Using Field-level Characteristics as Proxy Measures to Test for the Presence of Economies of Scale in Nonpoint Pollution Control

Arthur J. Caplan, John Gilbert, and Devalina Chatterjee

We use parametric and nonparametric methods to estimate correlations between average control cost and three field-level characteristics—field size and delivered phosphorous per field and per acre—as proxies for economies of scale in controlling nonpoint pollution. We combine load and delivery-ratio estimates for more than 12,000 fields in the Bear River Basin, Utah, with estimates of control costs and effectiveness of management practices from the literature. Results suggest a negative relationship between control cost and delivered phosphorous per field and per acre. Ranking fields by phosphorous load therefore prioritizes management-practice subsidies by economies of scale.

Key Words: economies of scale, nonpoint-source pollution, delivered load, control costs

Since passage of the 1972 and 1977 Federal Water Pollution Control Act Amendments (henceforth the Clean Water Act), approximately 34,000 of the nation's water bodies have either remained out of compliance or fallen out of compliance with Clean Water Act standards for drinking water, contact recreation, or aquatic life support (Environmental Protection Agency (EPA) 2003b). The main factor contributing to this widespread noncompliance is loading of nutrient- and pesticide-based pollutants from agricultural nonpoint sources (NPSs) such as crop and feedlot operations through natural run-off and leaching processes (Freeman 2002). Regulation of NPSs has been stymied by the very nature of the loadings—they are diffuse and susceptible to environmental and informational uncertainties, factors that obviate the continuous monitoring needed to assign particular loadings to their sources within a watershed. Nevertheless, control of NPS loadings is a crucial determinant of whether predominantly agricultural watersheds can meet the provisions of the Clean Water Act. This study demonstrates two methods—calculation of Pearson's correlation coefficients via Monte Carlo simulation and panel data estimation—that may prove useful to watershed planners in their efforts to accommodate the uncertainty inherent to field-level control costs and

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This research was funded by the U.S. Environmental Protection Agency's Targeted Watersheds Grant Program and Utah Experiment Station Grant UTA-043. The views expressed in this paper are the authors' and do not necessarily represent the policies or views of the sponsoring agencies.

the effectiveness of best management practices (BMPs) and thus help planners manage NPS control efforts in a more cost-effective manner.[1]

Both methods are premised on the normative assumption that cost-effectiveness is the preferred criterion for design of a watershed-wide NPS control program. By *cost-effective*, we mean that control efforts that target farmers' fields abide by the equimarginal principle whereby least-cost efforts (measured in this case as control cost per unit abated per field or average control cost) are undertaken first, followed by progressively more costly field-by-field control efforts. Because our average control cost measure is adjusted for the "potency" of a field's estimated load via estimation of the field's delivery ratio (explained in detail hereafter), the methods we propose provide a ranking mechanism based on what Babcock et al. (1997) called "optimal targeting." Similar to Babcock et al. (1997), which examined conditions under which alternative targeting rules for enrollment of land in the U.S Department of Agriculture's (USDA's) Conservation Reserve Program (CRP) led to different rankings, our methods are probabilistic (they reflect uncertainties inherent to benefits and costs of NPS pollution control). Unlike Babcock et al. (1997), this study develops two methods that statistically test for correlations between economies of scale in the control of NPS pollution and various field-level characteristics and thus demonstrates how a regulator might achieve optimal targeting of BMP subsidies.[2]

Both Pearson's correlation coefficients and panel data estimation generate estimates of correlations between per-field average control cost (*ACC*) and three field-level characteristics: (i) field size, (ii) delivered phosphorous load per field, and (iii) delivered phosphorous load per acre. From the perspective of both a regulator and a nonpoint source, *ACC* is inherently uncertain for any given field. It therefore must be estimated based on distributional assumptions defined over BMP effectiveness and field-level control costs. Tests such as the ones undertaken in this study will help us surmise how well characteristics that are relatively easily measured, such as field size and delivered pollutant load, might serve as a proxy for the control cost, which is relatively difficult to measure. As we will explain in greater detail, delivered loads can be estimated with greater accuracy than ever before thanks to more sophisticated hydrological models. Estimates of field size also are more readily available via geographic-information-based land-use data sets. Where statistically significant negative correlations exist between average control cost (*ACC*) and these field characteristics, the field-level characteristics offer potentially valuable proxy measures for estimates of economies of scale in implementing control practices. Again, these types of correlation estimates are motivated by the fact that control costs are more uncertain (from the perspective of both regulators and the NPSs) than are field-level characteristics. Thus, standard cost-function approaches to estimating economies of scale (e.g., Christensen

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[1] The Pearson correlation coefficient is a widely used, unconditional measure of the strength of linear dependence between two (continuously measured) random variables that requires no prior restrictions on the variables' joint distribution (Rodgers and Nicewander 1988). The structure of the data also lends itself nicely to panel-data estimation because the set contains repeated observations (multiple field-level observations) per observational unit (i.e., farms).

[2] The alternative rules examined in Babcock et al. (1997) were based (i) solely on estimated cost, (ii) solely on estimated benefit, or (iii) on the estimated ratio of benefit to cost. The authors refer to the former two rules as being "suboptimal" and the latter rule as being "optimal." Wu, Zilberman, and Babcock (2001) extended the basic results in Babcock et al. (1997) to a general equilibrium setting.

and Greene 1976, MacDonald and Ollinger 2000) are precluded in the case of NPS pollution control.[3]

Our data set consists of estimates of loading and of delivery ratios for more than 12,000 fields within approximately 5,900 farms located in the Bear River Basin in Utah. The estimates of loading and of delivery ratios are derived from a newly developed hydrologic model of the basin that accounts for seasonal variability in nonpoint loadings and thus accommodates the inherent environmental uncertainties associated with attributes such as weather and field-specific topography. The estimates are then combined with estimates of the cost of control measures and effectiveness of BMPs that are based on a range of values reported in the literature. Two common density functions—normal and uniform—are assumed as separate cases to define distributions of phosphorus (P) loadings across farmers' fields. Using this framework, we find statistical evidence of a negative relationship between ACC and delivered P load per field and per acre. This suggests that one could rank fields according to delivered P load per field and per acre to prioritize which BMPs to subsidize according to economies of scale in BMP implementation. Evidence is mixed regarding the statistical relationship between ACC and field size.

The methods used in this study may be relevant for the Natural Resources Conservation Service's (NRCS's) Environmental Quality Incentives Program (EQIP) by demonstrating how the program's current ranking criteria (in terms of which BMPs to subsidize on which fields first) might be adjusted so that subsidies go to control efforts that are the most cost-effective for the watershed as a whole.[4] Although the NRCS generally obtains self-reported cost estimates (total cost per acre) from the NPSs when prioritizing EQIP funding applications, a host of other environmental attributes can be used to rank NPS fields according to their potential to control pollution; that is, cost-effectiveness on a watershed-wide basis is not explicitly the NRCS's top priority (NRCS 2009a). To the extent that cost-effectiveness should be its top priority in ranking control potential at the field level, our analysis and results provide a framework that NRCS could adopt to meet that objective.[5]

Parametric tests for the presence of economies of scale (and their scope) have been the focus of numerous previous studies. The majority of the studies found evidence of scale economies in various industries when estimating flexible cost functions with either plant-level or industry-level data.[6] A notable exception is Gyimah-Brempong (1987), which found diseconomies of scale and scope for municipal police departments. Hammond, Melander, and Shilling (1971) found scale economies with respect to operating expenses but diseconomies

[3] See Nelson (1988) and Moschini (1990) for approaches to estimating economies and returns to scale that are similar to ours.

[4] EQIP is a voluntary program offering financial assistance (in the form of cost-share subsidies of up to 90 percent) to farmers and ranchers for installation of BMPs on eligible fields. The goal of the program is to reduce NPS pollution, reduce soil erosion and sedimentation, and promote conservation of habitat for at-risk species (NRCS 2009b, 2009c).

[5] The aforementioned CRP may also benefit from using the proposed framework to allocate its subsidies and annual rental payments in a more cost-effective manner. As with EQIP, this voluntary program induces farmers and ranchers to plant resource-conserving vegetative cover crops to reduce nonpoint pollution and expand species habitat (Farm Service Agency (FSA) 2009b). The ranking criteria include cost but only as one of several other physical factors (FSA 2009a). See Taff and Runge (1987) and Reichelderfer and Boggess (1988) for further discussion of the deficiencies of CRP decision rules historically.

[6] See, for instance, Sung and Gort's (2000) study of the U.S. local telephone industry and Paul's (2001) study of the U.S. beef packing industry.

with respect to loss costs in the property and liability insurance industry. To our knowledge, no study has yet tested for scale economies in the control of NPS pollution.[7] As mentioned previously, such tests are complicated by uncertainty associated with control effectiveness and cost at the field level and a lack of input and input-cost information at the field or farm level. These issues preclude specification of any given cost function as a guiding empirical model. The parametric and nonparametric approaches explored here demonstrate possible ways to accommodate these uncertainties and data limitations.

