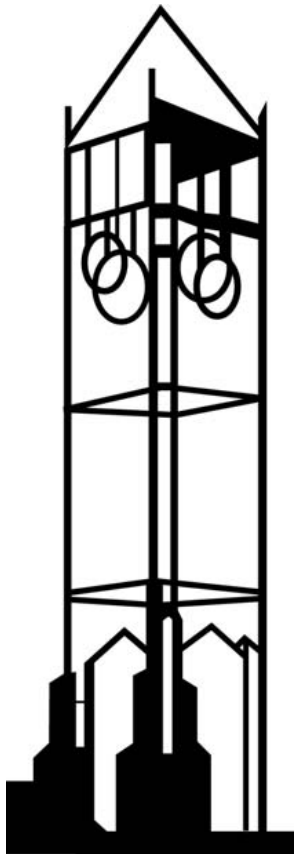


The Allocation of Nutrient Load Reduction Across a Watershed: Assessing Delivery Coefficients As an Implementation Tool

Hongli Feng, Manoj Jha, Philip W. Gassman



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**The Allocation of Nutrient Load Reduction across a Watershed:
Assessing Delivery Coefficients as an Implementation Tool**

Hongli Feng Manoj Jha Phil Gassman*

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25 **The Allocation of Nutrient Load Reduction across a Watershed:**

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

27

28 **Abstract**

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

41

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

44 **1. Introduction**

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

57 Delivery coefficients, which are simple parameters used to capture the impacts of land
58 uses, can potentially be used to support the design and implementation of policies aimed for
59 water quality improvement.¹ As early as the 1970s, economists used delivery coefficients to
60 study how market based mechanisms can be utilized to minimize the cost of pollutant
61 abatement (Montgomery, 1972). Recently, Khanna et al. (2003) used delivery coefficients to
62 assess the costs of pollution control in a watershed in Illinois. Horan et al. (2004) further
63 applied delivery coefficients to examine the coordination and design of water quality trading
64 programs and agri-environmental policies. A permit trading system, where trading ratios were
65 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.

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

68 While useful as a tool for policy making, delivery coefficients can be criticized for
69 being too simple and potentially not representative of the complex hydrologic process in a
70 watershed. In his seminal paper of pollution permits, Montgomery (1972) acknowledged that
71 the linearity assumption implicit in delivery coefficients could be an important limitation for a
72 permit market system. In water pollution, the impacts of polluting sources are often determined
73 by a complex process. In particular, pollutant loadings discharged from specific source areas
74 can be impacted by ongoing in-stream processes including deposition or assimilation along the
75 waterway and additional inputs through atmospheric deposition. Thus, biophysical simulation
76 models designed to capture the complex hydrologic process are often employed to aid our
77 understanding. In fact such models have been used to develop many TMDLs (Benham et al.,
78 2006; Borah et al., 2006, Vellidis et al., 2006).

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

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

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

108

109

110

111 2. Theoretical Modeling Framework

112 Suppose there is a goal of reducing nutrient loading at the watershed outlet
 113 by \bar{N} kilograms for a watershed divided into J subwatersheds. Let the cost of nutrient
 114 application reduction be $C_j(N_j A_j)$, where N_j is the nutrient application reduction in kilograms
 115 per hectare, and A_j is the total hectares in subwatershed j . The effect of nutrient application
 116 reduction at all subwatersheds (i.e., the total nutrient loading reduction at the watershed outlet)
 117 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
 118 characteristics and natural elements such as weather. A biophysical model that is calibrated for
 119 the watershed can be considered as an example of $f(\bullet)$, which reflects the complex hydrologic
 120 processes in the watershed. We can write the total nutrient standard as

$$121 \quad (1) \quad N = f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w}) \geq \bar{N},$$

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

123 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.,

$$124 \quad (2) \quad f(N_1 A_1, N_2 A_2, \dots, N_J A_J; \mathbf{w}) = \sum_{j=1}^J d_j N_j A_j.$$

