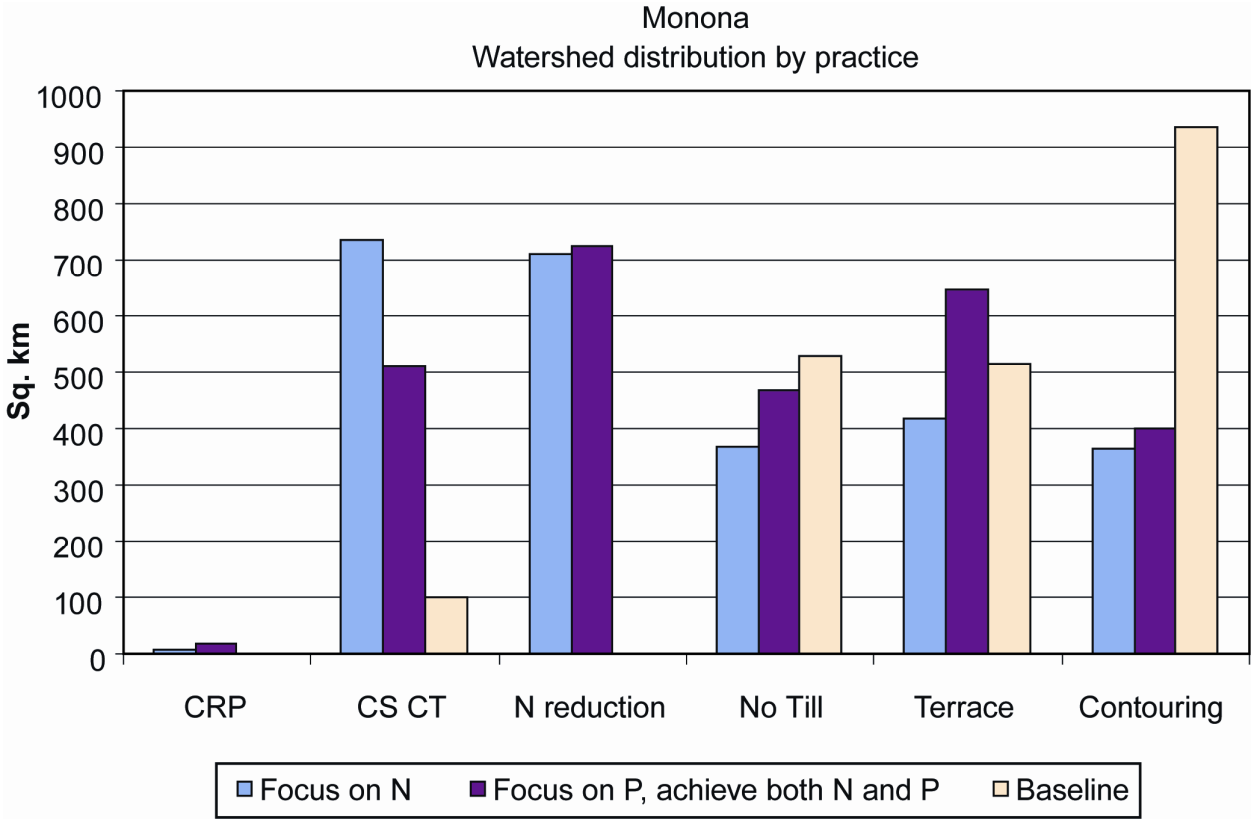

Little Sioux
Subbasin distribution by practice for baseline
Subbasins
10
9
8
7
6
5
4
3
2
1
0
200
400
600
800
1000
1200
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

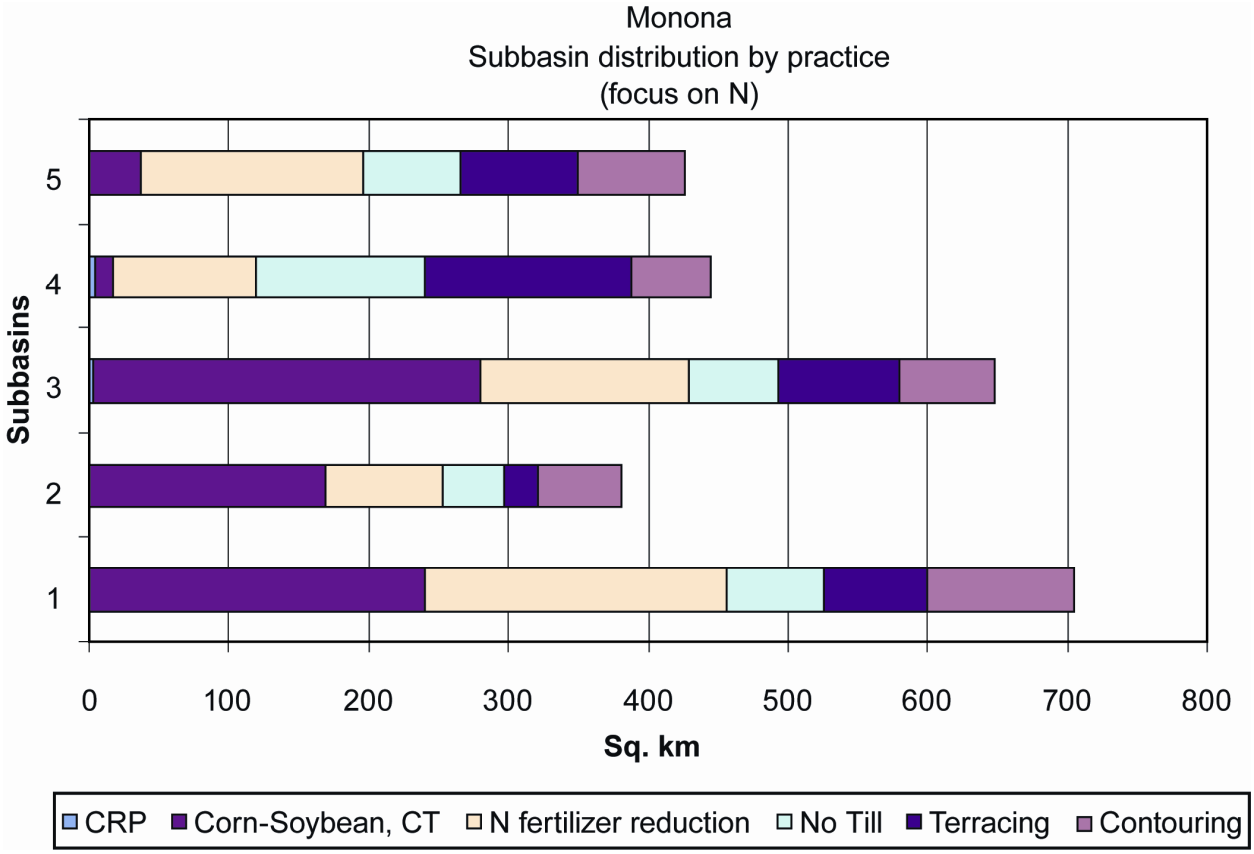

Maquoketa
Watershed distribution by practice
Sq. km
3000
2500
2000
1500
1000
500
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

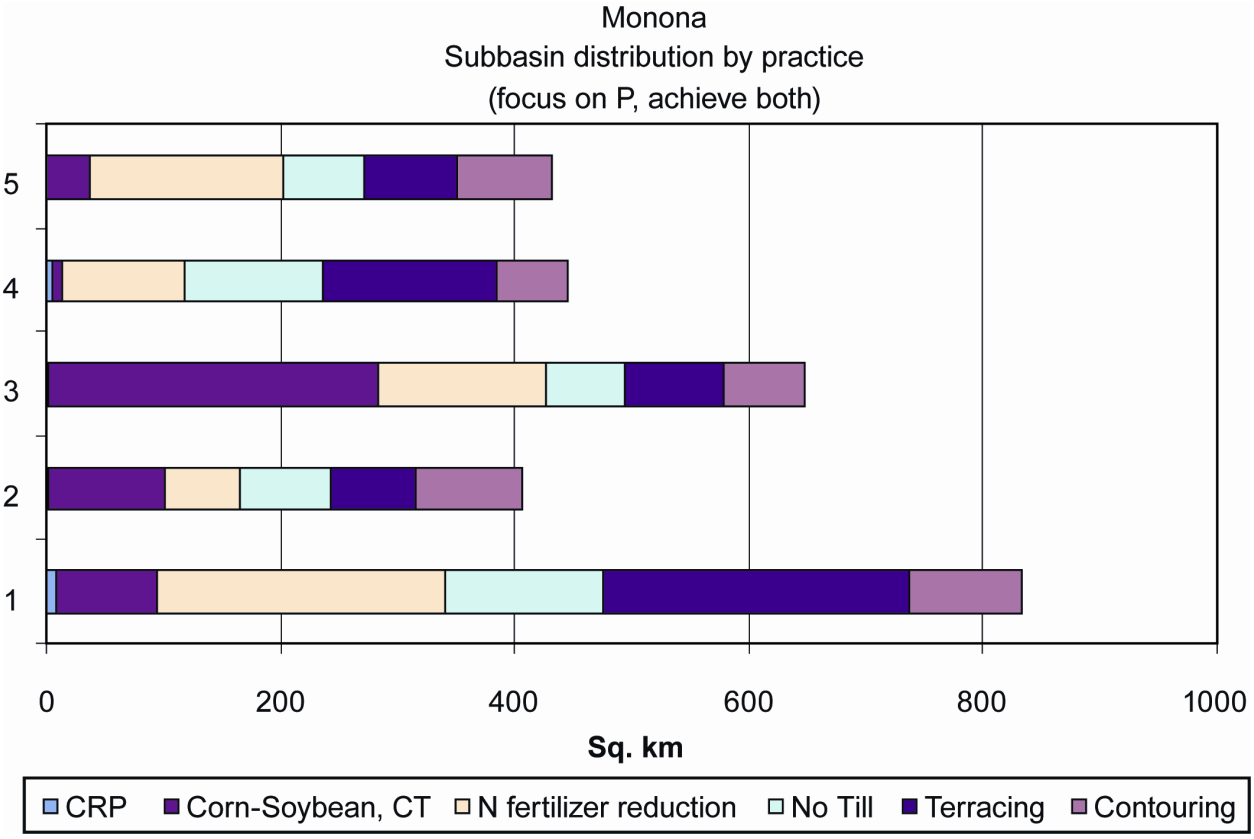

Maquoketa
Subbasin distribution by practice
(focus on N)
Subbasins
10
9
8
7
6
5
4
3
2
1
0
100
200
300
400
500
600
700
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