The following section briefly describes our study area, the Bear River Basin of Utah. The next section provides a synopsis of the basin's environmental and economic profiles. The hydrologic model and loading and delivery-ratio estimates thus obtained are discussed first, followed by information on the economic data (estimates of control costs and BMP effectiveness). We then present a section on the methodologies of and results from our parametric and nonparametric tests for the existence of economies of scale in NPS pollution control. The final section summarizes our findings and offers concluding thoughts.

Bear River Basin

The Bear River Basin comprises 19,000 square kilometers of mountain and valley land located in northeastern Utah (44 percent of the watershed), southeastern Idaho (36 percent), and southwestern Wyoming (20 percent). See Figure 1 for a map of the area and its major rivers. The basin ranges in elevation from 1,283 meters to more than 3,962 meters and is enclosed entirely by mountains. Both agricultural land and urban areas are located in valleys along the main stem of the Bear River and its tributaries. Currently, several water bodies in the basin are on the Clean Water Act 303(d) list of impaired waters in each of the three states. Two of the 303(d)-listed water bodies, the Cub River and Cutler Reservoir, form the focus area for this study. Figure 1 identifies the specific location of the basin's receptor point at the northern end of Cutler Reservoir. The water bodies are listed because of depletion of dissolved oxygen during summer months that stems primarily from excessive P loadings from both point and nonpoint sources.

Currently, total maximum daily load (TMDL) limits under the Clean Water Act are being updated or developed for the Cub River and Cutler Reservoir. Cutler Reservoir impounds the waters of the Bear, Logan, and Little Bear rivers and other small drainages. The reservoir provides water for agricultural use and power generation (Utah Department of Environmental Quality (DEQ) 2008).[8] Crops commonly grown in the basin include dryland and irrigated pasture, hay, alfalfa, and corn, all used locally to feed cattle and dairy cows. From its point of entry in Utah, the Bear River and most of its tributaries flow through agricultural lands. As a result, the primary anthropogenic sources of P loads are NPSs (comprised of approximately 12,500 agricultural fields within approximately 5,900 farms) and five city-owned wastewater treatment plants.

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[7] Pittman (1981) tested for the existence of economies of scale in pollution control solely among industrial point sources (PSs) and found evidence of scale economies.

[8] The Utah Department of Environmental Quality (2008) provides a detailed description of the study area's physical, biological, and socio-economic characteristics. Total population in the study area is roughly 100,000 (U.S. Census Bureau 2009).

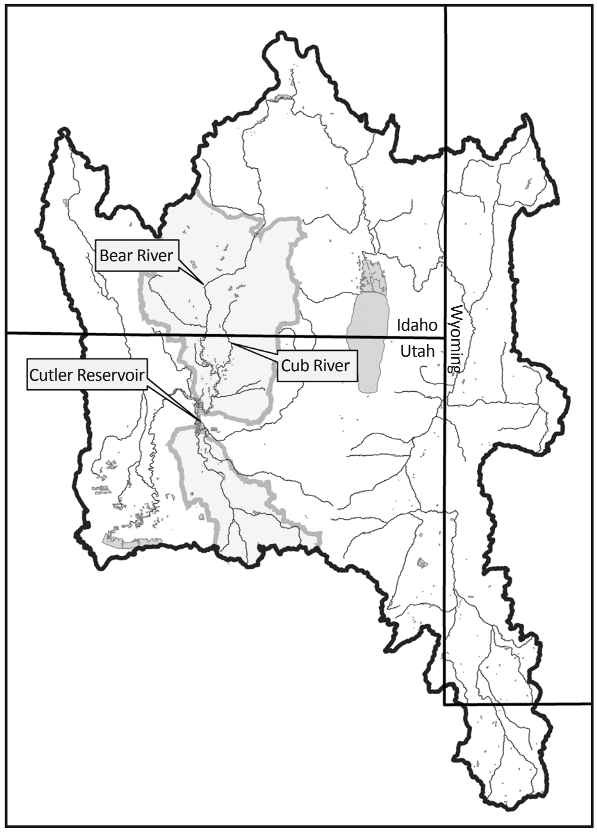

Figure 1. The Bear River Basin, Utah

Aggregate annual delivered loads from these two source groups are estimated to be roughly the same as loads for the Cutler Reservoir receptor point.[9]

Basin Profile

Hydrologic Model and Environmental Data

As previously mentioned, key information regarding both NPS loadings and the amount of loading that ultimately reaches a given receptor point (via delivery ratios) is necessary to establish whether there are economies of scale in nonpoint control. However, delivery ratios primarily depend on in-stream processes and withdrawals and can be particularly difficult to estimate. To quantify loadings and delivery ratios associated with individual owners' fields, Caplan, Neilson, and Baker (2009) developed a hydrologic modeling framework consisting of a combination of models, modeling approaches, and analysis

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[9] Aggregate annual delivered loads to Cutler Reservoir are roughly 2,400 kilograms from point sources and 2,600 kilograms from nonpoint sources. As in Caplan, Neilson, and Baker (2009), this study assumes that loadings from animal feeding operations (both confined and unconfined) are already or are in the process of being completely controlled through a variety of state and federally funded programs (Utah Department of Environmental Quality 2008).

techniques to assess the feasibility of water quality trading. We use that same framework here.[10]

As described in Neilson et al. (2009), the framework utilizes (i) the TOPNET hydrology model (Bandaragoda, Tarboton, and Woods 2004), (ii) variable source area (VSA) calculations to resolve spatial areas that are contributing surface run-off (Lyon et al. 2004), (iii) a model component for sub-basin loading that is based on the VSA calculations, event mean concentrations, and spatially distributed land-use information, and (iv) a component for water body response that incorporates the QUAL2E model (Brown and Barnwell 1987) to determine delivery ratios. This combination of models provides a representation of the physical hydrology at the watershed scale and the associated in-stream response at a daily time step. The approach also results in representation of the spatial variability of daily loadings at the field scale and daily delivery ratios for receptor points of interest.

Figure 2 shows the generic flow of information between the modeling components. In the Bear River application of the model, TOPNET was populated using (i) SSURGO soils data (NRCS 2007), (ii) the 30-meter National Elevation Dataset digital elevation model (U.S. Geological Survey (USGS) 2009), (iii) land cover data from the National Land Cover Dataset (EPA 2001), (iv) Utah water-related land-use data (Utah Department of Natural Resources 2009), and (v) data on local weather, water diversions, and reservoir discharges (USGS 2009) for a simulation period spanning October 1, 1989, through September 30, 2004. TOPNET was calibrated using streamflow measurements at multiple locations throughout the six-year period of 1989 through 1995. Model validation occurred from 1995 through 2004.

Uncertainty associated with each of the modeling components is a concern that must be addressed when incorporating modeling results into an economic analysis. In this study, we accommodated the daily values resulting from variable conditions within a season by averaging the daily loads and the delivery ratios over each season (winter, spring, summer, and fall). These seasonal values, which differed over the range of annual hydrologic conditions, were then averaged again over the simulation period (October 1, 1989, through September 30, 2004), providing an average seasonal field load and an average seasonal delivery ratio for each sub-basin.[11] As a result, we effectively treated the loading and delivery-ratio estimates as known with certainty by the regulator so that we could focus on persisting uncertainty concerning control costs and BMP effectiveness at the field level.[12] Figure 3 shows the resulting

[10] See Neilson et al. (2009) for a full description of the hydrologic modeling framework used in support of our study. To our knowledge, only a handful of previous studies have used watershed or in-stream hydrologic models in support of water quality trading (WQT). Each aggregated the results to the watershed level so the results were not "operational" in the sense of providing regulators with the tools necessary to assess the potential of programs like WQT on a per-farm or per-field basis. For example, to estimate mean-event NPS loadings in the preliminary assessment of WQT opportunities in the Great Miami River Basin in Ohio, Keiser, Fang, and Hall (2004) used the Soil and Water Assessment Tool (SWAT) model in conjunction with EPA's geographic information system (GIS) modeling platform known as BASINS (Better Assessment Science Integrating Point and Nonpoint Sources). Estimated PS and NPS abatement costs were taken from the literature, and ad hoc, exogenously determined trading ratios were used to account for the spatial nonuniformities that exist between (downstream) PSs and (upstream) NPSs.

[11] In practice, annual maximum values can be substituted for the average seasonal values used in this study if the regulatory authority determines that an extra "margin of safety" is required for risk-reduction purposes.

