The Allocation of Nutrient Load Reduction Across a Watershed: Assessing Delivery Coefficients As an Implementation Tool

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3 **Assessing Delivery Coefficients as an Implementation Tool**

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Assessing Delivery Coefficients as an Implementation Tool

Abstract

Delivery coefficients have long been used in economic analysis of policies that seek to address environmental problems like water pollution (Montgomery, 1972). However, the derivation and validity of delivery coefficients have not been examined carefully by empirical analyses. In this study, we derived estimates of delivery coefficients and then evaluated them as a bridge between complex biophysical models and economic policies. Specifically, delivery coefficients were first derived for the effects of nitrogen application reduction based on the simulation results of a watershed based model, the Soil and Water Assessment Tool (SWAT). Nutrient load reduction responsibilities were then allocated to subwatersheds based on the delivery coefficients using four different allocation principles. We found that the allocations based on delivery coefficients achieved results that differed from the water quality goals by only a few percentage points in general. Moreover, our results indicated that potential cost savings, measured in percentages, outweighed the deviation from water quality goals.

Key words: Allocation principles, Delivery coefficients, Soil and Water Assessment Tool (SWAT), Water quality trading.

1. Introduction

The U.S. Environmental Protection Agency (USEPA) currently lists nearly 39,000 impaired waterways (USEPA, 2006a), which have been submitted by state and other governmental bodies in accordance with requirements in the 1972 U.S. Clean Water Act (USEPA, 2006b). In response, Total Maximum Daily Loads (TMDLs) have been or must be developed for each of these impaired water bodies which: (1) establish the maximum level of a pollutant(s) that must be maintained to still meet water quality standards, and (2) also allocates pollutant loadings among sources (USEPA, 2006b). Application of a TMDL requires subsequent implementation of recommendations generated during the TMDL process, with the attainment of the desired water quality standard being the ultimate goal. There are a wide variety of policy instruments that can be used to support the TMDL implementation process and other water quality initiatives. Water quality trading is one of the policy tool options which has received considerable attention in recent years (USEPA, 2004).

Delivery coefficients, which are simple parameters used to capture the impacts of land uses, can potentially be used to support the design and implementation of policies aimed for water quality improvement.¹ As early as the 1970s, economists used delivery coefficients to study how market based mechanisms can be utilized to minimize the cost of pollutant abatement (Montgomery, 1972). Recently, Khanna et al. (2003) used delivery coefficients to assess the costs of pollution control in a watershed in Illinois. Horan et al. (2004) further applied delivery coefficients to examine the coordination and design of water quality trading programs and agri-environmental policies. A permit trading system, where trading ratios were determined by delivery coefficients, was shown to be able to achieve the least cost to reach a

¹ There is a broad literature of nutrient delivery coefficients by land-cover type based on decades of field-based research (Beaulac and Reckhow, 1982; Johnes, 1996; and Zobrist and Reichert, 2006). In this literature, delivery coefficients are usually referred to as export coefficients.

water quality goal (Hung and Shaw, 2005). In addition to determining trading ratios, the delivery coefficients can also be directly used as a targeting tool for conservation measures.

While useful as a tool for policy making, delivery coefficients can be criticized for being too simple and potentially not representative of the complex hydrologic process in a watershed. In his seminal paper of pollution permits, Montgomery (1972) acknowledged that the linearity assumption implicit in delivery coefficients could be an important limitation for a permit market system. In water pollution, the impacts of polluting sources are often determined by a complex process. In particular, pollutant loadings discharged from specific source areas can be impacted by ongoing in-stream processes including deposition or assimilation along the waterway and additional inputs through atmospheric deposition. Thus, biophysical simulation models designed to capture the complex hydrologic process are often employed to aid our understanding. In fact such models have been used to develop many TMDLs (Benham et al., 2006; Borah et al., 2006, Vellidis et al., 2006).

While biophysical models are very helpful in assessing the impacts of various pollution sources and conservation practices, it can be difficult to use them directly in some economic policies due to their complexity. In this study, we assess the efficacy of delivery coefficients as a bridge between complicated biophysical models and policy making. Specifically, we first derive delivery coefficients from outputs of a biophysical model that has been calibrated to the study region. Then we use these delivery coefficients to implement different allocation policies of nutrient load reduction across a watershed. In the allocations, the biophysical model plays no direct role. Finally, we use the biophysical model to assess how well allocations based on the delivery coefficients achieve water quality goals.

The allocation policies we consider reflect four common principles. The first is absolute equity, which often requires that every subwatershed contributes the same percentage of load reduction. The second is equity based on ability, which can be represented by an allocation where areas with lower marginal costs of abatement are required to make bigger cuts in pollutant load. This principle can be implemented with a market-based mechanism such as water quality trading. Geographical proximity is a third criteria often used to target pollution control efforts. For example, conservation measures are sometimes assumed to be implemented in the entire county where the cropland impaired water body lies (USEPA, 2001). Fourth, conservation measures can be targeted at critical areas responsible for a disproportionate share of loading, or having the most potential for improvement.