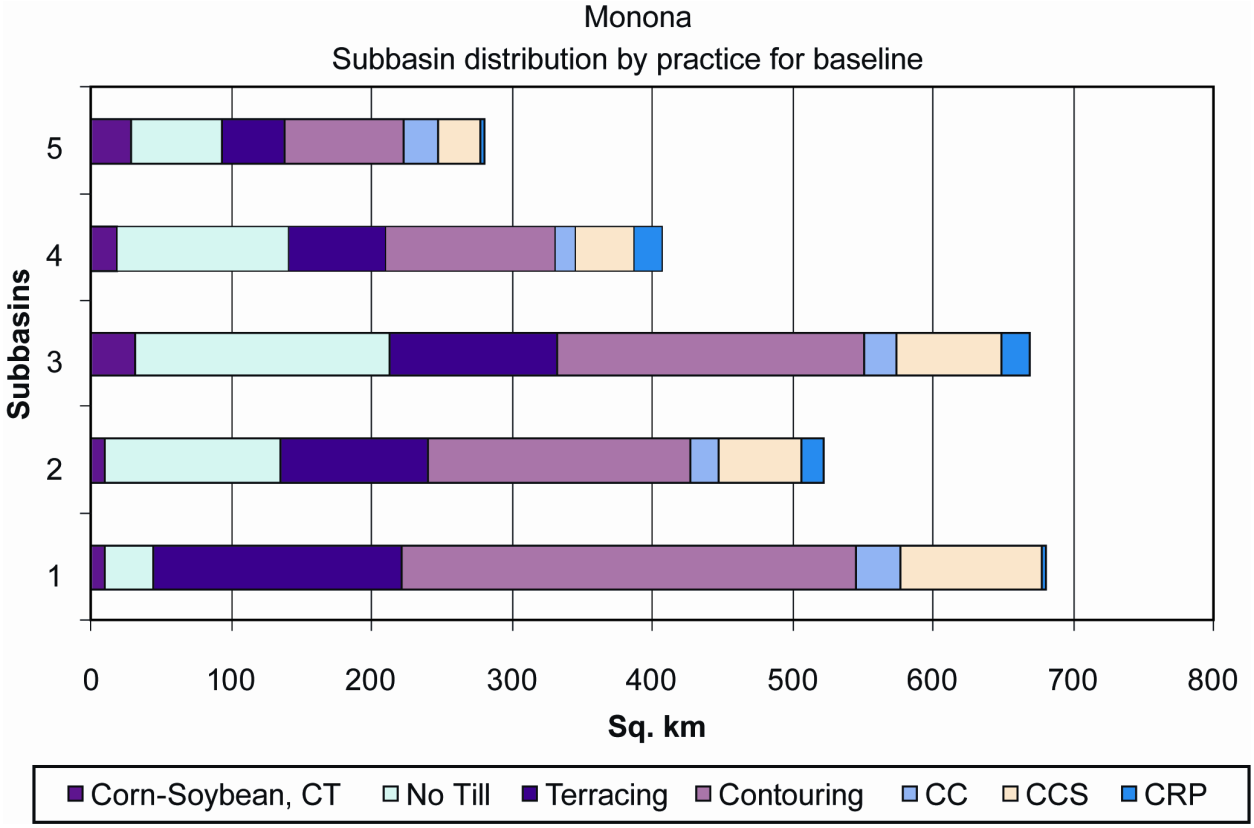

Maquoketa
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
10
9
8
7
6
5
4
3
2
1
0
100
200
300
400
500
600
700
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

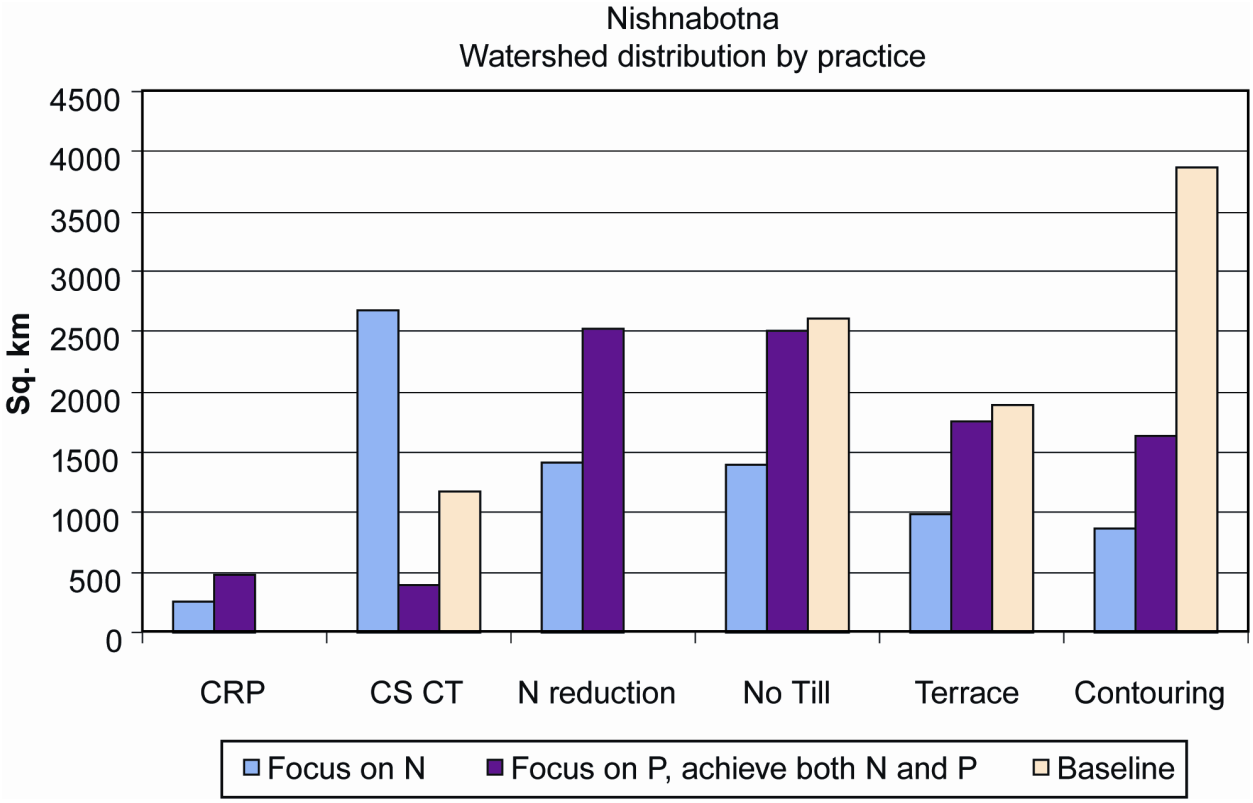

Maquoketa
Subbasin distribution by practice for baseline
Subbasins
9
7
5
3
1
0
200
400
600
800
1000
1200
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

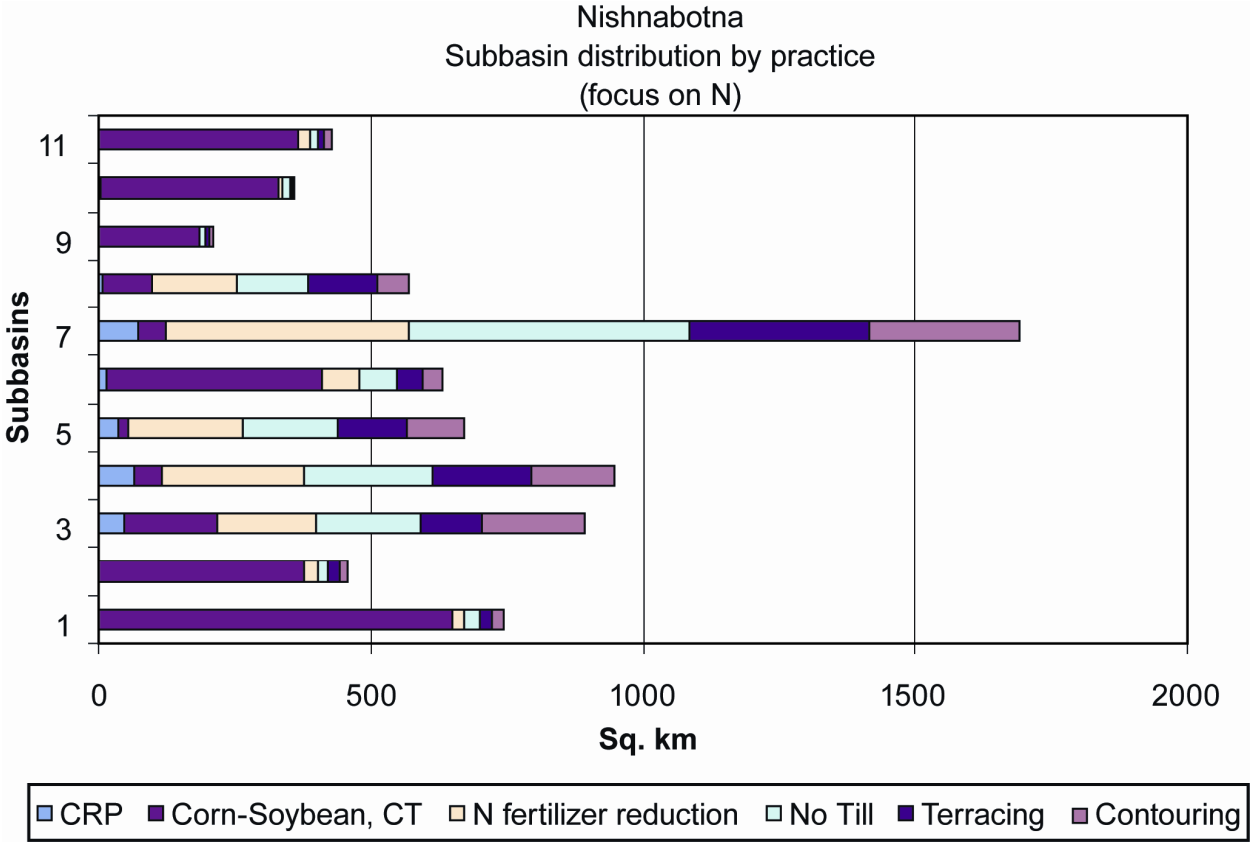

Monona
Watershed distribution by practice
Sq. km
1000
900
800
700
600
500
400
300
200
100
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

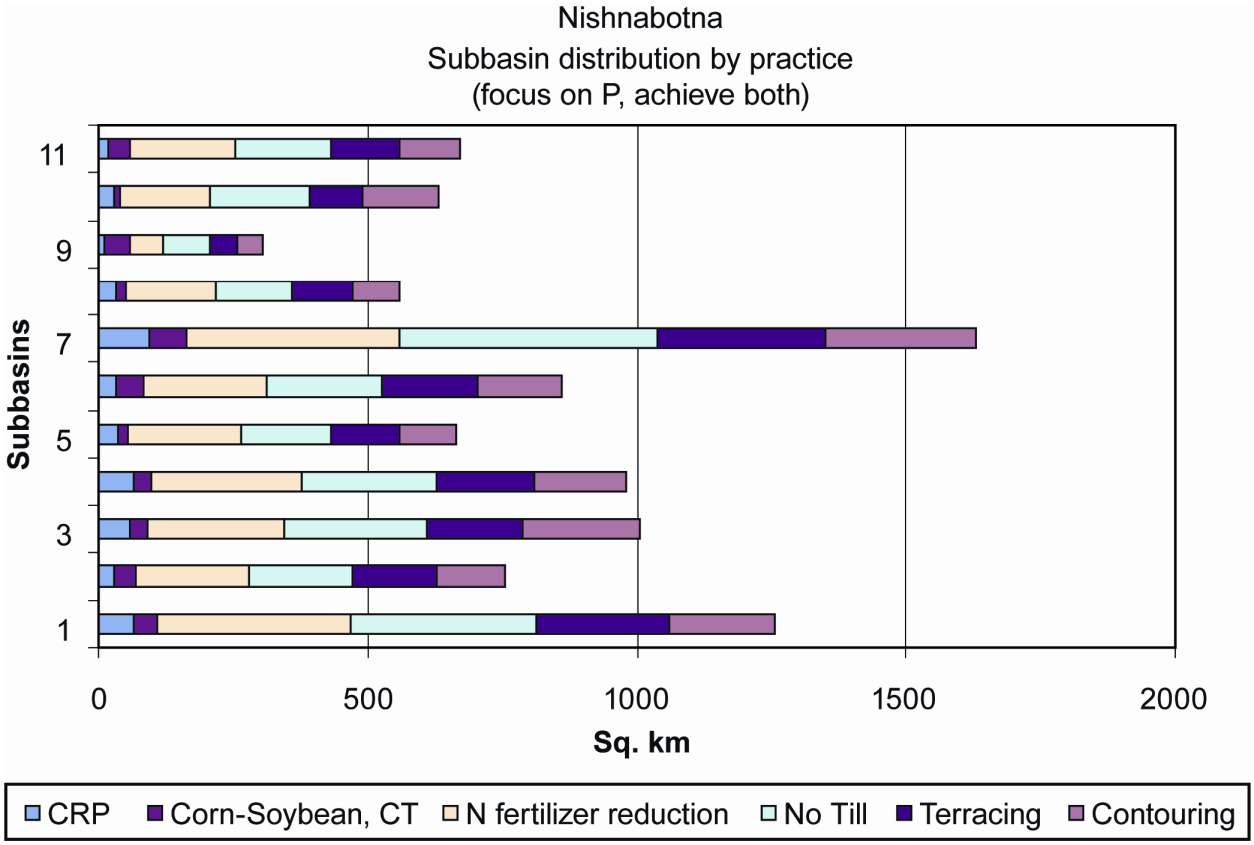

Monona
Subbasin distribution by practice
(focus on N)
Subbasins
5
4
3
2
1
0
100
200
300
400
500
600
700
800
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