[12] We acknowledge this simplification for the purposes of the ensuing analysis. Theoretical

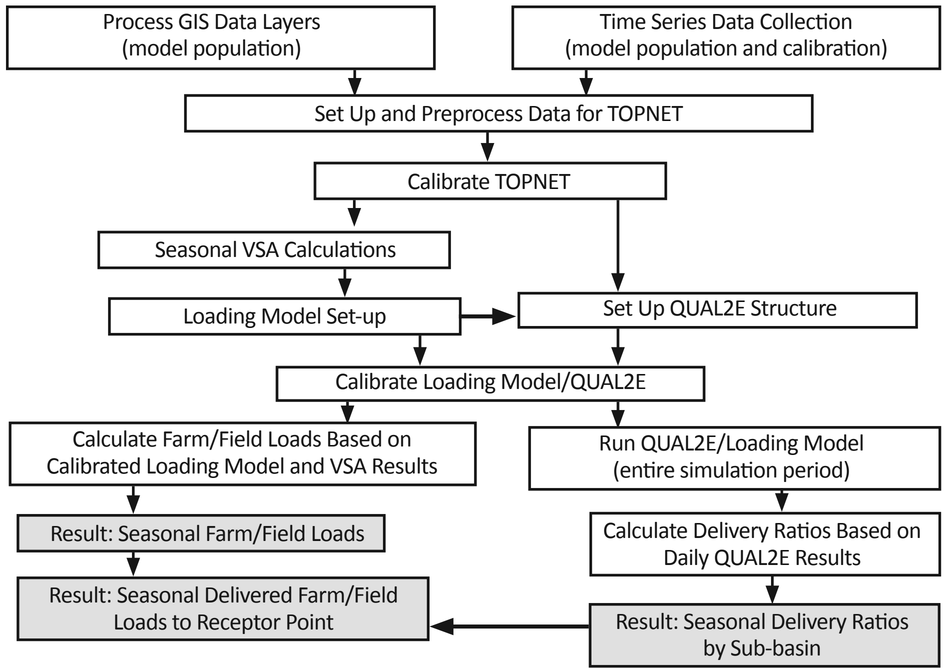

Figure 2. Detailed Outline of Information Flow for Hydrological Modeling Framework

average seasonal loads for the fields in the Utah portion of the Bear River Basin (shaded).

Economic Data

Our estimates of NPS control costs and BMP effectiveness come from the existing literature. Beginning with the BMPs that are most relevant for the Bear River Basin, we considered two cultural practices: conservation tillage and nutrient management. Based on estimates contained in Haith and Loehr (1979), Beasley et al. (1985), Hamlett and Epp (1994), Johnes and Heathwaite (1997), Mostaghimi et al. (1997), Walter et al. (2001), Sharpley et al. (2002), and EPA (2003a), conservation tillage was assumed to range between 60 percent and 80 percent effectiveness and nutrient management was assumed to range between 40 percent and 50 percent. The per-acre cost of the BMPs was assumed to range from approximately \$3 for conservation tillage to approximately \$15 for nutrient management.[13]

The *ACC* for field $i = 1, \ldots, I$ owned by NPS $j = 1, \ldots, J$ is defined as

$$ACC_{ij} = \frac{c_{ij} S_{ij}}{b_{ij} L_{ij}} \tag{1}$$

papers incorporating both types of uncertainty include Malik, Letson, and Crutchfield (1993), Shortle and Abler (1997), Shortle and Horan (2001), and Wu and Babcock (2001). Empirical papers that account for uncertainty in a fashion similar to ours include Horan et al. (2002), Horan, Shortle, and Abler (2002), Feng, Easter, and Brezonik (2005), and Keiser, Fang, and Hall (2004).

[13] To our knowledge, the literature to date has reported only constant per-acre control costs.

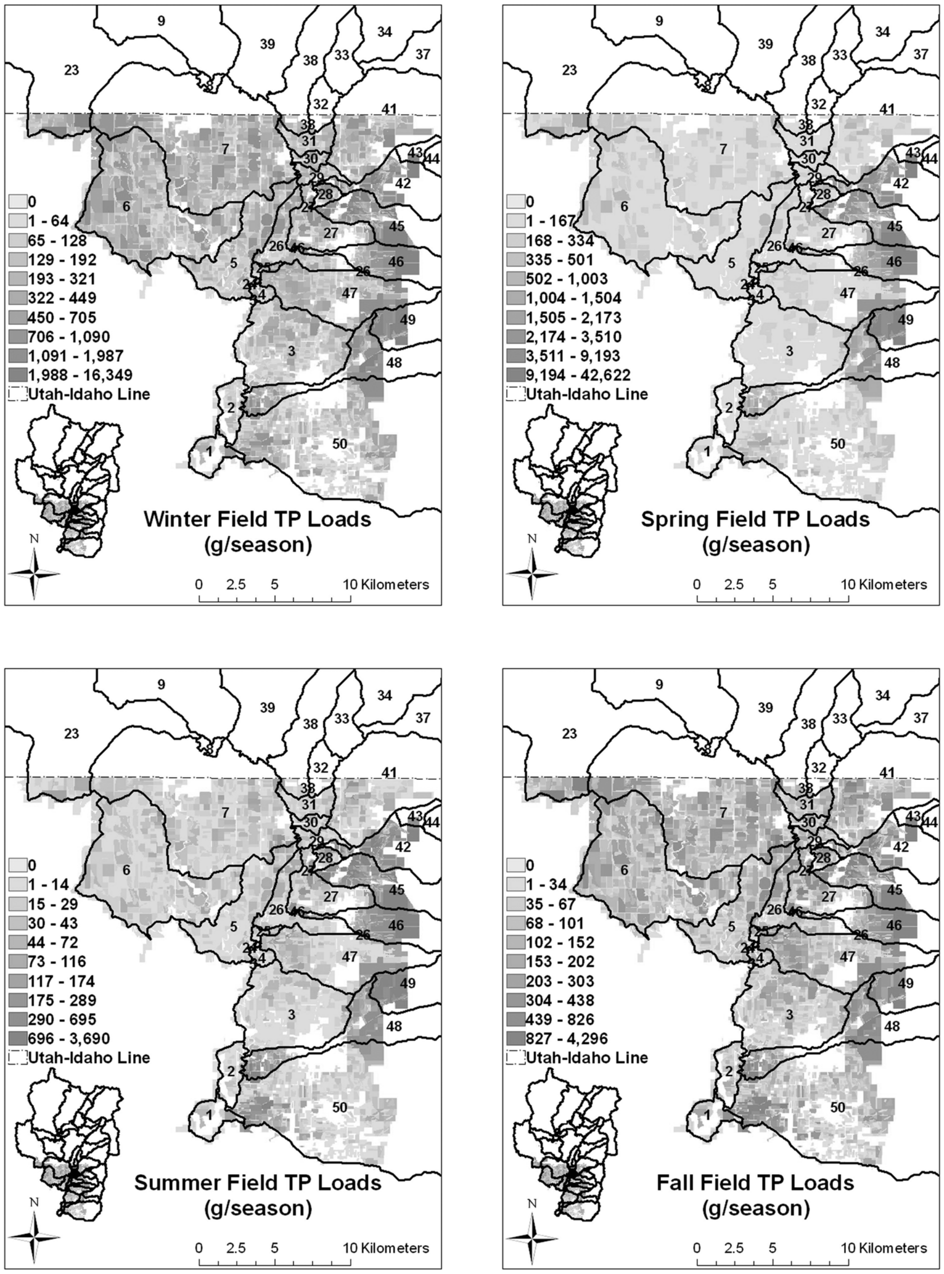

Figure 3. Field-level Seasonal Total Phosphorus Loadings in the Study Area

where c_{ij} represents the per-acre cost of the BMP in dollars, b_{ij} represents the effectiveness of the BMP in reducing delivered load in percent, S_{ij} represents field size in acres, and L_{ij} represents delivered load per field in grams per year in the absence of any explicit abatement. L_{ij} is further defined as

$$L_{ij} = t_{ij} P_{ij} \tag{2}$$

where t_{ij} and P_{ij} are field *i*'s delivery ratio and *P* load, respectively, as estimated from the hydrology model described in the previous subsection. Thus, *ACC* is defined as the total cost of implementing a BMP divided by the delivered load abated per field. In the textbook case, economies of scale are driven by cases in which the total cost of production increases in output but at a slower rate than output itself. Similarly, economies of scale in nonpoint pollution control arise when the total cost of abating *P* increases more slowly than the amount of *P* abated. In the case of nonpoint pollution, however, uncertainty concerning the per-acre cost and effectiveness of the BMP (c_{ij} and b_{ij}) requires an assumption by the regulator of probability distributions for these two facets of BMPs across all fields $i = 1, \ldots, I$ and for NPSs $j = 1, \ldots, J$. Further, as mentioned previously, we test three potential correlates with *ACC* for which data are more likely to be available to the regulator than quantities of *P* abated are. These correlates are field size, delivered phosphorous load per field, and delivered phosphorous load per acre. Increases in field size increase the numerator of (1) directly and the denominator indirectly (all else being equal, larger fields are associated with larger delivered loads of *P*). These direct and indirect effects on economies of scale for *P* loads are the opposite of the textbook case in which increases in output increase the denominator directly and the numerator indirectly via the total cost function. However, increases in delivered *P* load per field and per acre follow the textbook case (again, all else being equal, larger fields are associated with larger delivered loads). We discuss these relationships further in subsequent sections.