The utility of delivery coefficients as a bridge between biophysical models and policy making will depend on how well allocations based on delivery coefficients achieve their intended water quality goals. The focus of this study is to derive delivery coefficients empirically and then test the validity of allocating nutrient load reduction responsibility based on these coefficients in our study area. By using the four principles as allocation criteria, we also provide some general guidance to researchers and watershed planners in selecting treatment areas. For many watersheds where calibration and validation of a biophysical model have been performed or will be carried out as part of the TMDL process, delivery coefficients can be developed at minimal costs from the biophysical model. Thus, delivery coefficients can potentially be a very practical tool for the design and implementation of water quality policies.

2. Theoretical Modeling Framework

Suppose there is a goal of reducing nutrient loading at the watershed outlet by $\bar{N}$ kilograms for a watershed divided into J subwatersheds. Let the cost of nutrient application reduction be $C_j(N_j A_j)$, where N_j is the nutrient application reduction in kilograms per hectare, and A_j is the total hectares in subwatershed j . The effect of nutrient application reduction at all subwatersheds (i.e., the total nutrient loading reduction at the watershed outlet) is represented by a function $N = f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w})$, where $\mathbf{w}$ represents other land use characteristics and natural elements such as weather. A biophysical model that is calibrated for the watershed can be considered as an example of $f(\bullet)$, which reflects the complex hydrologic processes in the watershed. We can write the total nutrient standard as

$$(1) \quad N = f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w}) \geq \bar{N},$$

that is, the overall reduction in nutrient loading has to exceed a preset standard $\bar{N}$.

In this study, we explore a linear approximation of $f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w})$, i.e.,

$$(2) \quad f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w}) = \sum_{j=1}^J d_j N_j A_j.$$

where d_j , the delivery coefficient for subwatershed j , provides an approximation of the amount of nutrient loading reduction at the watershed outlet achieved by one unit of nutrient application reduction in the subwatershed j . The main subject of this paper is to examine whether allocations based on this simplified version of $f(\bullet)$ achieve water quality standards. In other words, our goal is to examine the validity of using d_j as an intermediary between policy making and biophysical models that attempt to mimic the whole hydrological process in a watershed.

The constraint in (1) can be satisfied by many different sets of N_j for $j = 1, 2, \dots, J$, each of which will have a different total cost, $TC \equiv \sum_{j=1}^J C_j(N_j A_j)$. As we discussed in the Introduction, different principles can be used to determine N_j . For the absolute equity principle, then N_j can be set equal for all j or it can be set such that every subwatershed has equal percentage reduction. For the geographic proximity, some subwatersheds, i.e., a subset of $\{1, 2, \dots, J\}$, will be identified as being close to the watershed outlet. Denote this subset as $\{downstream\}$, then one example allocation can be set as follows: $N_j = 0$ for $j \notin \{downstream\}$ and $N_j > 0$ for $j \in \{downstream\}$. For critical area targeting, a subset of subwatersheds, denoted as $\{critical\}$, will be identified and then load reduction responsibilities can be allocated similarly: $N_j = 0$ for $j \notin \{critical\}$ and $N_j > 0$ for $j \in \{critical\}$.

Unlike equal allocation and downstream targeting where information on the function $f(\bullet)$ is not necessary, some information on $f(\bullet)$ is usually required in order to identify the critical areas. If we know d_j for all subwatersheds, then we can designate those with higher d_j 's as critical areas. As we discussed in the Introduction, the equity based on ability principle can require those with lower marginal costs of reduction to cut back more of their nutrient application. As is well known in the economics literature, such requirement will be met by the least cost allocation which is a solution to the following problem,

$$(3) \quad \min_{N_j} \sum_{j=1}^J C_j(N_j A_j)$$

subject to the constraint (1) and $N_j \geq 0$.

151 The solutions can be characterized as²

152 (4)
$$\frac{\partial C_j(N_j^* A_j) / \partial N_j}{\partial f(N_1^* A_1, N_2^* A_2, \dots, N_J^* A_J; \mathbf{w}) / \partial N_j} = \frac{\partial C_k(N_k^* A_k) / \partial N_k}{\partial f(N_1^* A_1, N_2^* A_2, \dots, N_J^* A_J; \mathbf{w}) / \partial N_k},$$

153 for all $j, k = 1, 2, \dots, J$, and $j \neq k$, where $\partial C_j(N_j A_j) / \partial N_j$ represents the marginal cost incurred

154 from an incremental change in N_j and $\partial f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w}) / \partial N_j$ represents the

155 marginal benefit, i.e., the extra loading reduction achieved from an incremental change in N_j .

156 Equation (4) requires that the ratio of marginal cost over the marginal benefit be equalized to

157 achieve the least cost allocation.

158 Theoretically, we can obtain the least-cost allocation by solving N_j for $j = 1, \dots, J$ from

159 equations (1) and (4) with (1) binding (i.e., the nutrient reduction standard will be just met).