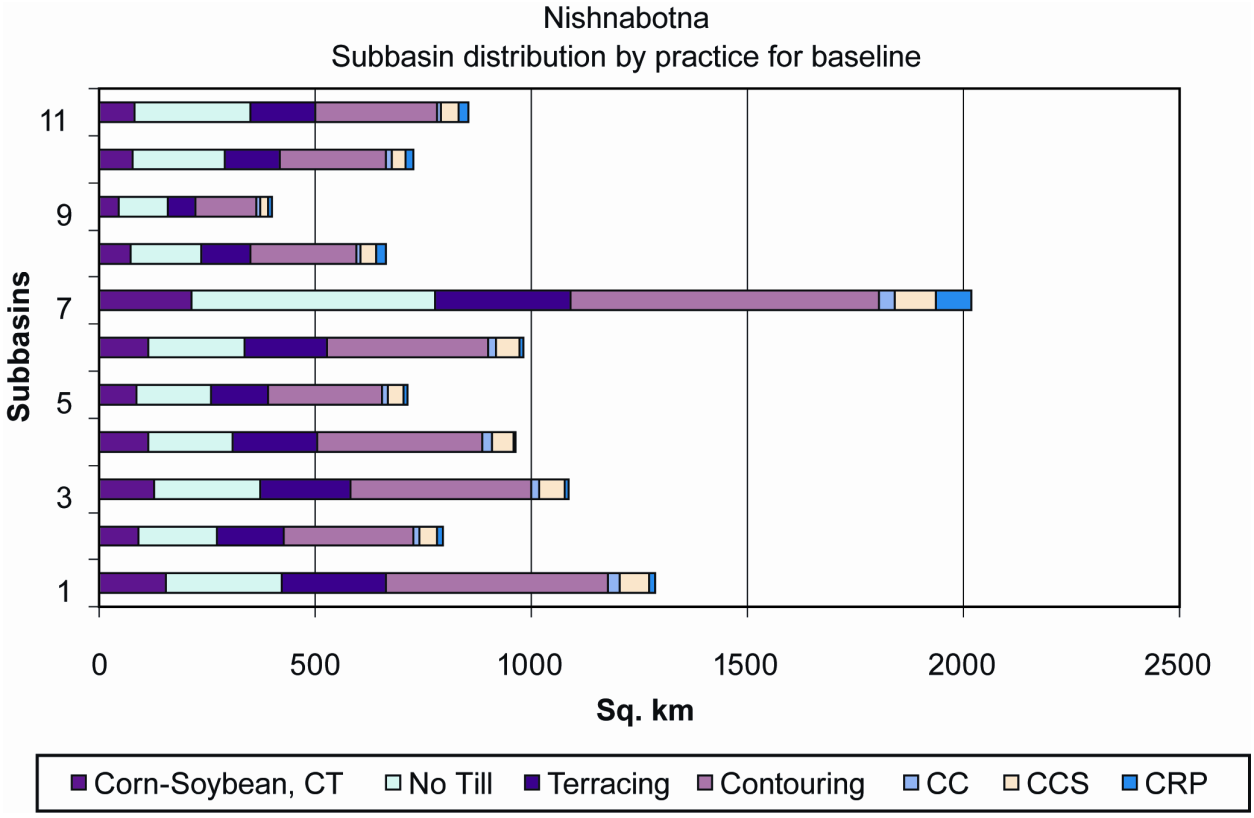

Monona
Subbasin distribution by practice
(focus on P, achieve both)
5
4
3
2
1
0
200
400
600
800
1000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

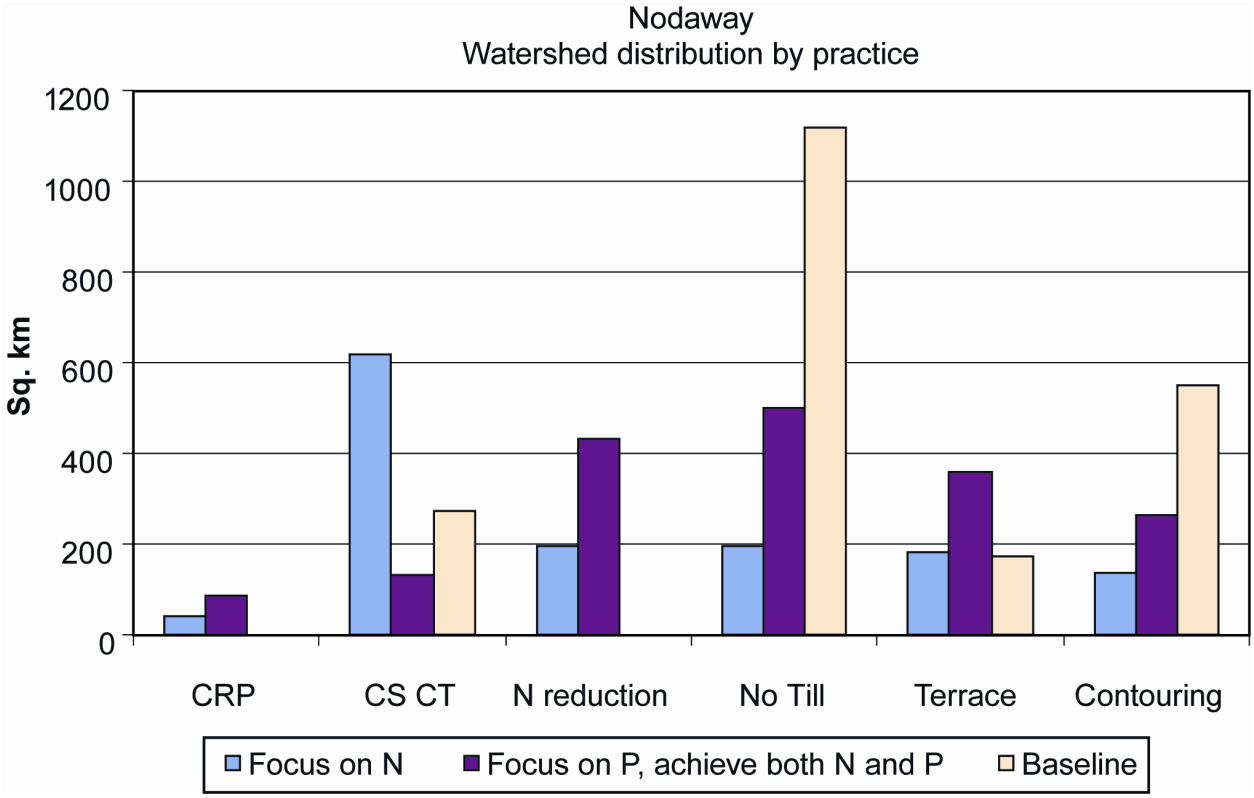

Monona
Subbasin distribution by practice for baseline
Subbasins
5
4
3
2
1
0
100
200
300
400
500
600
700
800
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

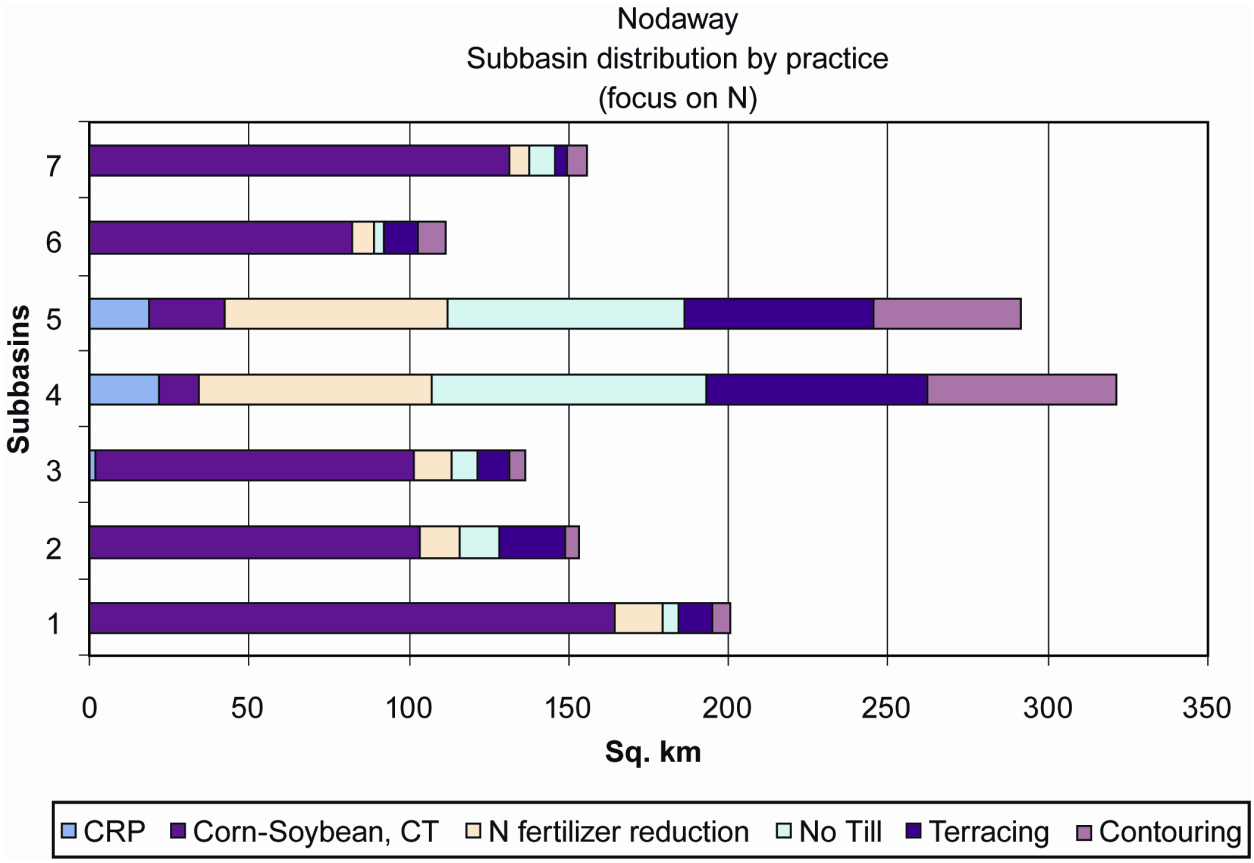

Nishnabotna
Watershed distribution by practice
Sq. km
4500
4000
3500
3000
2500
2000
1500
1000
500
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

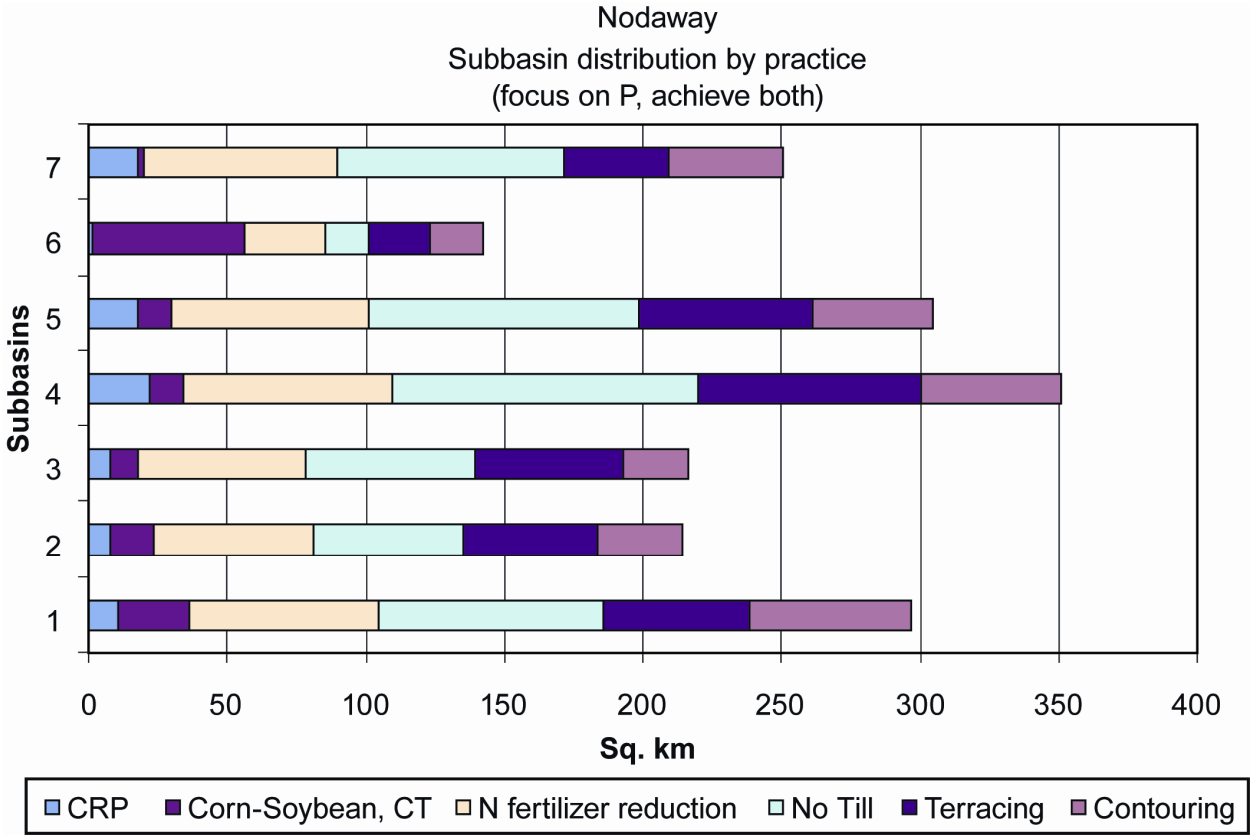

Nishnabotna
Subbasin distribution by practice
(focus on N)
Subbasins
11
9
7
5
3
1
0
500
1000
1500
2000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