Tests for Economies of Scale in Nonpoint Pollution Control

Nonparametric Analysis

Table 1 contains summary statistics for b_{ij}, c_{ij}, S_{ij}, and L_{ij}.[14] As indicated, the average field size in our data set was approximately seven acres and the average delivered load per field was approximately 200 grams of *P* per year. The standard deviations associated with these average values indicate relatively large amounts of variation across fields. As discussed in more detail later, the statistics listed for b_{ij} and c_{ij} are the moments used to create empirical

[14] The sample size for calculation of these statistics is 12,318, which equals the number of fields in our data set.

Table 1. Summary Statistics

	Uniform Distribution		Normal Distribution	
Variable	**(low, high)**	**(mean, std. dev.)**	**mean (std. dev.)**	**(min., max.)**
b_{ij}	(0.6, 0.9)	(0.75, 0.075)	—	—
c_{ij}	(3, 15)	(9, 3)	—	—
S_{ij}	—	—	6.67 (15.74)	(0.22, 501.93)
L_{ij}	—	—	201.60 (689.54)	(0, 28,967.93)

distributions (uniform and normal) from 5,000 draws (with replacement) taken from actual corresponding distributions for each. We assumed that both empirical probability distributions for b_{ij} and c_{ij} were calculable by the regulator. In other words, we adopted the standard assumption for incomplete-information problems where the regulator cannot accurately determine b_{ij} and c_{ij} for any particular field *i* due to unobservable NPS behavior and unpredictable behavior by nature. However, the regulator knows (or assumes) with certainty the probability distributions for b_{ij} and c_{ij} across all *i* and two of the most likely candidates for the nature of those distributions are normal and uniform.

As indicated in Table 1, in the case where b_{ij} (effectiveness of the BMP) was drawn from a (continuous) normal distribution, the distribution's mean was assumed to be 0.75 with a standard deviation of 0.075. In the case where b_{ij} was drawn from a (continuous) uniform distribution, the supports of the distribution were assumed to be 0.6 and 0.9. The corresponding distribution parameter values for c_{ij} are a mean of 9.0 and a standard deviation of 3.0 for the normal distribution and supports (3, 15) for the uniform distribution.[15] These mean values and associated standard deviations, along with the minimum and maximum values for S_{ij} and L_{ij}, indicate that the distributions for these two measures are skewed strongly to the right. Histograms for those values and for L_{ij}/S_{ij} bear this out (see Figures 4 through 6). In addition, the (simple linear) correlation coefficients for S_{ij} and L_{ij} and for S_{ij} and L_{ij}/S_{ij} are 0.61 and –0.02, respectively (Figure 7 presents a scatter plot with a trend line for an ocular assessment of the relationship between L_{ij}/S_{ij} and S_{ij}).[16]

As mentioned previously, we calculated Pearson correlation coefficients based on random draws of b_{ij} and c_{ij} from the probability distributions to test nonparametrically for correlation between ACC_{ij} and (i) field size (S_{ij}), (ii) estimated delivered *P* load per field (L_{ij}), and (iii) estimated delivered *P* load per acre (L_{ij}/S_{ij}).[17] The Pearson coefficient (henceforth denoted ρ^k for $k = S_{ij}$, L_{ij}, and L_{ij}/S_{ij}, respectively) was defined (as in Myers and Well (2003)) as

$$\rho^k = \frac{n\left(\sum_{i=1}^{n} x_i y_i^k\right) - \left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i^k\right)}{\sqrt{n\left(\sum_{i=1}^{n} x_i^2\right) - \left(\sum_{i=1}^{n} x_i\right)^2}\sqrt{n\left(\sum_{i=1}^{n} \left(y_i^k\right)^2\right) - \left(\sum_{i=1}^{n} y_i^k\right)^2}} \tag{3}$$

where *n* is the total number of fields *i* located in the basin, x_i is the rank-order value of ACC_{ij} (from highest to lowest across all *i* irrespective of farms *j*), and y_i^k is the corresponding rank-order value of $k = S_{ij}$, L_{ij}, and L_{ij}/S_{ij}, respectively (across all *i* irrespective of farms *j*).

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[15] We acknowledge that the parameter values for b_{ij} for both the normal and the uniform distribution align more closely with the conservation-tillage percentages than with the nutrient-management percentages. The same is true for c_{ij}'s parameters for the normal distribution. This alignment reflects the preeminence of conservation tillage as a BMP in the Bear River Basin.

[16] Because of the large size of our data set, it was not feasible to include all observations in the scatter plot. We therefore took a random sample of 5 percent of the multi-field farms (roughly 500 observations) for the graph.

[17] As discussed at the end of the preceding section, since S_{ij} is in the numerator of (1), the test for economies of scale with respect to field size is, per force, a test of whether a (positive) correlation between S_{ij} and L_{ij} in the denominator is large enough to offset the direct effect of S_{ij} in the numerator. Similarly, the test for economies of scale with respect to delivered *P* load is a test of whether the correlation between S_{ij} and L_{ij} in the numerator is large enough to offset the direct effect of L_{ij} in the denominator.

Figure 4. Histogram for S_{ij}

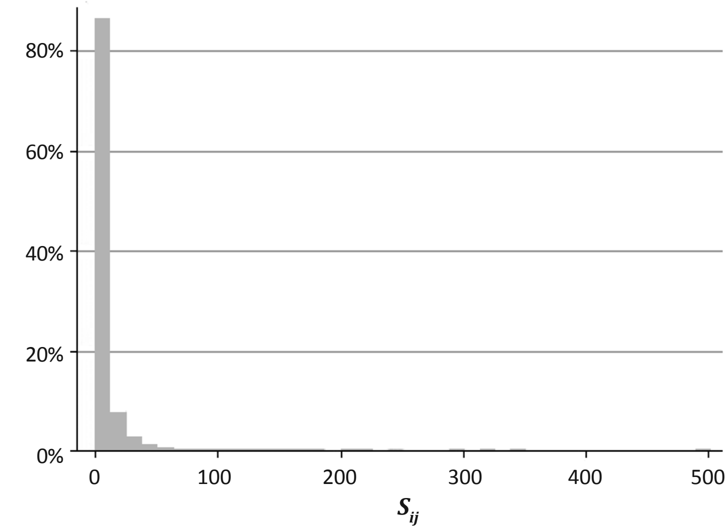


Figure 5. Histogram for L_{ij}

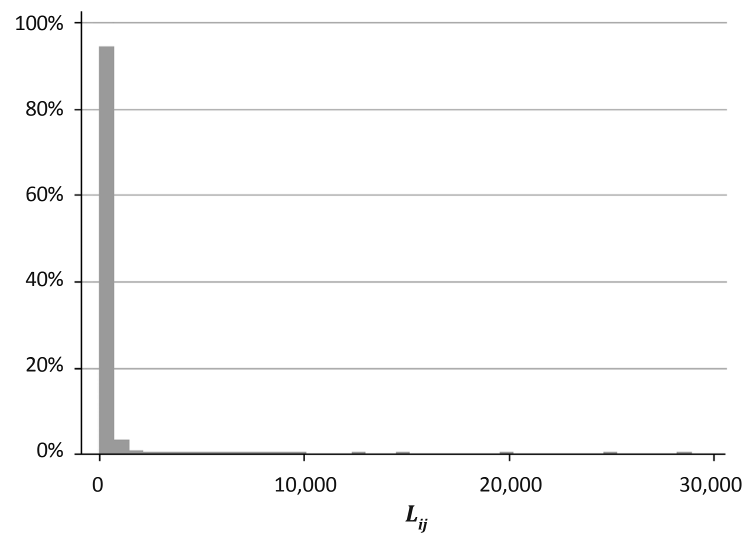
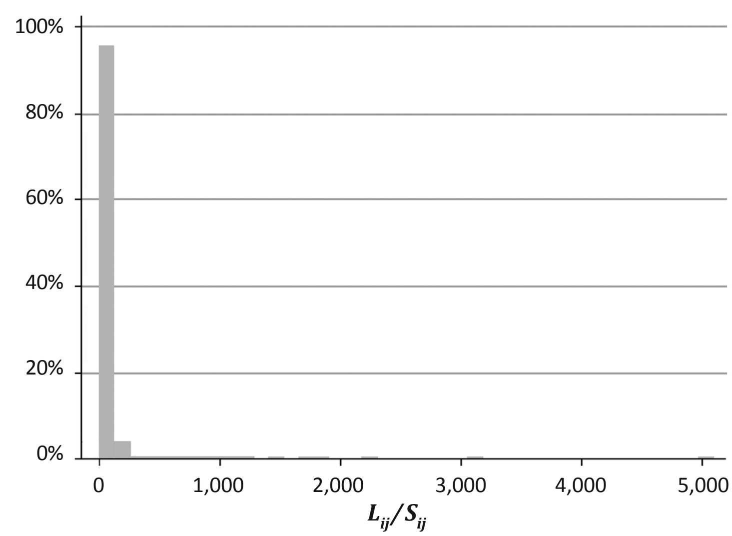