160 However, if $f(\bullet)$ is solely represented by a biophysical model, then it will be very complex,

161 which poses challenges for finding the least-cost allocation. With the linear approximation of

162 $f(\bullet)$ in (2), it is straightforward to find the least cost allocation. In order to explicitly solve the

163 problem represented by (3), we assume that $C_j(N_j A_j) = A_j c_j(N_j)$, with

164 (5)
$$c_j(N_j) = \alpha_0 + \gamma_j \alpha \frac{\theta}{\theta + 1} N_j^{\frac{\theta + 1}{\theta}}.$$

165 Parameters α_0 and α determine the scale of the cost function. The parameter θ determines the

166 curvature of the cost function—the smaller the θ , the faster the cost increases as N_j increases.

167 For a very large θ , the cost function is approximately linear in N_j , i.e., $c_j(N_j) = \alpha_0 + \gamma_j \alpha N_j$.

168 If $\theta = 1$, then $c_j(N_j)$ is quadratic, or $c_j(N_j) = \alpha_0 + \frac{1}{2} \gamma_j \alpha N_j^2$. The heterogeneity of the cost

² In the Appendix, we provide details as to how the optimization problem is solved.

function among subwatersheds is reflected by γ_j . If $\gamma_j = 1$ for all j then the cost function is the same for all subwatersheds.

The function in (5) is very flexible and all of the parameters can be calibrated to the abatement cost in a particular watershed. The flexibility is needed to accommodate the diverse opinions on the costs of nutrient application reduction. The yield effect of a moderate reduction in nitrogen fertilizer application has been estimated to be almost none, positive, or negative. Some states still recommend more fertilizer for a higher yield goal, while others have discontinued the practice (Lory and Scharf, 2003). It is difficult to estimate the impacts of fertilizer application because the effects may be masked by weather, previous crops, soil condition, etc. Moreover, the reduction of fertilizer may have an insignificant effect in the short run; however, the long run effect may be large. In addition to the issues related to yield effects, *Babcock* [1992] also showed that the seemingly over-application of nitrogen fertilizer is actually consistent with profit maximization, which implies that a payment will be needed for farmers to reduce their nitrogen fertilizer application. In our study, different parameter values will be examined to represent the spectrum of estimates regarding the cost of nutrient application reduction.

With (2) and (5), we can derive a closed form solution for the problem in (3) as follows:³

$$(6) \quad N_j^* = \frac{\bar{N} d_j^\theta \gamma_j^{-\theta}}{\sum d_i^{\theta+1} \gamma_i^{-\theta} A_i}.$$

Thus, the optimal nitrogen application reduction in subwatershed j depends on the delivery coefficients and cost parameters in all subwatersheds. The solution in equation (6) is fortuitous for our empirical analysis in that we do not need to know the precise size of the abatement cost

³ Please see Appendix for details.

function in order to allocate nutrient load, because α_0 and α do not appear in equation (6). As far as abatement cost is concerned, we only need to know the shape of the cost function as represented by θ and the heterogeneity of cost across the subwatersheds as represented by γ_j . This not only facilitates our empirical analysis but also is important in the real world policy assessment given that the exact magnitude of cost for nutrient reduction can be hard to obtain.

The implementation of N_j^* in the real world can pose challenges. It is generally recognized in the economics literature that centralized policies such as source specific regulations are often difficult to be carried out with success. For example, it would be impractical for the regulator to accurately set N_j^* for every subwatershed. This is because such regulations would require the regulator to know the cost of changing N_j , information which can be hard to obtain with accuracy. On the other hand, decentralized policies such as water quality trading are attractive in the sense that sources would achieve any preset water quality standard at the least cost if they are allowed to trade their reduction responsibilities. That is, N_j^* would emerge as an outcome of the market. Even though there are also challenges in actually implementing water quality trading, that trading has the potential to minimize costs is a very desirable attribute and has drawn considerable attention from researchers as well as practitioners.

3. The watershed and the biophysical model

In our empirical application, we focus our analysis on the Raccoon River Watershed in west central Iowa (Figure 1). With a total drainage area of about 9397 km², the land use in the watershed is dominated by agriculture: 75.3% in cropland, 16.3% in grassland, and 4.4% in

forest. Urban use accounts for the remaining 4.0% of the total area. The Raccoon River and its tributaries drain all or parts of 17 counties before joining the Des Moines River in Des Moines, and is the primary source of drinking water for over 350,000 people who live in central Iowa.

Intensive agriculture with widespread application of nitrogen fertilizer has been identified as the primary source of high nitrate concentrations in the Raccoon River, which is a major concern both locally and regionally. Since the late 1980s, the Des Moines Water Works has operated the world's largest nitrate removal facility, due to the high concentration of nitrate. Sections of the Raccoon River are included in Iowa's Federal Clean Water Act 303(d) list of impaired waters, due to the high nitrate or bacteria levels. Nitrates discharge from the Raccoon and other rivers in the Upper Mississippi River Basin have been further implicated as a key source of the Gulf of Mexico seasonal hypoxic zone, which has covered upwards of 20,000 km² in recent years (Rabalais et al., 2002). The Committee on Environment and Natural Resources (CENR) recommended the implementation of several on-farm practices for reducing nitrogen discharge to the Mississippi River stream system, including a 20% reduction in nitrogen fertilizer application, to help mitigate the hypoxic zone problem (Mitsch et al., 1999).