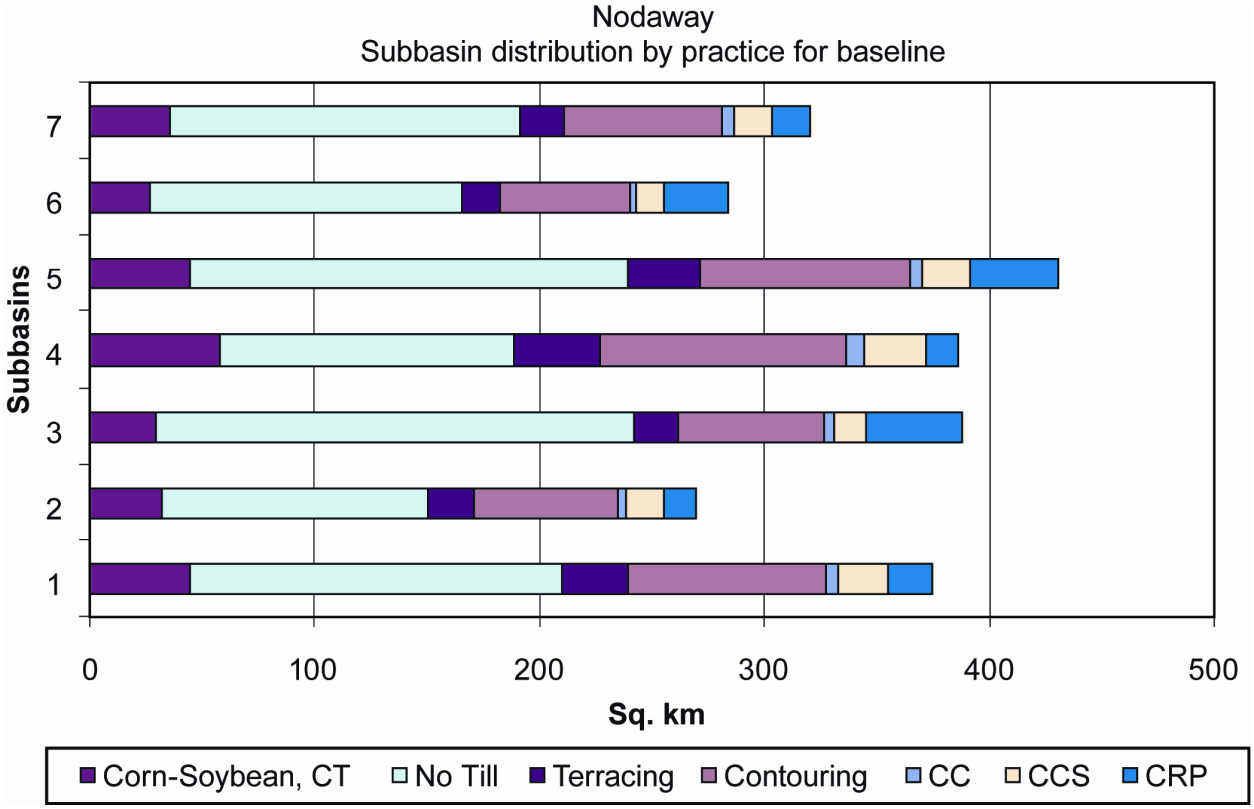

Nishnabotna
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
11
9
7
5
3
1
0
500
1000
1500
2000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

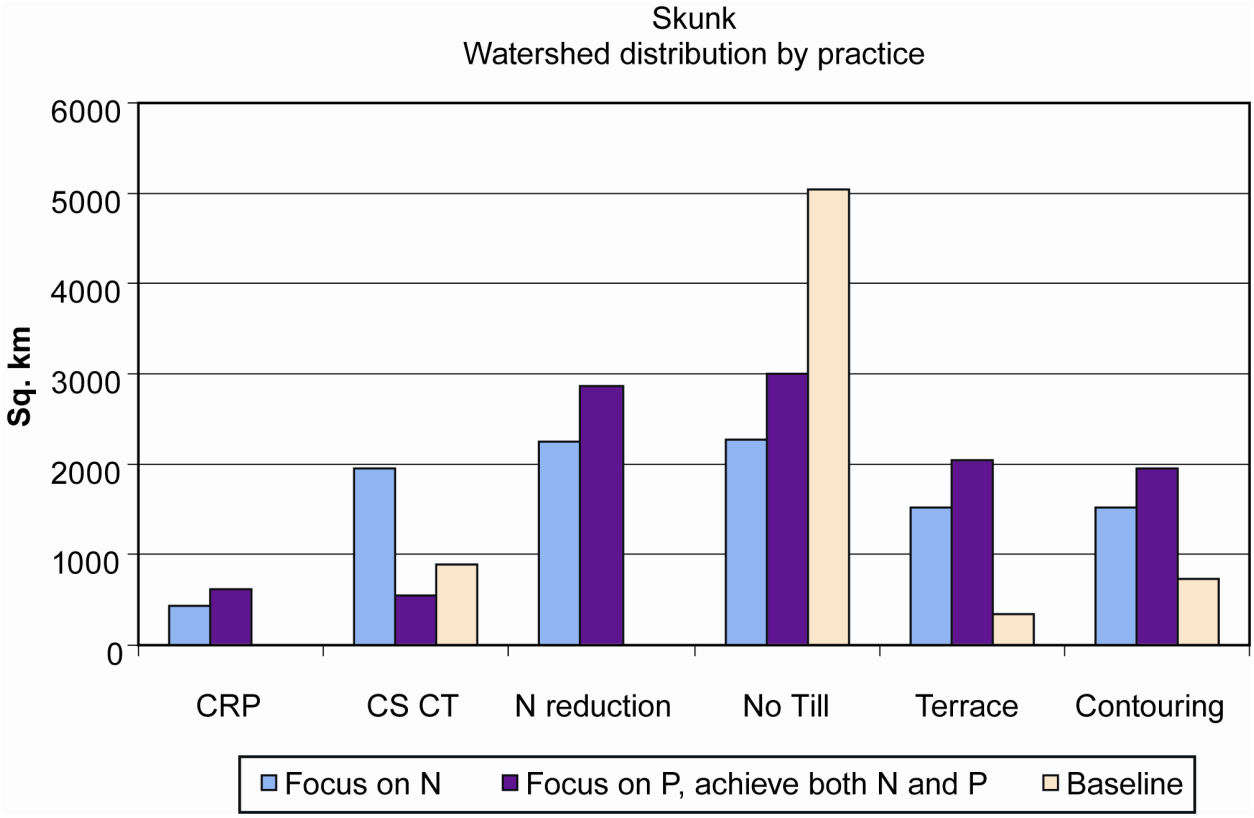

Nishnabotna
Subbasin distribution by practice for baseline
Subbasins
11
9
7
5
3
1
0
500
1000
1500
2000
2500
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

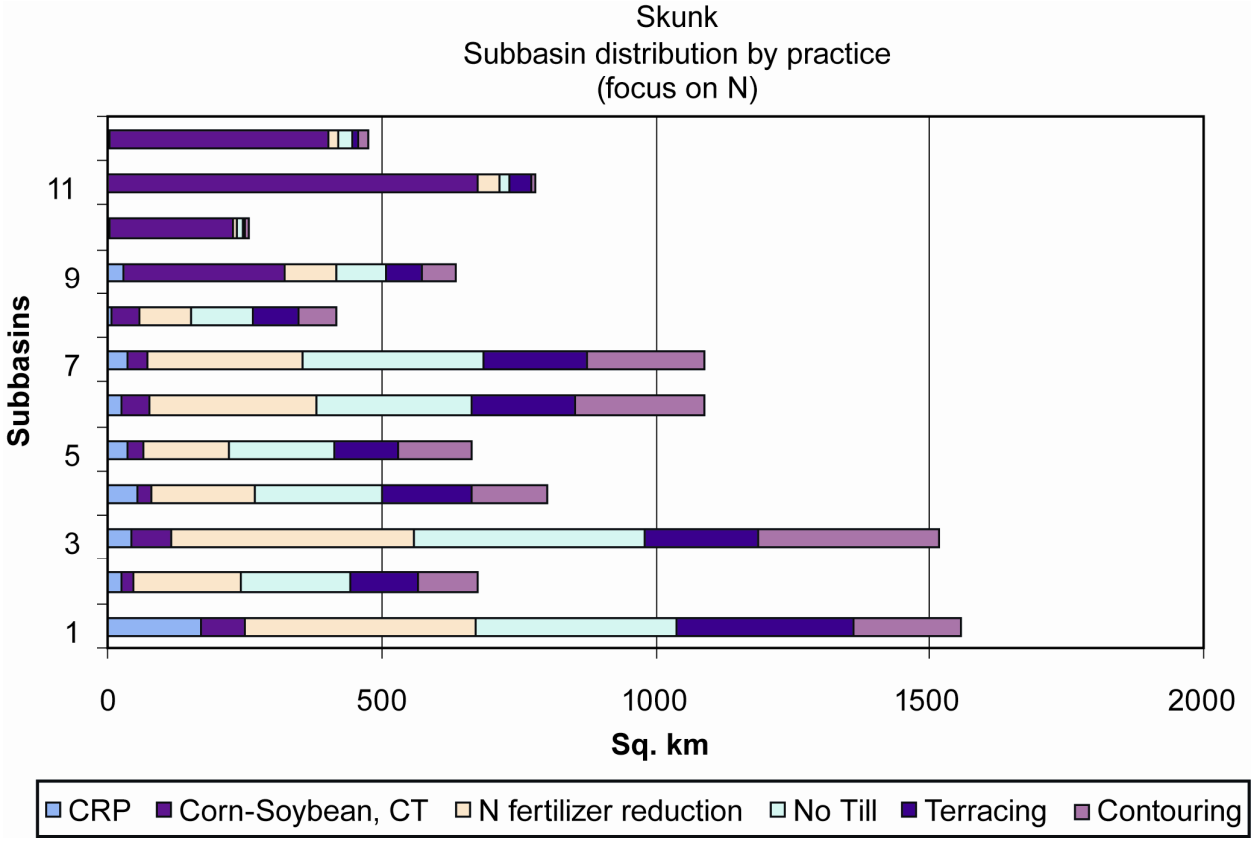

Nodaway
Watershed distribution by practice
Sq. km
1200
1000
800
600
400
200
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