Figure 6. Histogram for L_{ij}/S_{ij}



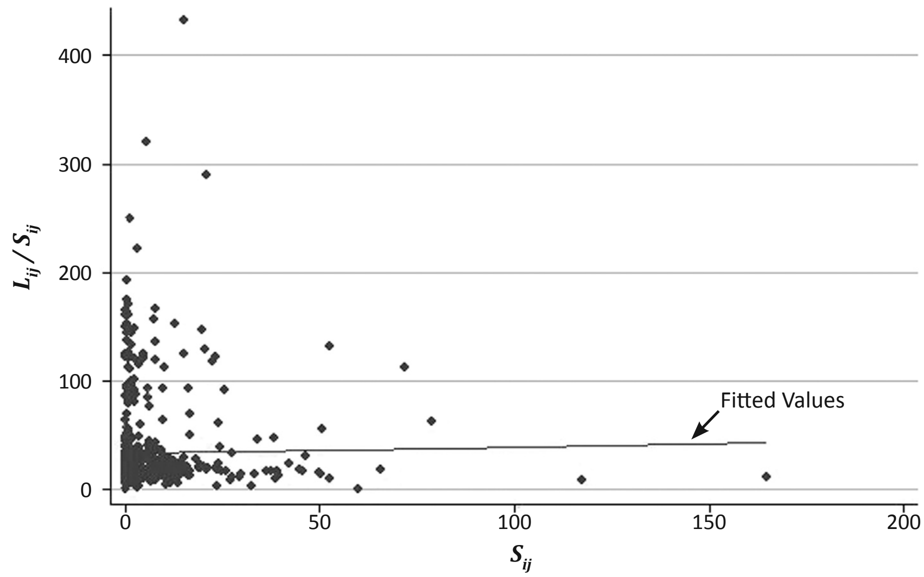


Figure 7. Scatter Plot with Trend Line for L_{ij}/S_{ij} versus S_{ij}

Five-thousand random draws were taken from both of the aforementioned distributions for b_{ij} and c_{ij}. For each draw, ACC_{ij} was calculated according to (1). The corresponding ρ^k value was subsequently calculated according to (3) for $k = S_{ij}$, L_{ij}, and L_{ij}/S_{ij}, respectively, across all i. Because the ranges of the normal distributions span possible negative values for both b_{ij} and c_{ij}, we truncated the distributions at zero.[18] The resulting mean values for ρ^k are presented in Table 2.

As Table 2 indicates, the negative relationship between ACC_{ij} and S_{ij} is statistically insignificant under the assumption of uniform distributions for b_{ij} and c_{ij} and weakly significant under the assumption of normal distributions for these two random variables. The relationships between ACC_{ij} and L_{ij} and between ACC_{ij} and L_{ij}/S_{ij}, on the other hand, are statistically significant at the 1 percent level, which suggests, given our distributional assumptions, that the average control cost decreases, all else being equal, as both delivered load

18 There was no need for truncation of the uniform distributions since the supports for b_{ij} and c_{ij} are positive.

Table 2. Pearson Coefficients

Coefficient	Uniform Distribution	Standard Error	Normal Distribution	Standard Error
ρ^S	–0.0066	(0.0054)	–0.0071*	(0.0048)
ρ^L	–0.3512***	(0.0051)	–0.3640***	(0.0046)
$\rho^{L/S}$	–0.1483***	(0.0003)	–0.1486***	(0.0009)

Notes: *** indicates significance of ρ^k at the 1 percent level and * indicates significance at the 10 percent level. Given the large size of the sample for this test (n = 5,000), ρ^k is assumed to follow the Student t-distribution. The calculated t-statistics, therefore, are the respective mean values divided by their corresponding standard deviations.

per field and delivered load per acre increase. Bear River Basin regulatory authorities such as the NRCS that have access to reliable estimates of delivered loads per field or per acre but not field-specific estimates of control costs or BMP effectiveness could potentially leverage that information to prioritize individual fields for BMP subsidies in a probabilistically cost-effective manner. By ranking fields from highest to lowest by delivered load—or, better yet, from highest to lowest delivered load per acre—as a proxy measure for economies of scale, the regulator could reduce the expected total cost of its subsidy program while also reaching the target level of NPS load reduction in the basin. This result is robust to the assumed probability distributions defined over per-acre estimates of the average control cost and BMP effectiveness.

Bear in mind that these nonparametric results are unconditional in the sense that they do not separately control for other factors at the farm or field level that might also influence the relationship between ACC_{ij} and S_{ij}, L_{ij}, and L_{ij}/S_{ij}. To investigate how controlling for farm- and field-level heterogeneity might affect the results explicitly, we turn to a parametric analysis of the data.

Parametric Analysis

For our parametric analysis of the statistical relationship between ACC_{ij} and S_{ij}, L_{ij}, and L_{ij}/S_{ij}, we begin with a standard panel data model for multi-field farms (Greene 2003):[19]

$$ACC_{ij} = \mathbf{x}_{ij}^{\mathbf{k}'}\beta^{\mathbf{k}} + v_{ij}^{k} \quad i=1,\ldots,I,\ j=1,\ldots,J,\ k=S_{ij}, L_{ij}, L_{ij}/S_{ij} \tag{4}$$

where $\mathbf{x}_{ij}^{\mathbf{k}'}$ is a vector of field-variant explanatory variables and $\boldsymbol{\beta}^{\mathbf{k}}$ is a corresponding coefficient vector. For this study, the explanatory variables include b_{ij}, c_{ij}, and k equals S_{ij}, L_{ij}, or L_{ij}/S_{ij}. The expression for v_{ij}^{k} depends on whether pooled OLS, fixed, or random effects are assumed. For pooled ordinary least squares (OLS), $v_{ij}^{k} = \alpha^{k} + \varepsilon_{ij}^{k}$ where α^{k} is a common intercept term across all farms and fields and ε_{ij}^{k} is an independently and identically distributed error term with constant variance. For fixed effects, $v_{ij}^{k} = \alpha_{j}^{k} + \varepsilon_{ij}^{k}$ where α_{j}^{k} is a farm-specific intercept term. For random effects, $v_{ij}^{k} = \alpha + u_{j}^{k} + \varepsilon_{ij}^{k}$ where u_{j}^{k} is a farm-specific random element that is similar to ε_{ij}^{k} except that a single draw for each farm enters the regression identically for each field.

Due to identification of specific farms in the panel analysis, we used discrete approximations to the continuous normal distributions for b_{ij} and c_{ij} to increase the likelihood that any given farm would be assigned equal per-field control cost and BMP-effectiveness values across its fields.[20] The discrete distributions for

[19] Estimation of the random-effects model relies on at least two fields per farm. For this analysis, we therefore dropped all farms composed of a single field from the data set, reducing our sample size from 12,318 to 9,920 fields and from approximately 5,900 farms down to approximately 2,600. A corresponding ordinary least square analysis of single-field farms was performed separately and is reported later.

[20] For this analysis, draws were taken solely from the (approximately) normal distribution for three additional reasons. First, as mentioned previously, our analysis is meant to be primarily illustrative. Thus, the added value of reporting results based on the uniform distribution was negligible. Second, as the nonparametric analysis in the previous section indicates, the statistical differences between results based on the two distributions are likely negligible. Third, since hypothesis testing requires that randomness in the data be normally distributed (and, thus, the standard errors must be based on normally distributed residuals), restricting our analysis to normally distributed b_{ij} and c_{ij} variables helps to ensure the normality of our residuals.

Table 3. Probability Distributions for b_{ij} and c_{ij} Used in Panel-Data Analysis

Variable	Distribution Value	Probability
b_{ij}	0.60	0.20
	0.75	0.60
	0.90	0.20
c_{ij}	3.00	0.20
	9.00	0.60
	15.00	0.20

b_{ij} and c_{ij} are presented in Table 3. Note the closeness of these approximations to the continuous normal distributions for the two variables presented in Table 1.

Results from the estimation of (4) are presented in Table 4.[21] Based on reported significance levels for the Breusch and Pagan (1980) and Hausman (1978) χ^2 specification tests for each model, respectively, we focus on results for the fixed-effects models.[22]

Beginning with model 1, which regresses S_{ij} on ACC_{ij} while controlling for b_{ij} and c_{ij}, we find a statistically significant *positive* relationship between S_{ij} and ACC_{ij}, which is inconsistent with the finding in the previous section of a (weak) negative relationship and our theoretical expectations. The null hypothesis for each model tested was "absence of scale economies." This result suggests that, when controlling for per-acre control cost and BMP effectiveness, larger fields are associated with a larger average control cost. Alternatively stated, this result suggests that per-acre control cost and BMP effectiveness are the factors driving the nonparametric finding of a weak negative relationship between field size and average control cost in the previous section rather than field size. The coefficient signs for b_{ij} and c_{ij} are nevertheless as expected—negative for the former and positive for the latter. In other words, the average control cost per field is expected to decrease (increase) with increases in per-acre BMP effectiveness (control cost).