We employ the Soil and Water Assessment Tool (SWAT) model to simulate water quality, or more specifically, nutrient loadings in the river stream (Arnold and Forher, 2005; Gassman et al., 2005). The SWAT model is a conceptual, physically based long-term continuous watershed scale simulation model that operates on a daily time step. In SWAT, a watershed is divided into multiple subwatersheds, which are then further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics. Key components of SWAT include hydrology, plant growth, erosion, nutrient transport and transformation, pesticide transport, and management practices. Detailed

theoretical description of the SWAT model and its major components can be found in Neitsch et al. (2002). Outputs provided by SWAT include streamflows and in-stream loading or concentration estimates of sediment, nutrients, and pesticides. Previous applications of SWAT for streamflows and/or pollutant loadings have compared favorably with measured data for a variety of watershed scales (Gassman et al., 2005).

This study is based on the SWAT modeling framework developed by Jha et al. (2006), who calibrated and validated SWAT for streamflow, sediment loads, and nitrogen and phosphorus losses for the Raccoon River Watershed. This framework facilitates analyses of the impacts of potential policy scenarios on flow, sediment and other water quality indicators in the region. Basic input data used to setup the SWAT simulation include topography, weather, land use, soil, and management data. A key source of land use, soil and management data was the National Resources Inventory (NRI) database (Nusser and Goebel, 1997). The NRI is a statistically based survey database that contains information for the entire U.S. such as landscape features, soil type, cropping histories, tile drainage, and conservation practices for the whole nation. The climate data were obtained from the National Climatic Data Center for 10 weather stations located in and around the watershed. In the modeling framework, the watershed is delineated into 26 subwatersheds identical to the 10-digit level of Hydrologic Unit Codes. The outlet of subwatershed 25 is also the outlet of the whole Raccoon River watershed (Figure 1).

The SWAT baseline simulation was executed for the same 24-year period of 1981-2003 as used by Jha et al. (2006). Corn production accounted for about 50% of the total watershed area and about two thirds of the total cropland area in a given year, which was consistent with the fact that corn-soybean was the dominant rotation in the watershed and other rotations also

included corn. The fertilizer application rates in the region, which were based on state and county fertilizer use information, had a mean of 148 kg/ha and a standard deviation of 4.7 kg/ha.

4. Empirical Analysis

In this section, we first describe the procedure used to obtain delivery coefficients and then we explain the alternative allocations of nutrient reduction responsibilities in the watershed. In our empirical modeling, we chose nitrate as our nutrient indicator since it was the predominant form of water pollution in the study region. We chose nitrogen fertilizer application reduction as the pollution control measure given that it was a practice recommended by the CENR (Mitsch et al., 1999) and was also most straightforward to model. The following procedure was used to obtain the delivery coefficient (d_j) which represented the amount of nitrate loading reduction achieved at the watershed outlet as a result of one unit of fertilizer application reduction implemented in subwatershed j :

1. Conduct one SWAT run: assuming no reduction at all in the watershed, obtain the baseline nitrate loadings at the watershed outlet.
2. Conduct 26 SWAT runs: assuming x percent nitrogen fertilizer application reduction in subwatershed j and 0% reduction at all other subwatersheds. Denote the amount of nitrate loading reduction obtained at the watershed outlet as y_j .
3. Let N_j^0 be the baseline per hectare nitrogen fertilizer application at subwatershed j ,

the delivery coefficient d_j is then defined as $d_j = \frac{y_j}{x * A_j * N_j^0}$.

Note that the delivery coefficient was calculated in terms of nitrogen fertilizer application in a subwatershed, instead of the nitrate loading at the subwatershed outlet. The

difference is that the former is a practice while the latter is a measure of pollutant loading. It would be more reasonable to use pollutant loading at a subwatershed outlet to capture the synergistic effects of multiple management practices, when two or more practices are considered. After obtaining the delivery coefficients, we then used them as a tool to allocate nutrient load reduction responsibilities to the 26 subwatersheds for the four principles as discussed in Section 2. Specifically, the following allocations were examined:

- (i) absolute equity: reduction in each subwatershed by the same percentage, say 20%⁴;
- (ii) equity based on ability: reduction in each subwatershed according to equation (6);
- (iii) critical area targeting: reduction in only 13 critical subwatersheds;
- (iv) geographical proximity: reduction in only 14 downstream subwatersheds.