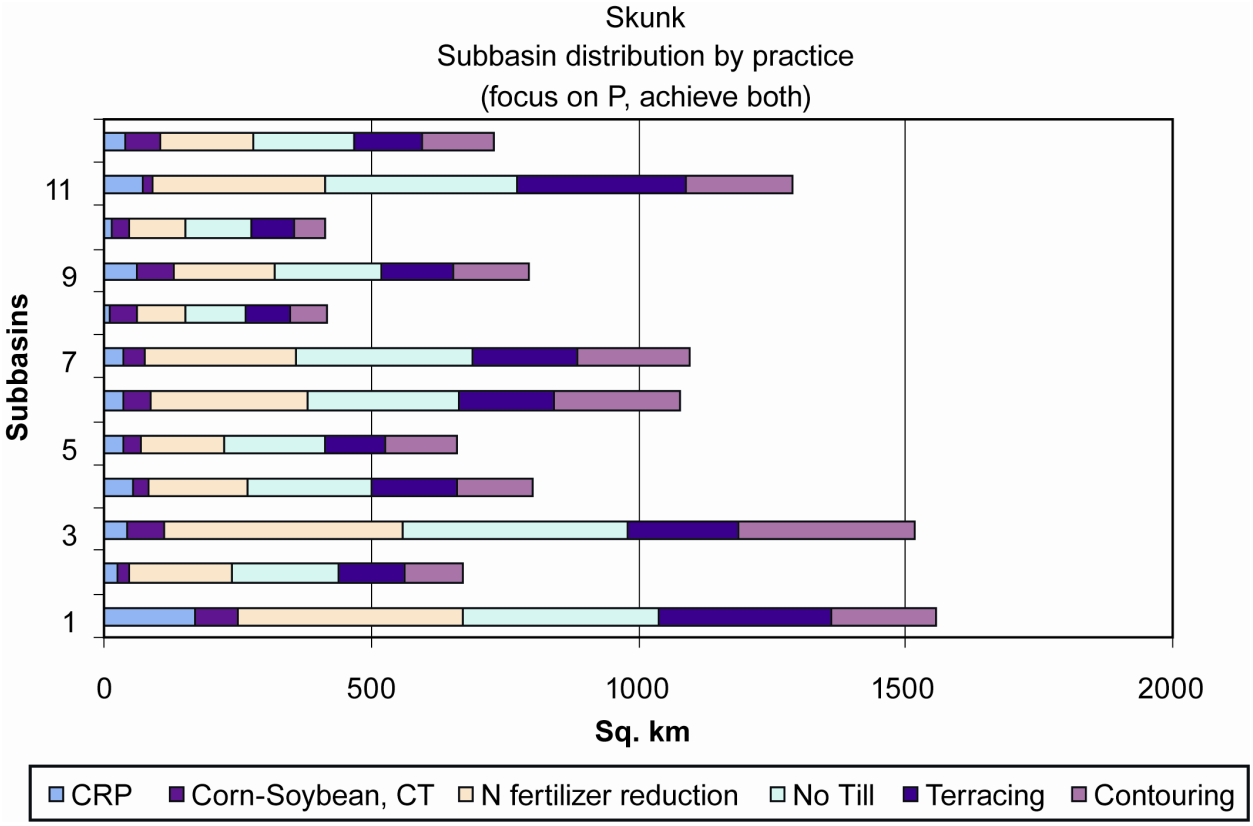

Nodaway
Subbasin distribution by practice
(focus on N)
Subbasins
7
6
5
4
3
2
1
0
50
100
150
200
250
300
350
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

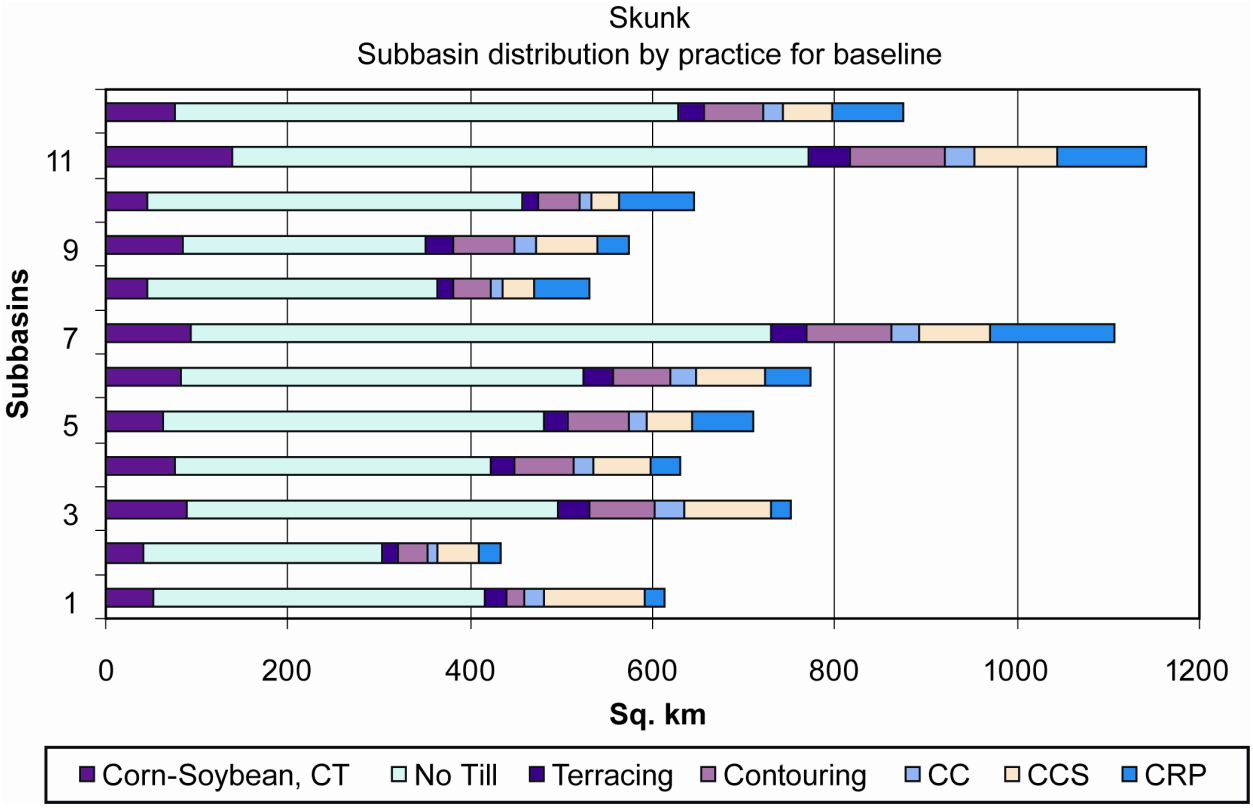

Nodaway
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
7
6
5
4
3
2
1
0
50
100
150
200
250
300
350
400
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

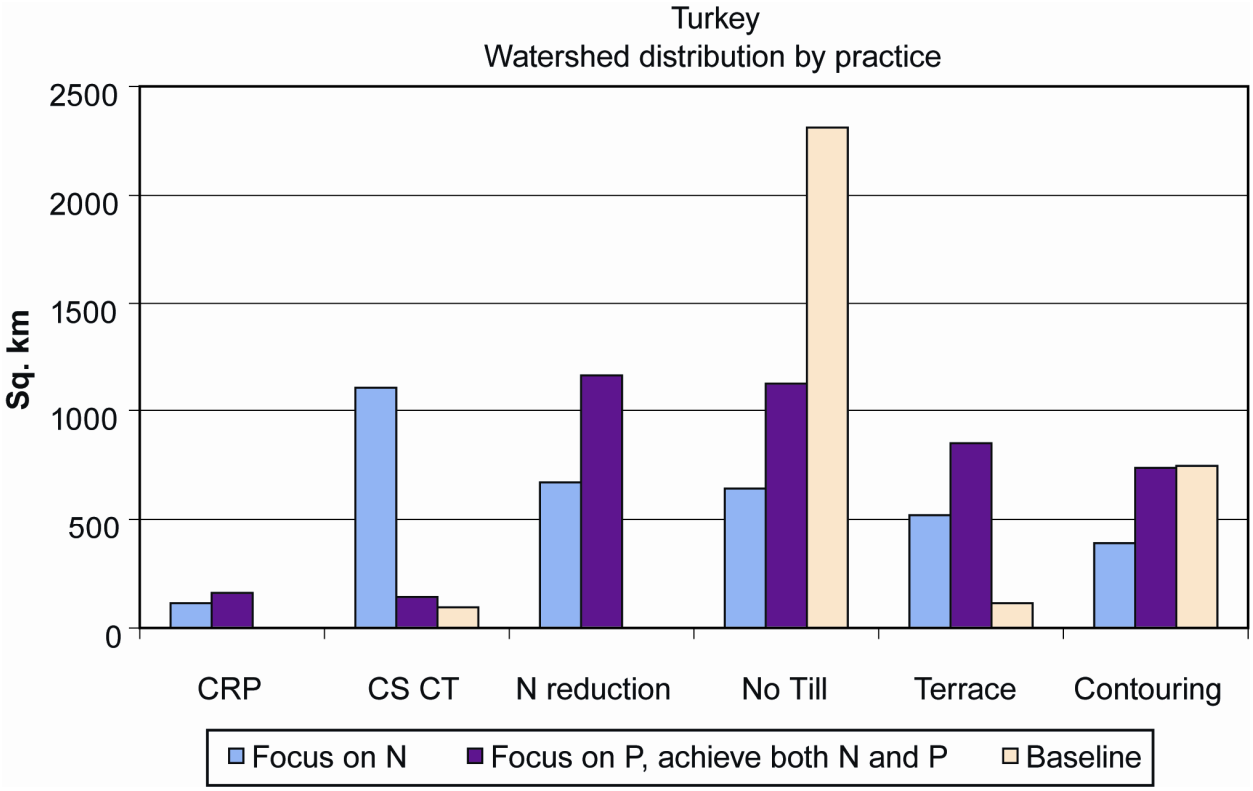

Nodaway
Subbasin distribution by practice for baseline
Subbasins
7
6
5
4
3
2
1
0
100
200
300
400
500
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

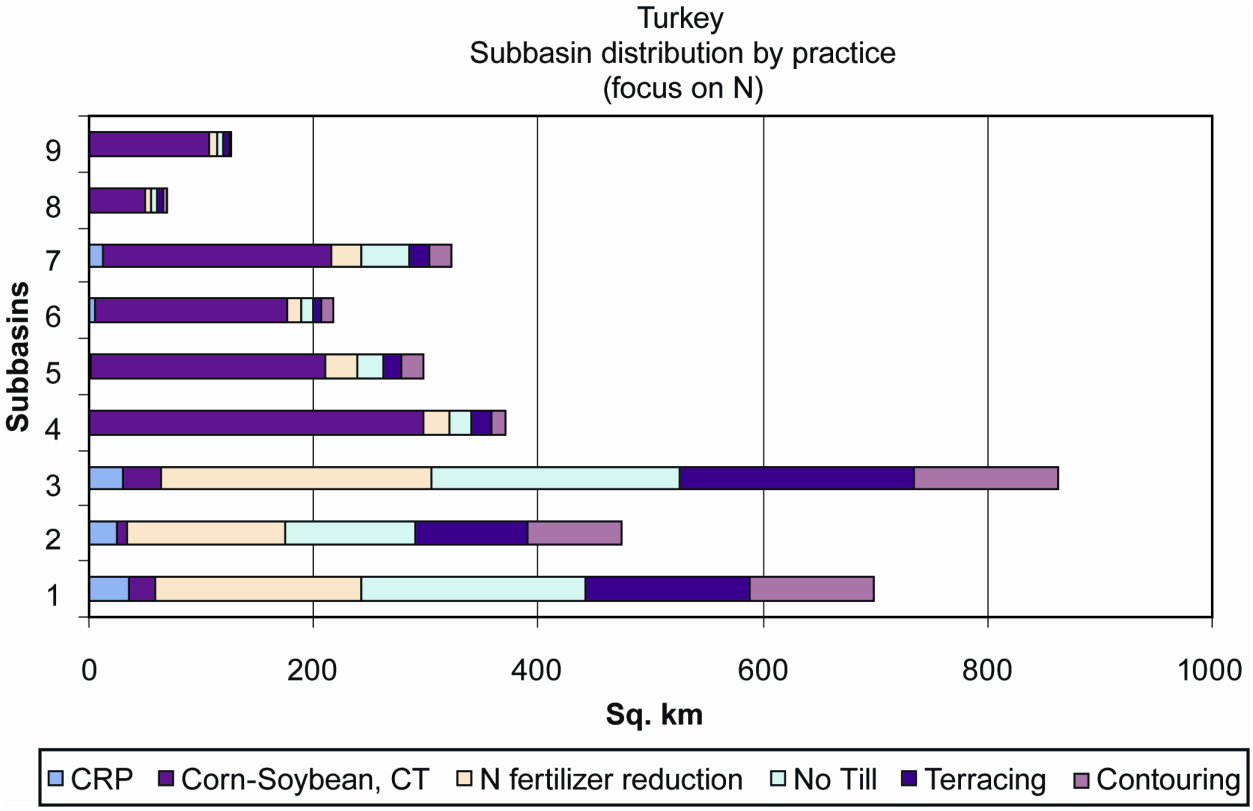

Skunk
Watershed distribution by practice
Sq. km
6000
5000
4000
3000
2000
1000
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