For model 2, which regresses L_{ij} on ACC_{ij} while controlling for b_{ij}, c_{ij}, and S_{ij}, we obtain results that support the findings from the nonparametric model in the previous section. In particular, we find a statistically significant negative relationship between per-field delivered load and average control cost. The magnitude of the relationship is admittedly small; a one-gram increase in delivered load per field corresponds to a \$0.001 decrease in the per-field average control cost. Nevertheless, it is the direction of the relationship that matters because that is the cost-effectiveness criterion upon which the subsidy ranking ultimately is based.

Similarly, for model 3, which regresses L_{ij}/S_{ij} on ACC_{ij}, we find a statistically significant negative relationship between per-acre delivered load and per-field average control cost. In this case, a one-gram increase in delivered load per acre corresponds to a \$0.005 decrease in the per-field average control cost. Again, the magnitude of the relationship is small, but its direction indicates that a BMP subsidy ranking based on delivered load per acre may be cost-effective.

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[21] We tested each model for heteroskedasticity and within-panel (AR1) autocorrelation using feasible generalized least squares (Greene 2003). The results of these corrections for possible error structures were qualitatively similar to those without the corrections, which we report.

[22] For each model, respective Lagrange Multiplier (LM) tests reject pooled OLS in favor of random effects, and the Hausman χ^2 tests reject random effects in favor of fixed effects.

Table 4. Results for Panel Data Analysis of Multi-field Farms

	Model 1			Model 2			Model 3		
Explanatory Variable	**OLS**	**Fixed Effects**	**Random Effects**	**OLS**	**Fixed Effects**	**Random Effects**	**OLS**	**Fixed Effects**	**Random Effects**
CONSTANT	0.607***	0.548***	0.568***	0.632***	0.559***	0.585***	0.674***	0.566***	0.602***
	(0.118)	(0.113)	(0.109)	(0.117)	(0.113)	(0.109)	(0.117)	(0.113)	(0.109)
b_{ij}	–0.835***	–0.722***	–0.769***	–0.853***	–0.730***	–0.783***	–0.841***	–0.720***	–0.769***
	(0.152)	(0.146)	(0.138)	(0.151)	(0.126)	(0.138)	(0.151)	(0.123)	(0.138)
c_{ij}	0.084***	0.083***	0.083***	0.083***	0.083***	0.083***	0.083***	0.083***	0.083***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
S_{ij}	0.004***	0.002***	0.003***	0.013***	0.005***	0.008***	0.004***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L_{ij}	–	–	–	–0.0003***	–0.0001***	–0.0001***	–	–	–
	–	–	–	(0.00002)	(0.00002)	(0.00002)	–	–	–
L_{ij}/S_{ij}	–	–	–	–	–	–	–0.002***	–0.0005***	–0.001***
	–	–	–	–	–	–	(0.0002)	(0.0001)	(0.0002)
$F(k, n-k)$	259.25***	353.93***		238.11***	273.60***		223.07***	268.54***	
Wald χ^2 ($k = 7$)			906.32***			971.76***			940.17***
Adjusted R^2	0.073	0.097	0.073	0.088	0.099	0.086	0.083	0.098	0.081
Lagrange Multiplier χ^2			243.42***			177.03***			190.22***
Hausman χ^2		10.30***			65.12***			46.02***	

Notes: Standard errors are shown in parentheses. The fixed-effects standard errors are corrected using Cornwell, Schmidt, and Wyhowski's (1992) method. Number of observations: 9,884 for each regression. *** denotes significant at the 1 percent level, ** denotes significant at the 5 percent level, and * denotes significant at the 10 percent level.

The results from models 2 and 3 are similar to those of the preceding section in that negative relationships are found between ACC_{ij} and L_{ij} and between ACC_{ij} and L_{ij}/S_{ij}. However, these two parametric models explicitly control for any effects that may be generated by the random assignment of values for BMP effectiveness and control cost at the field level and for NPS fixed and random effects. Of course, it is important to recognize that our results are more demonstrative than definitive in a statistical sense because the randomly (and independently) assigned values for b_{ij} and c_{ij} are based on single draws from the given probability distributions shown in Table 3. Different draws from these same distributions or from alternatively defined distributions might produce different results. Fortunately, given our relatively large sample size (approximately 10,000 fields and 2,600 farms), the Central Limit Theorem suggests that, on average, our results will hold in the case of different draws from the same distributions.

It is also important to note that these regression results (i.e., the positive relationship between S_{ij} and ACC_{ij} and respective negative relationships between L_{ij} and L_{ij}/S_{ij} on one hand and L_{ij} and ACC_{ij} on the other) are not predetermined by the definition of ACC_{ij} in (1). In general, coefficient estimates reflect covariance between the respective dependent and independent variables that exists in the data at hand, not partial derivatives of the definition of the dependent variable per se.[23] Likewise, all else being equal, the larger the sample size, the smaller the estimated standard errors of the coefficients (McCloskey and Ziliac 1996). Since our sample size is so large, we expect relatively small standard errors, which in turn implies relatively high significance levels for our coefficient estimates regardless of how much variation they ultimately explain in ACC_{ij} as a group.

Following McCloskey and Ziliac (1996), we tested the statistical power of the results presented in Table 4 by randomly drawing samples of various sizes (20 percent, 40 percent, 60 percent, and 80 percent of the overall sample of roughly 10,000 observations) and re-estimating each model based on the smaller sample sizes. For each of the smaller samples, the results for models 2 and 3 remained qualitatively the same as the ones shown in Table 4 with the exception of the 20 percent sample. In that case, the Hausman χ^2 test favored random effects over fixed. For model 1, the results were more varied. For the 20 percent sample, the Hausman χ^2 test favored random effects and the coefficient estimate for S_{ij} was positive and significant only at the 10 percent level. The Hausman χ^2 test again favored random effects with the 40 percent sample but the coefficient estimate for S_{ij} was statistically insignificant. Under the 60 percent sample, fixed effects were favored over random effects but the S_{ij} coefficient estimate was again positive and significant only at the 10 percent level. Only with the 80 percent sample did the results for model 1 fully mimic

[23] As proof of this point, consider the simplest of examples. Suppose our data set consists of the following two observations:

b_{ij}	c_{ij}	S_{ij}	L_{ij}	ACC_{ij}
0.5	3	4	5	4.8
0.1	1	1	1	10

where ACC_{ij} is determined according to (1). In this case, the OLS coefficient estimates for S_{ij}, L_{ij}, and L_{ij}/S_{ij}, respectively, are –1.73, –1.30, and –20.73. In particular, the estimate for S_{ij} is negative, not positive. In general, any configuration of coefficient estimates should be possible for S_{ij}, L_{ij}, and L_{ij}/S_{ij} depending on the data at hand.

those obtained using the full sample. Therefore, we concluded that the statistical power of models 2 and 3 is relatively high while the power of model 1 is not.[24]

To decompose the effects of field size on the relationship between ACC_{ij} and L_{ij} and between ACC_{ij} and L_{ij}/S_{ij}, we created sets of corresponding interaction terms defined as ($Acre_m \times L_{ij}$) and ($Acre_m \times L_{ij}/S_{ij}$), m = 1, 2, 3, 4, 5. $Acre_1$ denotes field sizes included in the 20th percentile, $Acre_2$ denotes field sizes between the 21st and 40th percentile, $Acre_3$ represents field sizes between the 41st and 60th percentile, $Acre_4$ is field sizes between the 61st and 80th percentile, and $Acre_5$ denotes field sizes that exceed the 80th percentile. We ran regressions that included solely those interaction terms (along with constant terms). The results are presented in Table 5.

For model 2 we find that, relative to the group of largest fields (corresponding to $Acre_5 \times L_{ij}$, the excluded interaction term), delivered loads from smaller fields have progressively stronger negative effects on average control cost; that is, scale economies associated with per-field delivered loads are decreasing in field size. For example (referring to the fixed-effects results), we find that a one-gram

[24] The Stata output for these results is available from the authors upon request.

Table 5. Piece-wise Regression Analyses for Models 2 and 3 (Multi-field Farms)

	Model 2			Model 3		
Interaction Term	OLS	Fixed Effects	Random Effects	OLS	Fixed Effects	Random Effects
$Acre_1 \times L_{ij}$	–0.005***	–0.002**	–0.003***	–	–	–
	(0.00100)	(0.00080)	(0.00090)	–	–	–
$Acre_2 \times L_{ij}$	–0.001***	–0.0006***	–0.0009***	–	–	–
	(0.00020)	(0.00020)	(0.00020)	–	–	–
$Acre_3 \times L_{ij}$	–0.0006***	–0.0002***	–0.0004***	–	–	–
	(0.00010)	(0.00008)	(0.00008)	–	–	–
$Acre_4 \times L_{ij}$	–0.0002***	–0.00009***	–0.0001***	–	–	–
	(0.00003)	(0.00003)	(0.00003)	–	–	–
$Acre_1 \times L_{ij}/S_{ij}$	–	–	–	–0.001***	–0.0003	–0.0006**
	–	–	–	(0.00020)	(0.00020)	(0.00020)
$Acre_2 \times L_{ij}/S_{ij}$	–	–	–	–0.002***	–0.0007***	–0.001***
	–	–	–	(0.00030)	(0.00020)	(0.00030)
$Acre_3 \times L_{ij}/S_{ij}$	–	–	–	–0.003***	–0.001***	–0.002***
	–	–	–	(0.00040)	(0.00040)	(0.00040)
$Acre_4 \times L_{ij}/S_{ij}$	–	–	–	–0.005***	–0.002***	–0.003***
	–	–	–	(0.00060)	(0.00050)	(0.00060)

Notes: Standard errors are shown in parentheses. The fixed-effects standard errors are corrected using Cornwell, Schmidt, and Wyhowski's (1992) method. Number of observations: 9,884 for each regression. *** denotes significant at the 1 percent level, ** denotes significant at the 5 percent level, and * denotes significant at the 10 percent level.