In the comparison of the four allocations, (i) was used as a benchmark. In other words, we first derived the water quality results from (i) through SWAT simulation. Then, allocations were made for (ii)-(iv), assuming that the nitrate loading reduction, estimated from the delivery coefficients, was fixed at the same level as that achieved by (i). SWAT simulations were then used to assess how water quality outcomes from (ii)-(iv) compared to that from (i). All SWAT simulations were performed for the same time period as the baseline (1981-2003); the annual average nitrate output was used for estimating the subwatershed nitrate loads for each scenario.

Allocations in (ii)-(iv) result in greater nitrogen reductions in some subwatersheds relative to others. Thus, it is an important issue as to how sensitive the delivery coefficients are to different degrees of nitrogen application reduction. To gain some insight on this issue, three application reduction levels were considered: 10, 20, and 30%. In the rest of the paper, we will call these the 10%, 20%, or 30% scenarios, respectively. In the 10% scenarios, the delivery

⁴ This implies that $N_j = 0.2N_j^0$.

coefficients were based on a 10% nitrogen fertilizer application reduction and the benchmark goal was the nitrate loading reduction achieved by a 10% nitrogen fertilizer application reduction in all 26 subwatersheds. Similar logic applies for the 20% and 30% scenarios.

5. Results

The estimated average annual nitrate loadings for the 24-year baseline SWAT simulation are presented for each subwatershed in Table 1. The results indicate that there was substantial variation in the nitrate loadings predicted for the different subwatersheds, reflecting in part the relative proximity of each subwatershed to the watershed outlet (Figure 1). The highest annual average nitrate load of 15.2 million kg was predicted at the watershed outlet, which coincides with the outlet of subwatershed 25.

5.1. The delivery coefficients for the subwatersheds

We present a schematic diagram of the Raccoon watershed (Figure 2) to highlight the connection and interactions among the 26 subwatersheds. The dark dots and gray circles represent the subwatersheds. The seven subwatersheds represented by the gray circles receive flow and nitrate from two or more upstream subwatersheds. Of the remaining subwatersheds, two have one upstream subwatershed and the others have no upstream subwatersheds. The delivery coefficients are provided for all three levels of nitrogen application reduction in Figure 3. The average delivery coefficient was about 0.23 for the 10% scenario, which indicates that for every 1 kilogram of reduction in nitrogen fertilizer application, a reduction of about 0.23 kilograms of nitrate reduction was achieved at the watershed outlet. Figures 2 and 3 show that there was not a clear pattern as to how the delivery coefficients vary with the location of a subwatershed. Some upstream subwatersheds had relatively high delivery coefficients (e.g.,

subwatershed 3), whereas some downstream subwatersheds had relatively low delivery coefficients (e.g., subwatershed 23).

Figure 3 also shows that the delivery coefficients were almost the same for the 20% and 30% scenarios. The robustness of the delivery coefficients with regard to different degrees of pollution control implies that efficiency loss is likely to be small if an allocation involves uneven percentage reductions across the subwatersheds and delivery coefficients were based on the same percentage of reduction in all subwatersheds. As we show later, least-cost allocations in general result in such uneven reductions. To examine whether the delivery coefficients are sensitive to tillage practices, we derived delivery coefficients when no till was adopted on all cropland. The distribution of the new delivery coefficients resembled that in Figure 3 and thus is not presented here. The average of the new delivery coefficients was 0.26, which was only slightly higher than the delivery coefficients presented in Figure 3. The result that the delivery coefficients were also quite robust in relation to different tillage practices also indicates their utility for supporting policy design and implementation.

5.2. Assessing delivery coefficients as a tool to allocate nutrient reduction responsibilities

After the delivery coefficients were derived, allocations were made as described in the previous section. For all allocations (i)-(iv), Table 2 provides the nitrogen reduction rates for each subwatershed and the resulting nitrate loading reduction at the watershed outlet. Given that the results for all three percentage scenarios were similar, only the 20% scenario is presented in the table. For the equal allocation scenario, the nitrate loading reduction achieved at the watershed was 17.13% as estimated by SWAT simulation. This achievement was then used as a goal for allocations (ii)-(iv).

For critical area targeting, we assume that subwatersheds that had delivery coefficients greater than the median should be managed with reduced nitrogen fertilizer application. There were 13 such subwatersheds, specifically, $\{critical\} = \{2,3,5,6,7,8,9,11,12,13,15,19,26\}$. For all three percentage scenarios, the average delivery coefficient for subwatersheds in $\{critical\}$ was 0.28, while the average for all others was 0.18. For simplicity, the allocation among critical subwatersheds was set equal and no nitrogen reduction was required at other subwatersheds.⁵ Specifically, let z be the rate of nutrient application reduction for subwatersheds in $\{critical\}$, which implies that the fertilizer application reduction is $N_j = z * N_j^0$. Then, z can be obtained from the following equation,

$$(7) \quad \frac{\sum_{j \in \{critical\}} z * N_j^0 * A_j * d_j}{(Baseline \ nitrate \ loading \ at \ watershed \ outlet)} = 0.1713,$$

where the denominator is the baseline nitrate loading at the watershed outlet and the numerator is the sum of nitrate loading reduction achieved by targeting at critical subwatersheds. The third column of Table 2 shows that $z = 0.3165$. That is, critical subwatersheds would be required to make about 32% reduction in fertilizer application in order for the nitrate loading at watershed outlet, as calculated from delivery coefficients, to be reduced by 17.13%. Running SWAT simulations for the allocation, we found that the nitrate loading reduction was actually 16.14%, lower than the target (17.13%) the allocation was assumed to achieve.