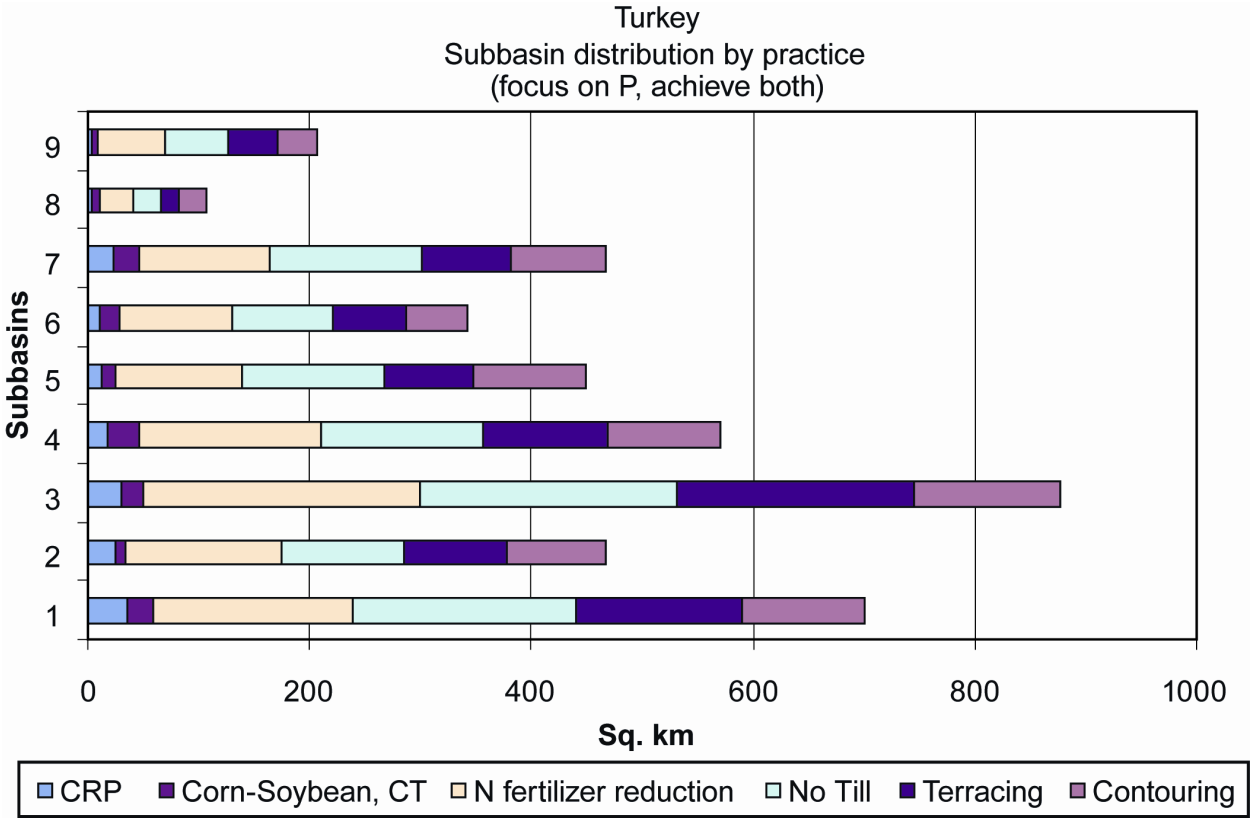

Skunk
Subbasin distribution by practice
(focus on N)
Subbasins
11
9
7
5
3
1
0
500
1000
1500
2000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

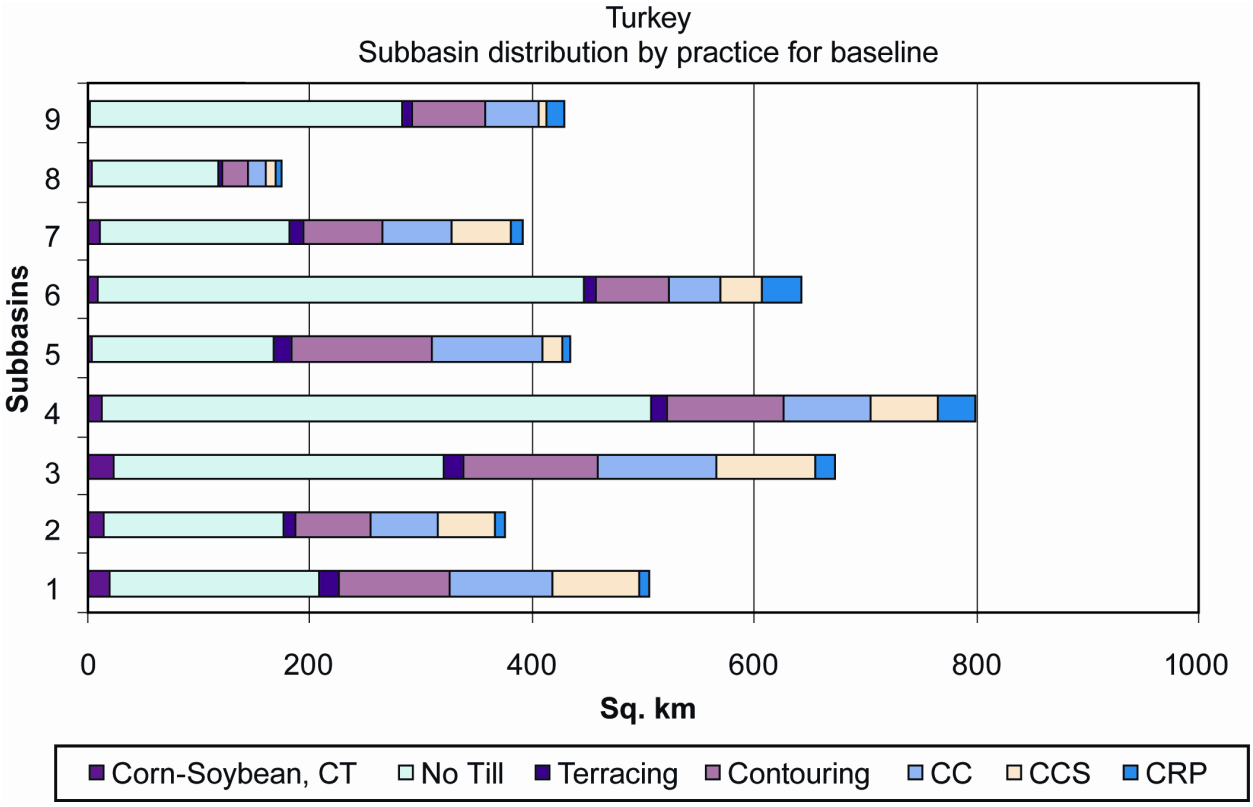

Skunk
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
11
9
7
5
3
1
0
500
1000
1500
2000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

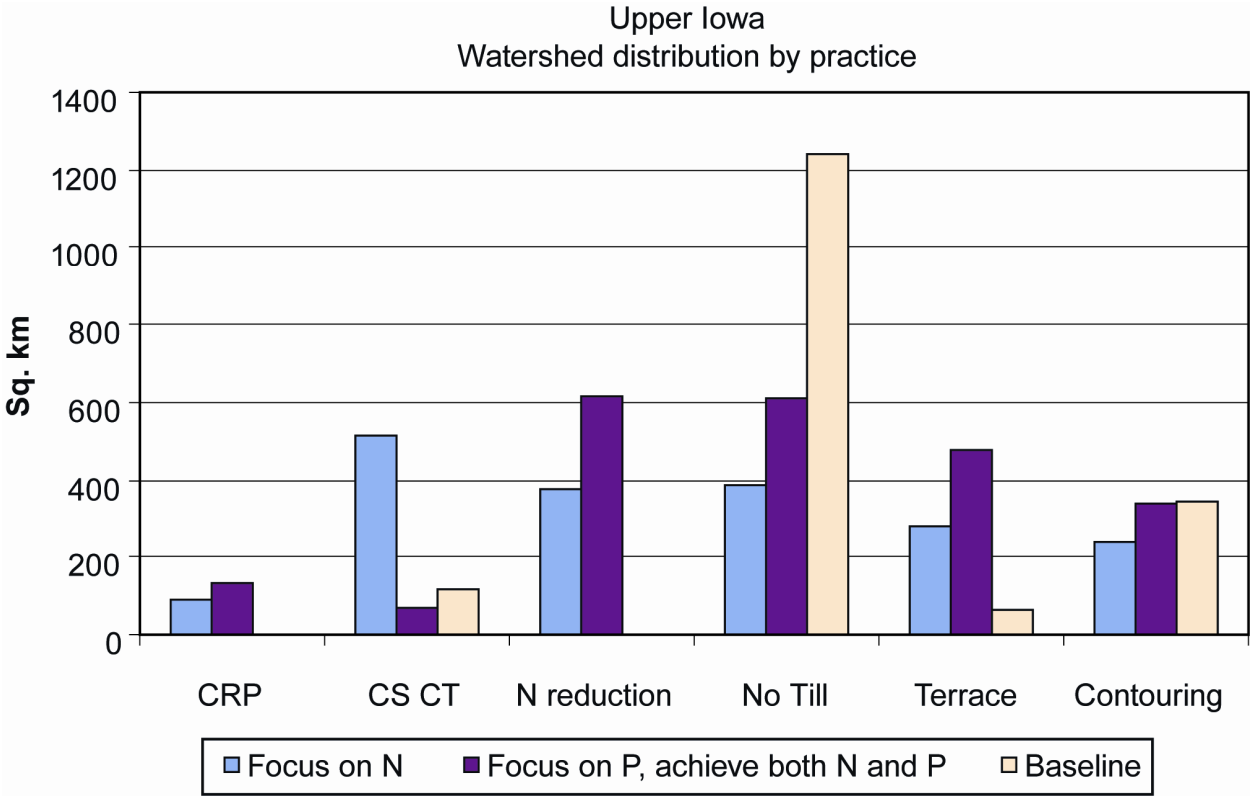

Skunk
Subbasin distribution by practice for baseline
Subbasins
11
9
7
5
3
1
0
200
400
600
800
1000
1200
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