Table 6. Results for Ordinary Least Square Analysis of Single-field Farms

Explanatory Variable	Model 1	Model 2	Model 3
CONSTANT	0.790***	0.837***	1.040***
	(0.10700)	(0.10500)	(0.10100)
b_{ij}	–1.032***	–1.096***	–1.104***
	(0.13900)	(0.13700)	(0.13000)
c_{ij}	0.073***	0.073***	0.073***
	(0.00300)	(0.00300)	(0.00300)
S_{ij}	0.004***	0.012***	0.005***
	(0.00100)	(0.00100)	(0.00100)
L_{ij}	—	–0.0002***	—
	—	(0.00002)	—
L_{ij}/S_{ij}	—	—	–0.007***
	—	—	(0.00040)
$F(k, n-k)$	234.25***	206.18***	284.31***
Adjusted R^2	0.227	0.256	0.322

Notes: Standard errors are shown in parentheses. Number of observations: 2,388 for each regression. *** denotes significant at the 1 percent level, ** denotes significant at the 5 percent level, and * denotes significant at the 10 percent level.

Table 7. Piece-wise Regression Analyses for Models 2 and 3 (Single-field Farms)

Interaction Term	Model 2	Model 3
$Acre_1 \times L_{ij}$	–0.020***	—
	(0.00200)	
$Acre_2 \times L_{ij}$	–0.006***	—
	(0.00100)	
$Acre_3 \times L_{ij}$	–0.003***	—
	(0.00040)	
$Acre_4 \times L_{ij}$	–0.0003***	—
	(0.00004)	
$Acre_1 \times L_{ij}/S_{ij}$	—	0.008***
		(0.00070)
$Acre_2 \times L_{ij}/S_{ij}$	—	–0.006***
		(0.00080)
$Acre_3 \times L_{ij}/S_{ij}$	—	–0.008***
		(0.00080)
$Acre_4 \times L_{ij}/S_{ij}$	—	–0.005***
		(0.00060)

Notes: Number of observations: 2,388 for each regression. *** denotes significant at the 1 percent level, ** denotes significant at the 5 percent level, and * denotes significant at the 10 percent level.

increase in delivered load from the fields in the $Acre_1$ group corresponds to a \$0.002 decrease in per-field average control cost compared to a one-gram increase in delivered load from the fields in the $Acre_5$ group. Similarly, a one-gram increase in delivered load from the fields in the $Acre_2$ group corresponds to a \$0.0006 decrease in per-field average control cost relative to a one-gram increase in delivered load from the fields in the $Acre_5$ group.[25]

Model 3 tells a different story. Per-acre delivered loads from smaller fields have progressively weaker negative effects on average control cost up to the largest field-size group. In other words, scale economies associated with per-acre delivered loads are increasing in field size up to group $Acre_5$. Specifically, a one-gram increase in delivered load per acre from the fields in the $Acre_1$ group fails to produce a decrease in per-field average control cost that is statistically different from a one-gram increase in per-acre delivered load from the fields in the $Acre_5$ group. However, one-gram increases in per-acre delivered loads from fields in groups $Acre_2$, $Acre_3$, and $Acre_4$ have progressively stronger negative effects on average control cost than do increases in per-acre delivered loads from fields in the $Acre_5$ group. In other words, scale economies associated with per-acre delivered loads occur in the middle range of field sizes, not at the extremes.

The results for single-field farms are, for the most part, similar to the panel data results for multi-field farms. As shown in Table 6, field size has a statistically significant positive effect on average control cost (model 1) while per-field and per-acre delivered loads have a negative effect (models 2 and 3). Like the results for multi-field farms in Table 5, the results in Table 7 show that scale economies associated with per-field delivered loads are decreasing in field size (model 2). Unlike the results for multi-field farms, however, there is no evidence for scale economies associated with per-acre delivered loads in the middle range of field sizes. Nor do we find evidence for diseconomies of scale in this range (model 3).

Summary and Conclusions

This work has demonstrated both parametric and nonparametric methods that use field-level characteristics as proxy measures to test for economies of scale in the control of nonpoint pollution. Given the standard assumption that the cost and effectiveness of field-level controls are inherently uncertain, we tested for the presence of economies of scale in correlations between control cost per unit abated (i.e., average control cost) and three characteristics: field size, estimated delivered phosphorous load per field, and estimated delivered phosphorous load per acre. Correlation estimation is necessary because control costs involve greater uncertainty than field-level characteristics do. Our data set is large, consisting of estimates of loads and delivery-ratios for more than 12,000 fields within approximately 5,900 farms in the Bear River Basin in Utah. These estimates, derived from a newly developed hydrologic model of the basin, were combined with estimates of control costs and effectiveness of BMPs taken from the extant literature and standard distributional assumptions concerning costs and effectiveness at the field level to create a joint environmental-economic profile of the basin.

[25] This decreasing scale economy is similar to that found in Sung and Gort (2000) for the U.S. local telephone industry.

In both parametric and nonparametric tests, we find statistical evidence of a negative relationship between average control cost and delivered phosphorus load per field and per acre—larger phosphorus loads per field and per acre are associated with lower average control costs. This suggests that ranking fields according to the phosphorus load delivered per field and per acre can, all else being equal, be used to prioritize subsidies for implementation of BMPs to generate more cost-effective results (a greater reduction in pollutant load per dollar of subsidy). The evidence regarding the statistical relationship between average control cost and field size is mixed. Of course, regulators must have accurate estimates of field size and delivered load per field on hand to formulate the rankings and that, in turn, requires access to output from a hydrologic model similar to the one used for this study. Even then, the rankings are probabilistic in nature due to the persistence of asymmetric information between the regulator and nonpoint sources concerning field-level control costs and BMP effectiveness.

The path for future research in this area is clear. Where possible, data sets similar to the one used for this study should be compiled for other basins to test for the same relationships between delivered loads and control costs. Alternative distributional assumptions could also be tested to assess the robustness of the relationships. Additional controls for field-level heterogeneity are also necessary to increase the total percentage of explained variation in control cost.

References

Babcock, B.A., P.G. Lakshminarayan, J. Wu, and D. Zilberman. 1997. "Targeting Tools for the Purchase of Environmental Amenities." *Land Economics* 73(3): 325–339.

Bandaragoda, C., D.G. Tarboton, and R. Woods. 2004. "Application of TOPNET in the Distributed Model Intercomparison Project." *Journal of Hydrology* 298(1): 178–201.

Beasley, D.B, E.J. Monke, E.R. Miller, and L.F. Huggins. 1985. "Using Simulation to Assess the Impacts of Conservation Tillage on Movement of Sediment and Phosphorus into Lake Erie." *Journal of Soil and Water Conservation* 40(2): 233–237.

Breusch, T., and A. Pagan. 1980. "The LM Test and Its Applications to Model Specification in Econometrics." *Review of Economic Studies* 47: 239–254.

Brown, L.C., and T.O. Barnwell. 1987. *The Enhanced Stream Water Quality Model QUAL2E and QUAL2E-UNCAS: Documentation and User Manual*. Athens, GA: U.S. Environmental Protection Agency.

Caplan, A.J., B. Neilson, and M. Baker. 2009. "Going with the Flow: Using a Water Quality Model to Operationalize Water Quality Trading." Working Paper, Economic Research Institute, Department of Applied Economics, Utah State University.

Christensen, L.R., and W.H. Greene. 1976. "Economies of Scale in U.S. Electric Power Generation." *Journal of Political Economy* 84(4): 655–676.

Cornwell, C., P. Schmidt, and D. Wyhowski. 1992. "Simultaneous Equations and Panel Data." *Journal of Econometrics* 51(1/2): 151–181.

Environmental Protection Agency. 2001. "National Land Cover Data." EPA, Washington, D.C.

———. 2003a. "Economic Analysis of Nutrient and Sediment Reduction Actions to Restore Chesapeake Bay Water Quality." Region III Report, Chesapeake Bay Program Office, EPA, Annapolis, MD.

———. 2003b. *Water Quality Trading Policy*. Washington, DC: U.S. Government Printing Office.