For downstream targeting, a similar procedure was used to make allocation and derive nitrate reduction impacts. First, about half of the subwatersheds were designated as downstream, shown by the subwatersheds inside the big gray loop in Figure 2. In other words,

⁵ Of course, different principles can also be used to make allocations among downstream subwatersheds or critical subwatersheds, or even within individual subwatersheds. However, such “fine-tuning” is not essential for the main purpose of this paper.

$\{downstream\} = \{8,9,10,11,12,13,14,15,19,20,23,24,25,26\}$ ⁶. Downstream subwatersheds did not necessarily have higher delivery coefficients than upstream subwatersheds. For all three percentage scenarios, the average delivery coefficients for downstream and upstream subwatersheds were about 0.21 and 0.24, respectively. As in the case of critical area targeting, the allocation among downstream subwatersheds was set equal and no nitrogen reduction was required at other subwatersheds. Specifically, the rate of nutrient application reduction (z) in this case is determined as follows,

$$(8) \quad \frac{\sum_{j \in \{downstream\}} z * N_j^0 * A_j * d_j}{(Baseline \ nitrate \ loading \ at \ watershed \ outlet)} = 0.1713,$$

which is the same as (7) except that $\{downstream\}$ replaces $\{critical\}$. The fourth column of Table 2 shows that $z = 0.4386$. Based on SWAT simulation outputs for the allocation, the nitrate loading reduction at the watershed outlet was only 15.42%, which was lower than the target (17.13%) the allocation was meant to achieve.

For the least-cost allocations, the per hectare nitrogen application rate in each subwatershed was given by equation (6). One least-cost allocation is presented in Table 2. (More least-cost allocations are discussed in the next subsection.) We can make two observations on the last column of the table. First, the allocation was quite uneven among the subwatersheds ranging from 8.87% for subwatershed 18 to 41.22% for subwatershed 26. Second, the nitrate reduction achieved (17%) was very close to the goal that the allocation was meant to achieve.

These observations are also applicable to the allocations based on downstream targeting and critical area targeting. All allocations in the last three columns of Table 2 were designed to

⁶ This designation is somewhat arbitrary. If a different set of subwatersheds is identified as downstream, similar analysis can be applied.

achieve the same nitrate loading reduction as the equal allocation; i.e., all cells in the last row should be equal to 17.13%. The last two rows of Table 2 show that the allocations based on delivery coefficients came very close to achieving the initial nitrate reduction goal. The largest deviation occurred in the downstream targeting allocation, which resulted in a nitrate loading that was about 10% short of the reduction goal.⁷ These results provide supporting evidence that it was not unreasonable to use delivery coefficients as a tool for allocation, at least for the watershed analyzed in this study.

5.3. Comparing the four principles of allocation

While our main purpose was to assess the delivery coefficients as a tool for nitrate allocation, we can also provide some insights on the cost-effectiveness of the four principles that were used as criteria for allocation in our analysis. Reducing nitrogen fertilizer in the downstream subwatersheds was slightly more effective overall, as indicated by the slightly higher average delivery coefficients of these subwatersheds. However, focusing on nitrogen fertilizer reduction in downstream subwatersheds could be more expensive especially when the abatement costs rise fast. For example, for $\theta = 1$ (i.e., abatement cost is quadratic and increases relatively fast), the total cost for downstream targeting could be twice as expensive as the equal allocation. However, for $\theta = 5$ (i.e., abatement cost was closer to being linear), the cost difference between the two scenarios would be reduced dramatically to a few percentage points.

Even though the delivery coefficients were much higher for the critical subwatersheds than for other subwatersheds, critical area targeting could still be more expensive than equal allocation if cost increases fast. This is mainly because the impacts of the delivery coefficients were linear as reflected in (7). In our simulation, for $\theta = 5$ and $\theta = 3$, critical targeting was

⁷ The 10% is derived from the expression: $(17.13-15.42)/17.13$.

slightly cheaper than the equal allocation. However, for $\theta = 1$, critical targeting was actually 34% more expensive. In our analysis of both downstream and critical area targeting, we assumed that nitrogen fertilizer reduction was only required within the targeted subwatersheds. One can also assume cases where nitrogen fertilizer reduction occurs both in the targeted and untargeted subwatersheds, although the magnitudes of the reductions would be greater in the targeted subwatersheds. In such cases, there may be more advantage for downstream or critical area targeting.