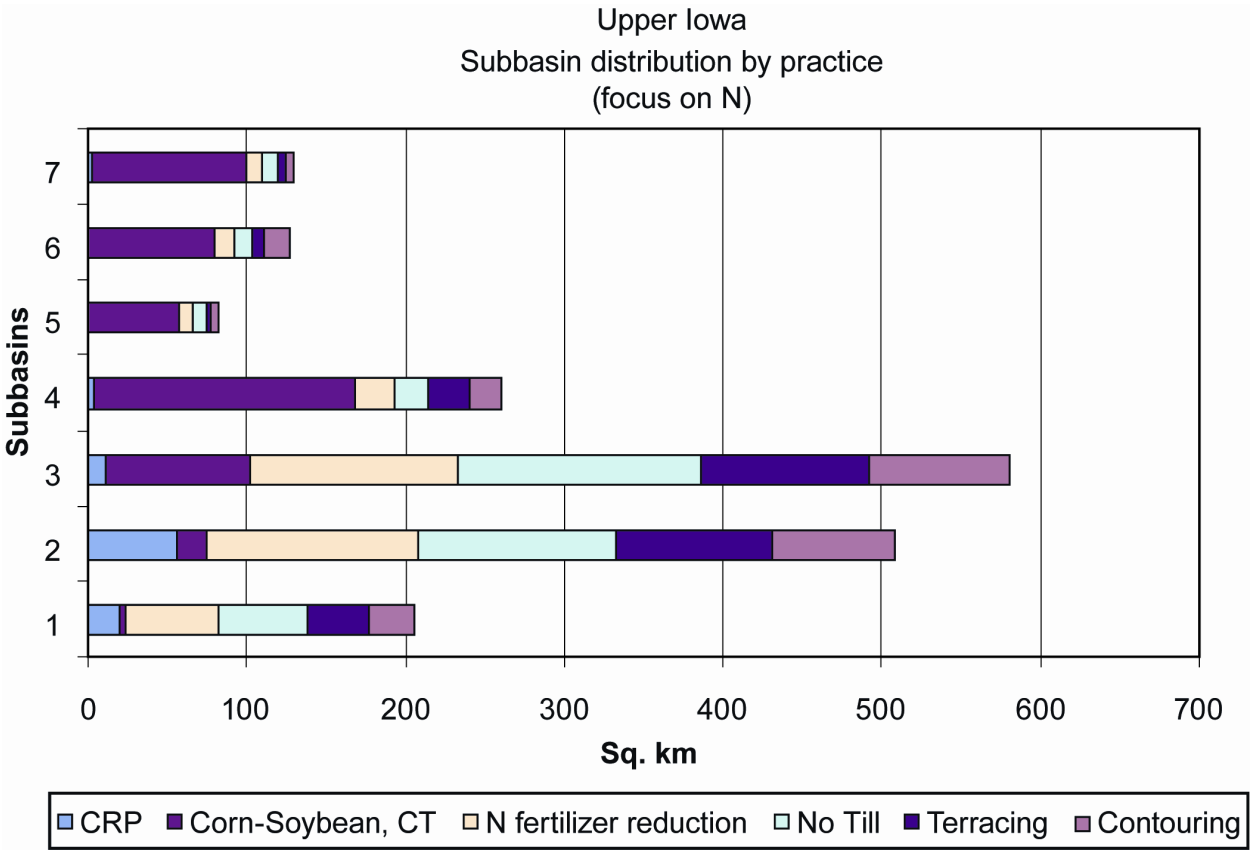

Turkey
Watershed distribution by practice
Sq. km
2500
2000
1500
1000
500
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

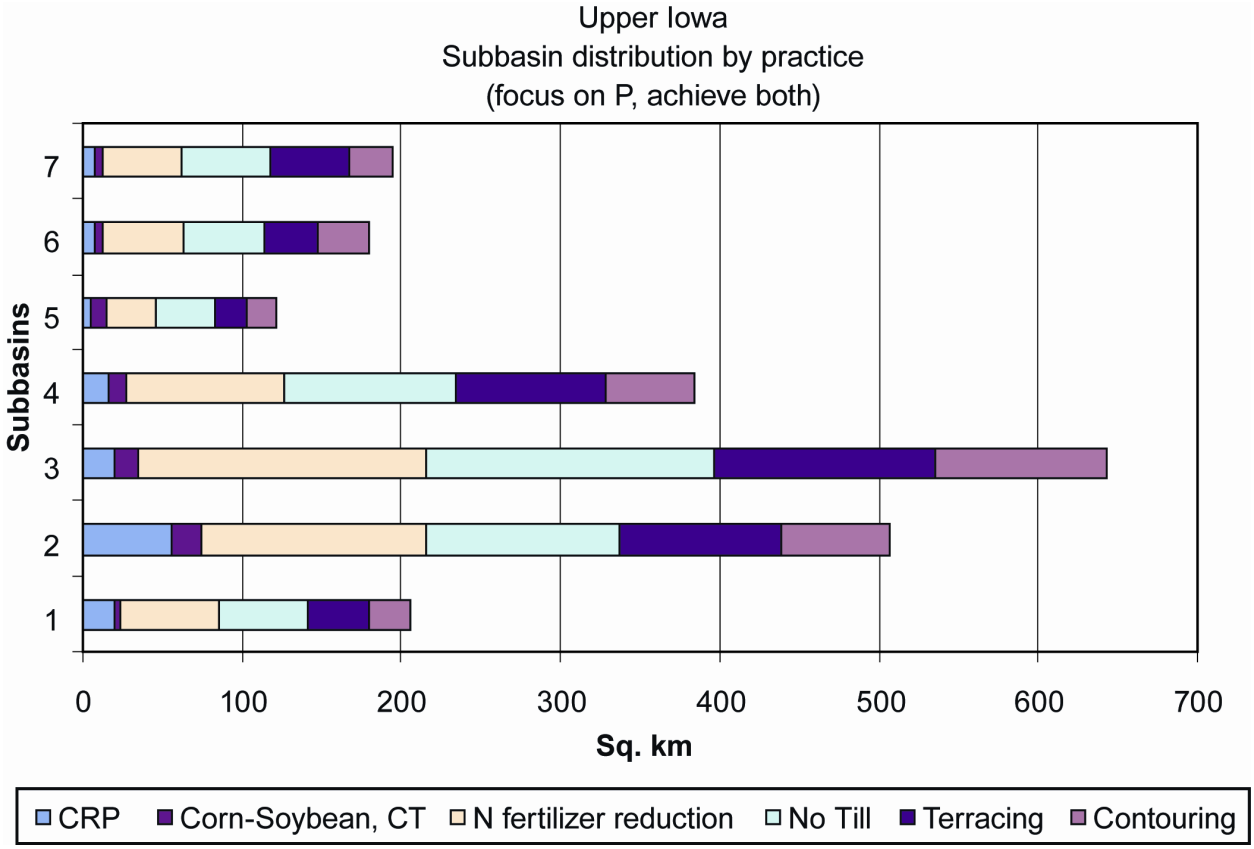

Turkey
Subbasin distribution by practice
(focus on N)
Subbasins
9
8
7
6
5
4
3
2
1
0
200
400
600
800
1000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

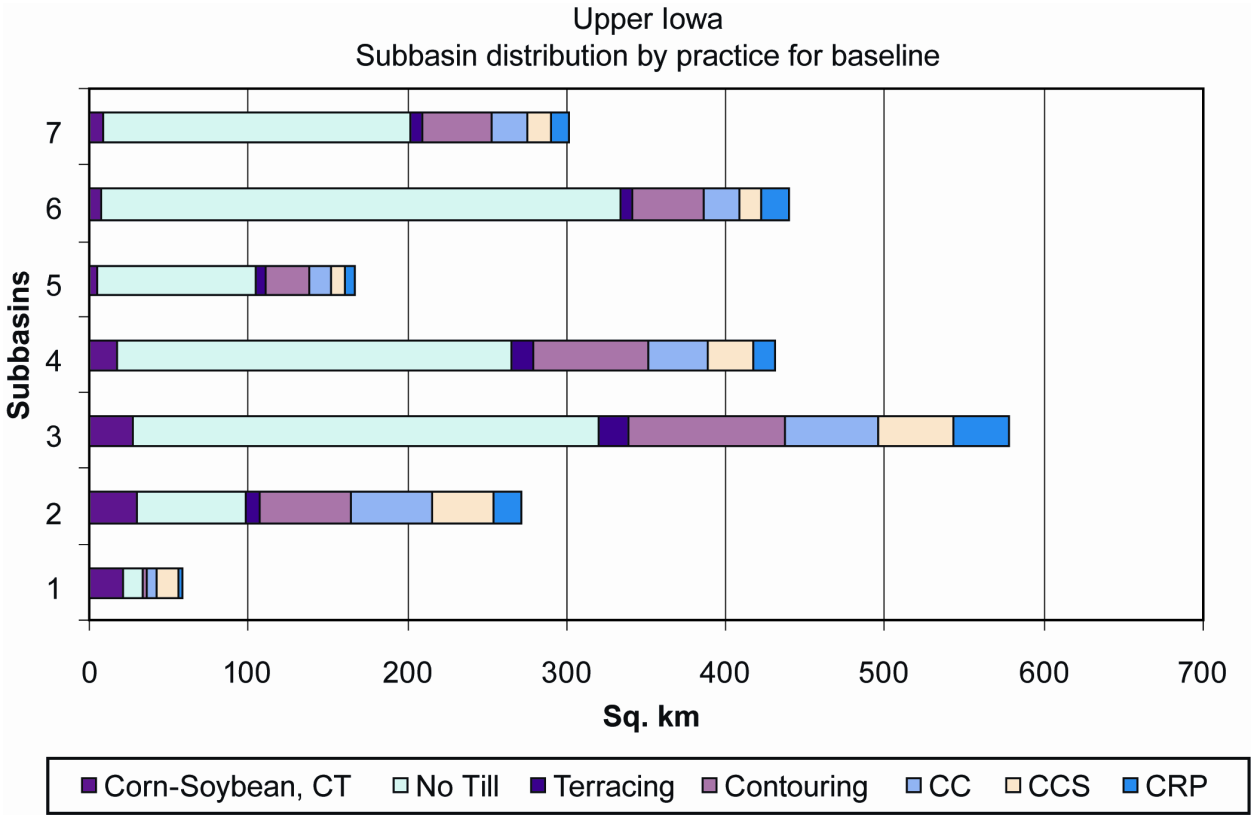

Turkey
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
9
8
7
6
5
4
3
2
1
0
200
400
600
800
1000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

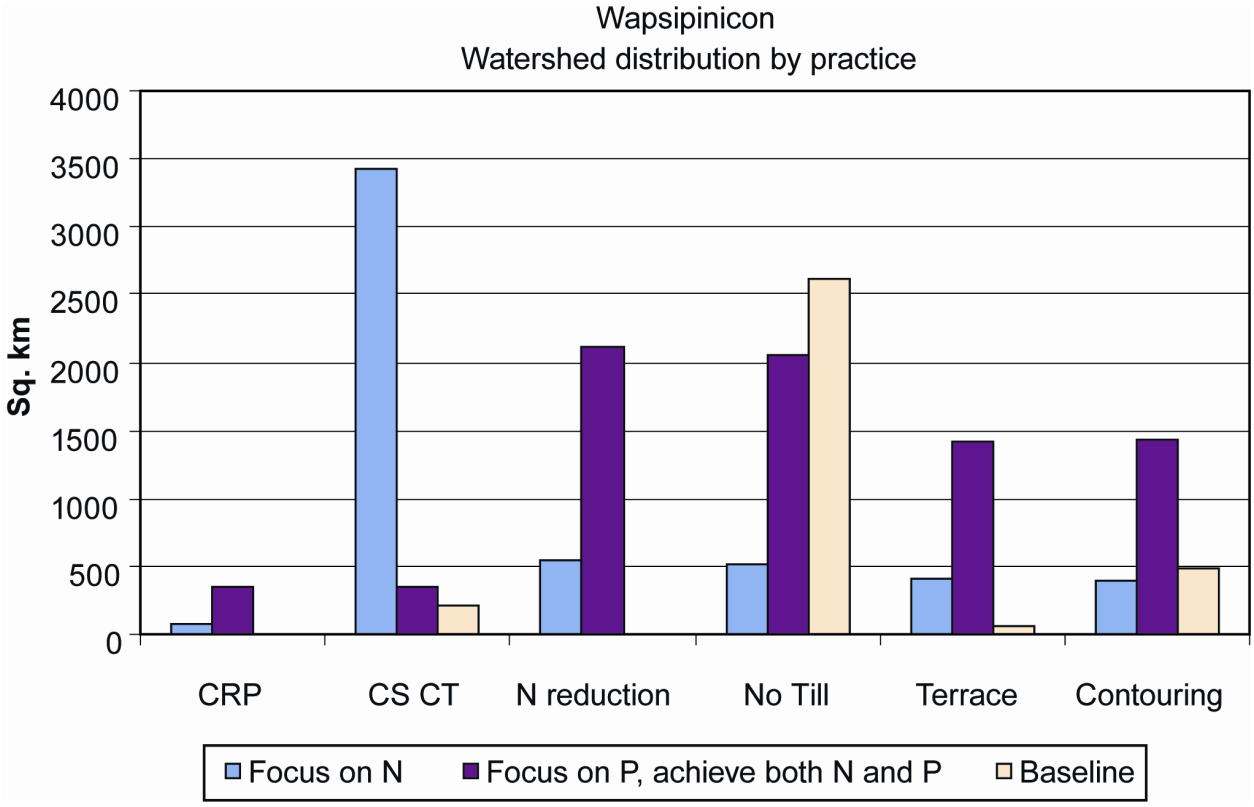

Turkey
Subbasin distribution by practice for baseline
Subbasins
9
8
7
6
5
4
3
2
1
0
200
400
600
800
1000
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP

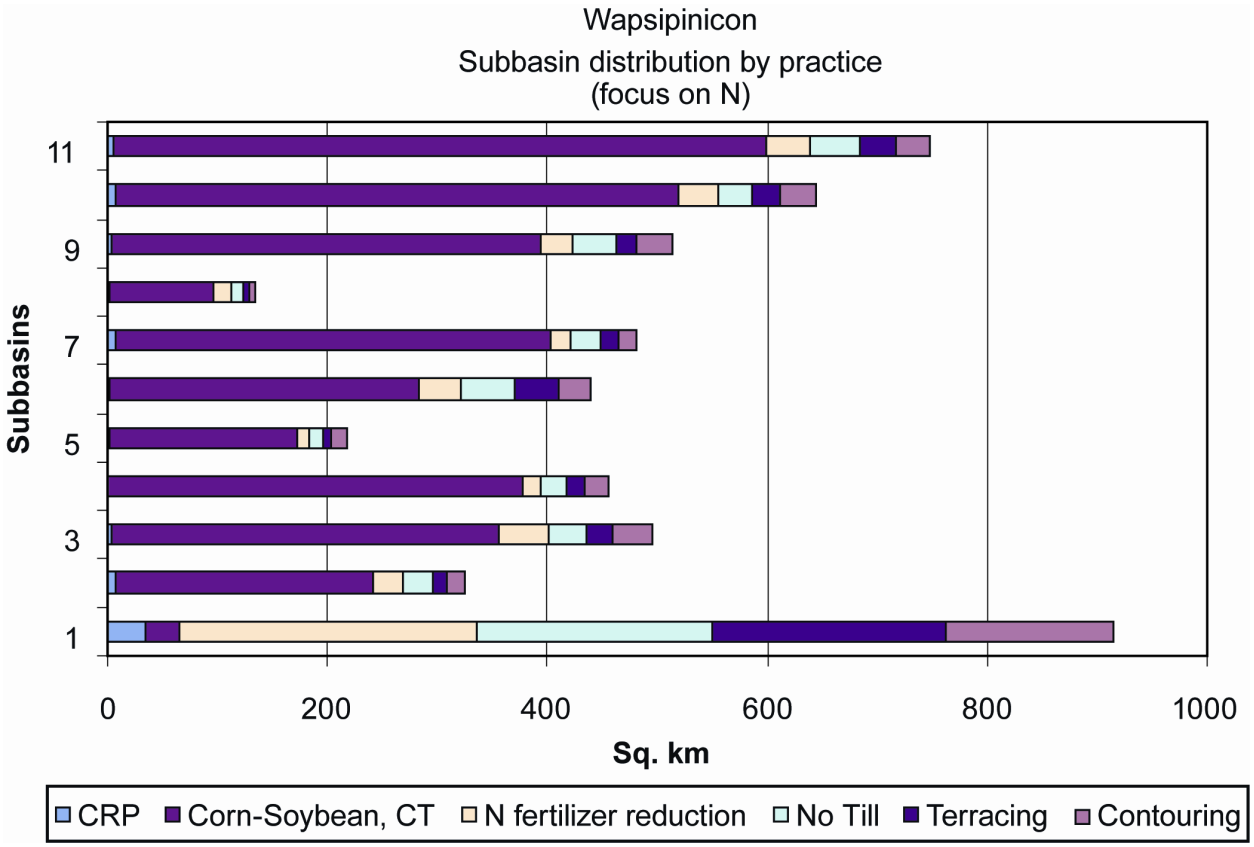

Upper Iowa
Watershed distribution by practice
Sq. km
1400
1200
1000
800
600
400
200
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline

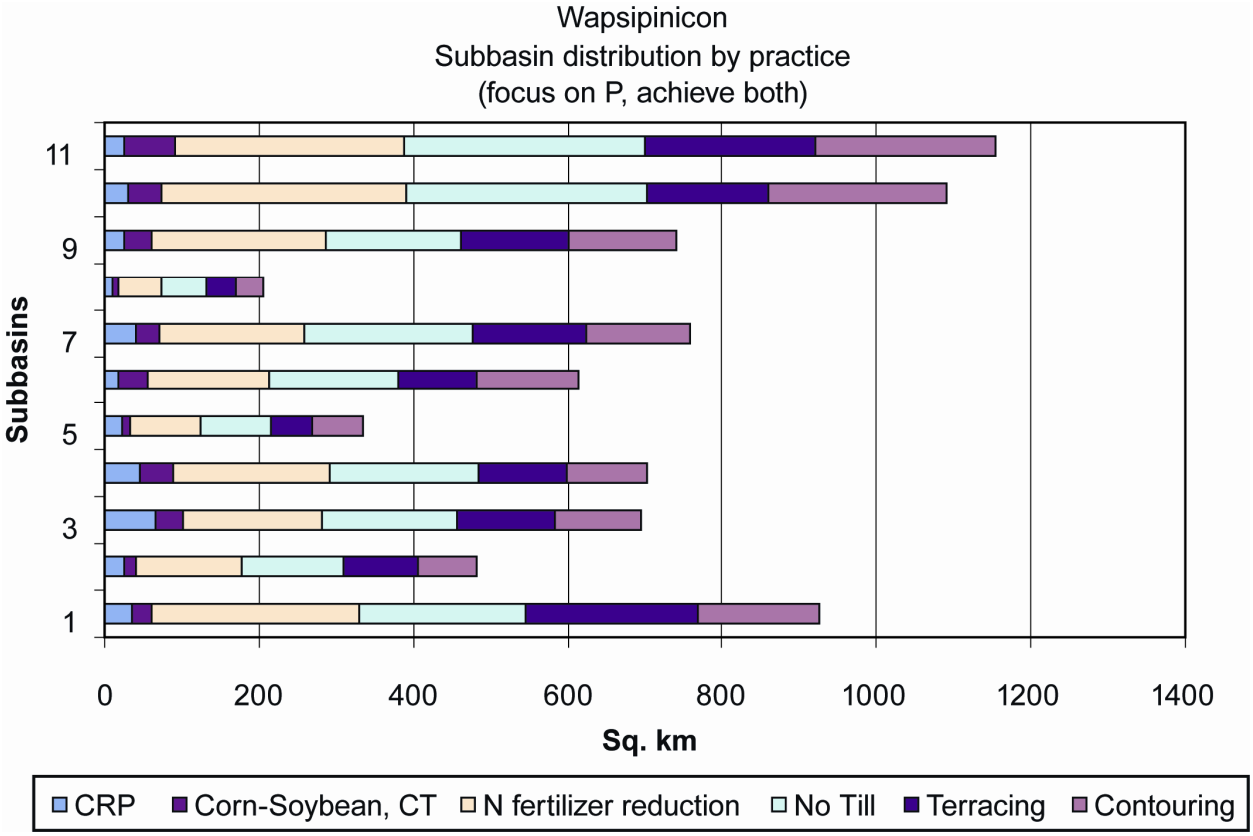

Upper Iowa
Subbasin distribution by practice
(focus on N)
Subbasins
7
6
5
4
3
2
1
0
100
200
300
400
500
600
700
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring

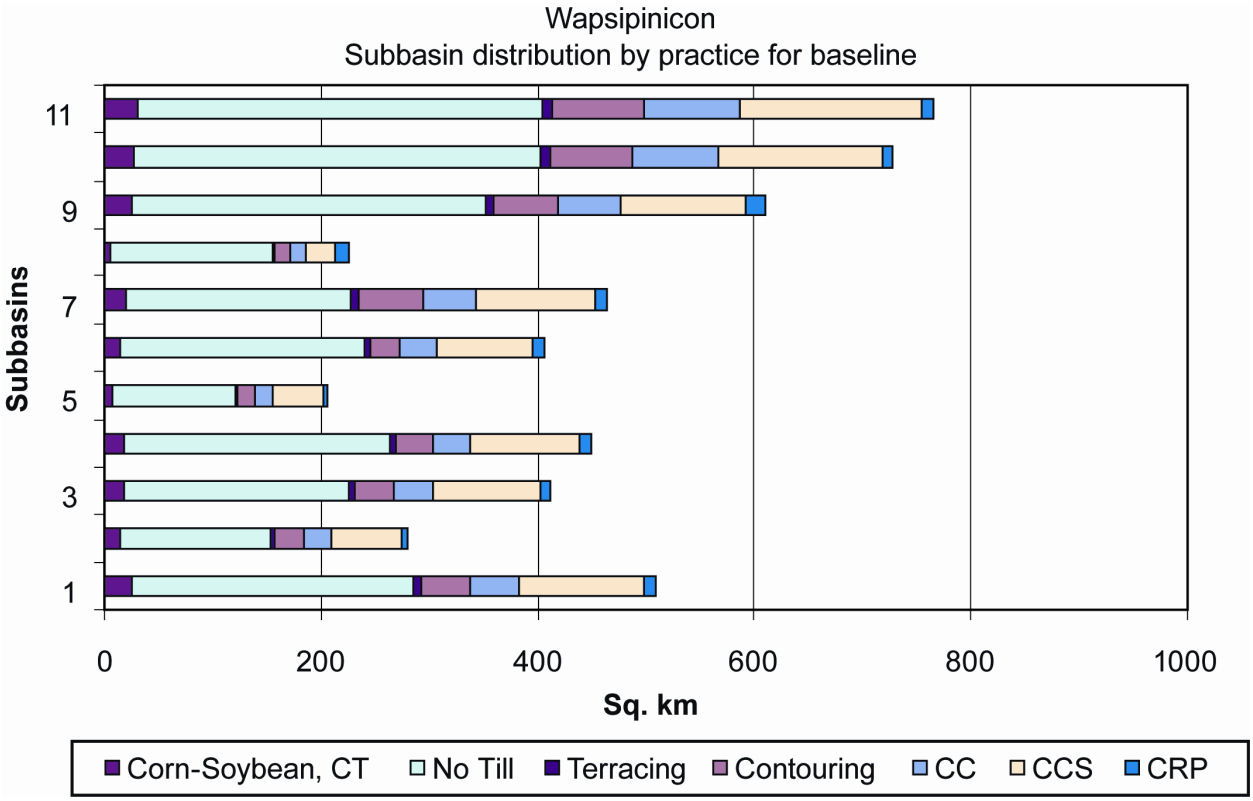

Upper Iowa
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
7
6
5
4
3
2
1
0
100
200
300
400
500
600
700
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring


Upper Iowa
Subbasin distribution by practice for baseline
Subbasins
7
6
5
4
3
2
1
0
100
200
300
400
500
600
700
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP


Wapsipinicon
Watershed distribution by practice
Sq. km
4000
3500
3000
2500
2000
1500
1000
500
0
CRP
CS CT
N reduction
No Till
Terrace
Contouring
Focus on N
Focus on P, achieve both N and P
Baseline


Wapsipinicon
Subbasin distribution by practice
(focus on N)
Subbasins
11
9
7
5
3
1
0
200
400
600
800
1000
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring


Wapsipinicon
Subbasin distribution by practice
(focus on P, achieve both)
Subbasins
11
9
7
5
3
1
0
200
400
600
800
1000
1200
1400
Sq. km
CRP
Corn-Soybean, CT
N fertilizer reduction
No Till
Terracing
Contouring


Wapsipinicon
Subbasin distribution by practice for baseline
Subbasins
11
9
7
5
3
1
0
200
400
600
800
1000
Sq. km
Corn-Soybean, CT
No Till
Terracing
Contouring
CC
CCS
CRP