Farm Service Agency. 2009a. "Conservation Reserve Program." Farm Service Agency, U.S. Department of Agriculture, Washington, DC. Available at www.fsa.usda.gov/fsa (accessed February 18, 2009).

———. 2009b. "Food, Conservation, and Energy Act of 2008, Title II, Subtitle B – Conservation Reserve Program." Farm Service Agency, U.S. Department of Agriculture, Washington, DC. Available at www.fsa.usda.gov/internet/fsa/file/2008fbcrpsummary.pdf (accessed February 18, 2009).

Feng, F., K.W. Easter, and P.L. Brezonik. 2005. "Point-Nonpoint Source Water Quality Trading: A Case Study in the Minnesota River Basin." *Journal of the American Water Resources Association* 41(3): 645–657.
Freeman, M.A. III. 2002. "Environmental Policy since Earth Day 1: What Have We Gained?" *Journal of Environmental Perspectives* 16(1): 125–146.
Gyimah-Brempong, K. 1987. "Economies of Scale in Municipal Police Departments: The Case of Florida." *The Review of Economics and Statistics* 69(2): 352–356.
Greene, W.H. 2003. *Econometric Analysis* (5th ed.). Singapore: Pearson Education.
Haith, D.A., and R.C. Loehr. 1979. "Effectiveness of Soil and Water Conservation Practices for Pollution Control." EPA-600/3-79-106, U.S. Environmental Protection Agency, Athens, GA.
Hamlett, J.M, and D.J. Epp. 1994. "Water Quality Impacts of Conservation and Nutrient Management Practices in Pennsylvania." *Journal of Soil and Water Conservation* 49(1): 59–66.
Hammond, J.D., E.R. Melander, and N. Shilling. 1971. "Economies of Scale in the Property and Liability Insurance Industry." *The Journal of Risk and Insurance* 38(2): 181–191.
Hausman, J. 1978. "Specification Tests in Econometrics." *Econometrica* 46(6): 1251–1271.
Horan, R.D., D.G. Abler, J.S. Shortle, and J. Carmichael. 2002. "Cost Effective Point-Nonpoint Trading: An Application to the Susquehanna River Basin." *Journal of the American Water Resources Association* 38(2): 467–477.
Horan, R.D., J.S. Shortle, and D.G. Abler. 2002. "Point-Nonpoint Nutrient Trading in the Susquehanna River Basin." *Water Resources Research* 38(5): 1050–1062.
Johnes, P.J., and A.L. Heathwaite. 1997. "Modeling the Impact of Land Use Change on Water Quality in Agricultural Catchments." *Hydrological Processes* 11(3): 269–286.
Keiser, M.S., F. Fang, and D.L. Hall. 2004. "A Preliminary Analysis of Water Quality Trading Opportunities in the Great Miami Watershed, Ohio." Unpublished manuscript, Keiser and Associates, Kalamazoo, MI. A copy of this document is on file with the authors.
Lyon, S.W., M.T. Walter, P. Gerard-Marchant, and T.S. Steenhuis. 2004. "Using a Topographic Index to Distribute Variable Source Area Runoff Predicted with the SCS Curve Number Equation." *Hydrological Processes* 18(15): 2757–2771.
MacDonald, J.M., and M.E. Ollinger. 2000. "Scale Economies and Consolidation in Hog Slaughter." *American Journal of Agricultural Economics* 82(2): 334–346.
Malik, A.S., D. Letson, and S.R. Crutchfield. 1993. "Point/Non-point Source Trading of Pollution Abatement: Choosing the Right Trading Ratio." *American Journal of Agricultural Economics* 75(3): 959–967.
McCloskey, D.N., and S.T. Ziliac. 1996. "The Standard Error of Regressions." *Journal of Economic Literature* 34(1): 97–114.
Moschini, G. 1990. "Nonparametric and Semiparametric Estimation: An Analysis of Multiproduct Returns to Scale." *American Journal of Agricultural Economics* 72(3): 589–596.
Mostaghimi, S., S.W. Park, R.A. Cooke, and S.Y. Wang. 1997. "Assessment of Management Alternatives on a Small Agricultural Watershed." *Water Resources* 31(8): 1867–1878.
Myers, J.L., and A.D. Well. 2003. *Research Design and Statistical Analysis* (2nd ed.). New York, NY: Lawrence Erlbaum Associates, Inc.
Natural Resources Conservation Service. 2007. "Soil Survey Geographic (SSURGO) Database." NRCS, U.S. Department of Agriculture, Washington, DC.
———. 2009a. "Application Ranking Summary Watershed Improvement—Crop Hayland." NRCS, U.S. Department of Agriculture, Washington, DC. Available at www.nrcs.ut.nrcs.usda.gov/programs/equip/2008/data/cropirraert.pdf (accessed February 12, 2009).
———. 2009b. "Environmental Quality Incentives Program." NRCS, U.S. Department of Agriculture, Washington, DC. Available at www.nrcs.usda.gov/programs/equip (accessed February 12, 2009).
———. 2009c. "National Priorities: Programmatic Fiscal Year 2006." NRCS, U.S. Department of Agriculture, Washington, DC. Available at www.nrcs.usda.gov/programs/natprgmpriorities/fy2006 (accessed February 12, 2009).
Neilson, B.T., C. Bandaragoda, M.E. Baker, J.S. Horsburgh, and D.K. Stevens. 2009. "Watershed Modeling for Water Quality Trading." Unpublished manuscript, Utah Water Research Laboratory, Utah State University. A copy of this document is on file with the authors.
Nelson, J.A. 1988. "Household Economies of Scale in Consumption: Theory and Evidence." *Econometrica* 56(6): 1301–1314.
Paul, C.J.M. 2001. "Market and Cost Structure in the U.S. Beef Packing Industry: A Plant-level Analysis." *American Journal of Agricultural Economics* 83(1): 64–76.

Pittman, R.W. 1981. "Issue in Pollution Control: Interplant Cost Differences and Economies of Scale." *Land Economics* 57(1): 1–17.

Reichelderfer, K., and W.G. Boggess. 1988. "Government Decision Making and Program Performance: The Case of the Conservation Reserve Program." *American Journal of Agricultural Economics* 70(1): 1–11.

Rodgers, J.L., and W.A. Nicewander. 1988. "Thirteen Ways to Look at the Correlation Coefficient." *The American Statistician* 42(1): 59–66.

Sharpley, A., P. Kleinman, R. McDowell, M. Gitau, and R. Bryant. 2002. "Modeling Phosphorus Transport in Agricultural Watersheds: Processes and Possibilities." *Journal of Soil and Water Conservation* 57(6): 425–439.

Shortle, J.S., and D.G. Abler. 1997. "Non-point Pollution." In H. Folmer and T. Tietenberg, eds., *International Yearbook of Environmental and Resource Economics*. Cheltenham, UK: Edward Elgar.

Shortle, J.S., and R.D. Horan. 2001. "The Economics of Non-point Pollution Control." *Journal of Economic Surveys* 15(3): 255–289.

Sung, N., and M. Gort. 2000. "Economies of Scale and Natural Monopoly in the U.S. Local Telephone Industry." *The Review of Economics and Statistics* 82(4): 694–697.

Taff, S.J., and C.F. Runge. 1987. "Supply Control, Conservation, and Budget Restraint: Conflicting Instruments in the 1985 Farm Bill." In D.W. Halback, C.F. Runge, and W.E. Larson, eds., *Making Soil and Water Conservation Work: Scientific and Policy Perspectives*. Ankeny, IA: Soil Conservation Society of America.

U.S. Census Bureau. 2009. Population data. U.S. Census Bureau, Washington, D.C. Available at http://quickfacts.census.gov/qfd/states/49/49005lk.html (accessed September 5, 2009).

U.S. Geological Survey. 2009. "National Elevation Dataset." USGS, Washington, D.C. Available at http://ned.usgs.gov (accessed September 5, 2009).

Utah Department of Environmental Quality. 2008. "Middle Bear River and Cutler Reservoir TMDLs." Unpublished document, Utah DEQ, Salt Lake City, UT. A copy of this document is on file with the authors.

Utah Department of Natural Resources, Water Resources Division. 2009. Water-related land-use data. Utah Department of Natural Resources, Salt Lake City, UT. Available at www.water.utah.gov/planning/landuse (accessed February 12, 2009).

Walter, M.T., E. Brooks, M.F. Walter, T.S. Steenhuis, C. Scott, and J. Boll. 2001. "Evaluation of Soluble Phosphorus Loading from Manure-applied Fields under Various Spreading Strategies." *Journal of Soil and Water Conservation* 56(4): 329–335.

Wu, J., and B.A. Babcock. 2001. "Spatial Heterogeneity and the Choice of Instruments to Control Nonpoint Pollution." *Environmental and Resource Economics* 18(2): 173–192.

Wu, J., D. Zilberman, and B.A. Babcock. 2001. "Environmental and Distributional Impacts of Conservation Tillage Strategies." *Journal of Environmental Economics and Management* 41(3): 333–350.