By construction, the least-cost allocation had the lowest total cost of reaching a given target. Figure 4 gives one illustration of the least-cost nitrogen application reduction (in percentage) for the 26 subwatersheds. The zigzagged pattern is obvious from the figure, which is in contrast with the equal allocation. Cost savings of the least-cost allocation (compared to the equal allocation) can depend on the curvature and heterogeneity of the abatement cost function across the subwatersheds. Given that there was not enough information on the abatement costs, we conducted some sensitivity analyses and presented the results in Table 3. The table indicates that the three reduction levels had about the same cost savings, which were quite small, about 5% for $\theta = 1$. However, for slower rising costs the savings could be as high as about 11.5%.

Heterogeneity in cost is a major reason for cost savings from least-cost programs (Newell and Stavins, 2003). Three sets of values were examined for the heterogeneity parameter γ_j . In the first one, there was no heterogeneity, i.e., γ_j was equal for all j . In the second set, there was some heterogeneity and γ_j was drawn from a transformed Beta distribution with a sample mean of 3.5 and a standard deviation of 0.8. In the last set, there was more heterogeneity— γ_j was drawn from a similarly transformed Beta distribution with about

the same sample mean but a standard deviation 75% larger. Table 3 shows that, when the variance of the heterogeneity parameter increased by 75%, the cost savings more than doubled. Nevertheless, such savings are quite modest compared to the SO₂ trading program which was estimated to be about 40% cheaper than “command and control” regulations (Carlson et al., 2000).

6. CONCLUSIONS

In this study, we assessed the utility of using delivery coefficients as an implementation tool for policies aimed at improving water quality. The delivery coefficients were examined as a bridge between a complex water quality model and policy making. On the one hand, the delivery coefficients were calculated from SWAT model simulation outputs and the impacts of allocations were also assessed by SWAT simulations. On the other hand, the alternative allocations were made directly based on the delivery coefficients and the SWAT model plays no direct role in making the allocations. In our study region, we found that allocations based on the coefficients had water quality results that were close to the goals they were set out to achieve. This finding indicates that delivery coefficients can be a useful tool in the implementation of water quality policies. In addition to being directly used as a targeting tool, the delivery coefficients will be especially important in water quality trading programs where they can be utilized to set the trading ratios among different polluting sources.

A markup (or markdown) in the policy goals can be used in the spirit of a margin of safety if implementation based on delivery coefficients tends to systematically under-achieve (or over-achieve) water quality goals. Moreover, for a specific watershed, the deviation from water quality goals should also be put in perspective. For example, the deviation can be contrasted with potential cost savings from implementing policies based on the coefficients. In

460 our study, in which we simulated the cost savings of allocations based on different principles,
461 we found that the extent of cost savings was much larger than the extent of non-attainment of
462 water quality goals. Given the potential of policies such as water quality trading as a cost-
463 effective approach to cleaner water, and the relatively little extra costs of developing the
464 delivery coefficients, it is likely that many watersheds can find it beneficial to test the utility of
465 delivery coefficients.

466 **Appendix: Derivation of the mathematical results in (4) and (6)**

467 We can write the Lagrangian function of (3) as follows (λ is the Lagrange multiplier),

468 (9)
$$Z = \sum_{j=1}^J C_j(N_j A_j) + \lambda[\bar{N} - f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w})]$$

469 Differentiating with respect of N_j and λ to derive the first-order condition,⁸

470 (10)
$$\frac{\partial Z}{\partial N_j} = \frac{A_j \partial C_j(N_j^* A_j)}{\partial N_j} - \lambda^* \frac{A_j \partial f(N_1^* A_1, N_2^* A_2, \dots, N_J^* A_J; \mathbf{w})}{\partial N_j} \geq 0, \quad \frac{\partial Z}{\partial N_j} N_j^* = 0, \text{ for all } j = 1, 2, \dots, J,$$

471 (11)
$$\frac{\partial Z}{\partial \lambda} = \bar{N} - f(N_1^* A_1, N_2^* A_2, \dots, N_J^* A_J; \mathbf{w}) \leq 0, \quad \frac{\partial Z}{\partial \lambda} \lambda^* = 0.$$

472 For the analysis to be interesting, we assume interior solutions, i.e, $N_j^* > 0$ for all $j = 1, 2, \dots, J$.

473 Then, the derivative (10) is equal to zero. Rearranging, we have

474 (12)
$$\frac{\partial C_j(N_j^* A_j)}{\partial N_j} = \lambda^* \frac{\partial f(N_1^* A_1, N_2^* A_2, \dots, N_J^* A_J; \mathbf{w})}{\partial N_j}, \text{ for all } j = 1, 2, \dots, J.$$

475 Dividing (12) by the same condition for another subwatershed k and then rearranging, we

476 obtain (4).

477 With the functional forms in (2) and (5), we have

478 (13)
$$\frac{\partial f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w})}{\partial N_j} = d_j A_j, \quad \frac{\partial C_j(N_j A_j)}{\partial N_j} = A_j \frac{\partial c_j(N_j)}{\partial N_j} = A_j \gamma_j \alpha N_j^{\frac{1}{\theta}}, \text{ for all } j = 1, 2, \dots, J.$$

479 Plugging (13) into (4), we obtain

480 (14)
$$\frac{\gamma_j \alpha N_j^{\frac{1}{\theta}}}{d_j} = \frac{\gamma_k \alpha N_k^{\frac{1}{\theta}}}{d_k} \text{ for all } j, k = 1, 2, \dots, J, \text{ and } j \neq k.$$

481 Then, N_j^* [i.e., (6)] can be solved from a system of J equations and J unknowns defined by (14)

482 and (1), with the latter holding as an equality.

⁸ The second order condition is satisfied with (2) and (5).

483 **Table 1. Baseline description of Raccoon River Watershed at subwatershed level.**

Subwatershed	Area (hectares)	Corn (% of total area)	Nitrogen Fertilizer* (kg/ha)	Nitrate loading (1000 kg)
1	90,000	50.2	148.8	1,600
2	68,000	49.9	146.1	1,700
3	22,000	50.3	145.6	500
4	54,000	49.7	145.6	6,100
5	23,000	47.7	161.1	400
6	38,000	53	147.2	700
7	33,000	48.2	156.3	900
8	19,000	54.6	147.9	400
9	39,000	50	152.4	10,600
10	42,000	50.2	145.6	800
11	44,000	51.2	145.6	1,200
12	35,000	55.1	137.5	1,200
13	19,000	47.3	152.3	600
14	18,000	50	153.1	200
15	48,000	49.5	147.4	11,700
16	65,000	55.1	150.0	300
17	32,000	49.3	148.8	300
18	30,000	53.1	145.6	800
19	30,000	50.9	148.0	600
20	28,000	45.3	145.6	900
21	36,000	48.9	145.5	300
22	37,000	50.7	145.6	400
23	26,000	52.1	145.6	2,800
24	17,000	54.1	153.2	200
25	26,000	54.4	145.6	15,200
26	21,000	51.3	141.7	300

484 *The nitrogen was applied as 100% nitrate equivalent.

Table 2. The rates of N application reduction for the 20% scenario as a result of different allocation strategies.

Sub-watersheds	Rate of N application reduction (%) in subwatersheds			
	Equal allocation	Critical area targeting	Downstream targeting	Least-cost allocation (no cost heterogeneity)
1	20.00	0	0	17.06
2	20.00	31.65	0	18.33
3	20.00	31.65	0	27.29
4	20.00	0	0	17.37
5	20.00	31.65	0	17.15
6	20.00	31.65	0	22.08
7	20.00	31.65	0	23.81
8	20.00	31.65	43.86	19.77
9	20.00	31.65	43.86	23.03
10	20.00	0	43.86	16.41
11	20.00	31.65	43.86	22.84
12	20.00	31.65	43.86	20.97
13	20.00	31.65	43.86	21.34
14	20.00	0	43.86	13.98
15	20.00	31.65	43.86	24.96
16	20.00	0	0	14.58
17	20.00	0	0	11.13
18	20.00	0	0	8.87
19	20.00	31.65	43.86	24.79
20	20.00	0	43.86	18.00
21	20.00	0	0	13.73
22	20.00	0	0	12.34
23	20.00	0	43.86	11.92
24	20.00	0	43.86	13.57
25	20.00	0	43.86	17.97
26	20.00	31.65	43.86	41.22
Watershed nitrate reduction based on delivery coefficients (%)	N/A [#]	17.13	17.13	17.13
Watershed nitrate reduction based on SWAT simulations (%)	17.13	16.14	15.42	17.00

[#] Not calculated since this allocation is used as a benchmark

Table 3. Sensitivity analysis to alternative cost structures

Sensitivity variables	Parameter values	Difference between the least cost allocation and the equal allocation (%)	
		Total costs	Total nitrate loading
Rate of N application reduction	10%	-5.00	0.00
	20%	-5.64	-0.82
	30%	-4.88	-0.77
Cost increasing rate ^{&}	$\theta = 1$	-5.00	0.00
	$\theta = 3$	-8.77	-1.46
	$\theta = 5$	-11.47	-2.96
Cost heterogeneity ^{&}	γ_j equal	-5.64	-0.82
	$Var[\gamma_j] = 0.8$	-10.13	-3.09
	$Var[\gamma_j] = 1.4$	-26.12	-1.56

[&]The smaller θ is, the faster the cost increases as more N application is reduced. A higher variance means higher heterogeneity. All cases are for the 20% reduction scenario. For the other two scenarios, the results are similar.

499 **Figure 1. Location of the Raccoon River Watershed in Iowa and the delineated**
500 **subwatersheds.**

504 **Figure 2. A schematic diagram of the 26 subwatersheds (with designated downstream**
505 **subwatersheds inside the big gray loop)**

508 **Figure 3. Delivery coefficients by the 26 subwatersheds.**

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511 **Figure 4. The distribution of the rate of nitrogen fertilizer application reduction in a least-**
512 **cost scenario (For $\theta = 1$ and no heterogeneity in costs).**

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