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

132 The constraint in (1) can be satisfied by many different sets of N_j for $j = 1, 2, \dots, J$, each
 133 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
 134 Introduction, different principles can be used to determine N_j . For the absolute equity
 135 principle, then N_j can be set equal for all j or it can be set such that every subwatershed has
 136 equal percentage reduction. For the geographic proximity, some subwatersheds, i.e., a subset of
 137 $\{1, 2, \dots, J\}$, will be identified as being close to the watershed outlet. Denote this subset as
 138 $\{downstream\}$, then one example allocation can be set as follows: $N_j = 0$ for
 139 $j \notin \{downstream\}$ and $N_j > 0$ for $j \in \{downstream\}$. For critical area targeting, a subset of
 140 subwatersheds, denoted as $\{critical\}$, will be identified and then load reduction responsibilities
 141 can be allocated similarly: $N_j = 0$ for $j \notin \{critical\}$ and $N_j > 0$ for $j \in \{critical\}$.

142 Unlike equal allocation and downstream targeting where information on the function
 143 $f(\bullet)$ is not necessary, some information on $f(\bullet)$ is usually required in order to identify the
 144 critical areas. If we know d_j for all subwatersheds, then we can designate those with higher
 145 d_j 's as critical areas. As we discussed in the Introduction, the equity based on ability principle
 146 can require those with lower marginal costs of reduction to cut back more of their nutrient
 147 application. As is well known in the economics literature, such requirement will be met by the
 148 least cost allocation which is a solution to the following problem,

149 (3)
$$\min_{N_j} \sum_{j=1}^J C_j(N_j A_j)$$

150 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 $\partial C_j(N_jA_j)/\partial N_j$ represents the marginal cost incurred

154 from an incremental change in N_j and $\partial f(N_1A_1, N_2A_2, \dots, N_JA_J; \mathbf{w})/\partial N_j$ 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 $C_j(N_jA_j) = A_jc_j(N_j)$, 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.

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

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

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

186 (6)
$$N_j^* = \frac{\bar{N}d_j^\theta \gamma_j^{-\theta}}{\sum d_i^{\theta+1} \gamma_i^{-\theta} A_i}.$$

187 Thus, the optimal nitrogen application reduction in subwatershed j depends on the delivery
 188 coefficients and cost parameters in all subwatersheds. The solution in equation (6) is fortuitous
 189 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.

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

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

207

208 **3. The watershed and the biophysical model**

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

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

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

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

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

240 This study is based on the SWAT modeling framework developed by Jha et al. (2006),
241 who calibrated and validated SWAT for streamflow, sediment loads, and nitrogen and
242 phosphorus losses for the Raccoon River Watershed. This framework facilitates analyses of the
243 impacts of potential policy scenarios on flow, sediment and other water quality indicators in the
244 region. Basic input data used to setup the SWAT simulation include topography, weather, land
245 use, soil, and management data. A key source of land use, soil and management data was the
246 National Resources Inventory (NRI) database (Nusser and Goebel, 1997). The NRI is a
247 statistically based survey database that contains information for the entire U.S. such as
248 landscape features, soil type, cropping histories, tile drainage, and conservation practices for
249 the whole nation. The climate data were obtained from the National Climatic Data Center for
250 10 weather stations located in and around the watershed. In the modeling framework, the
251 watershed is delineated into 26 subwatersheds identical to the 10-digit level of Hydrologic Unit
252 Codes. The outlet of subwatershed 25 is also the outlet of the whole Raccoon River watershed
253 (Figure 1).

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

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

260
 261 **4. Empirical Analysis**

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

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

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

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

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

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

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

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

⁴ This implies that $N_j = 0.2N_j^0$.

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

305

306 **5. Results**

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

313

314 **5.1. The delivery coefficients for the subwatersheds**

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

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

328 Figure 3 also shows that the delivery coefficients were almost the same for the 20% and
329 30% scenarios. The robustness of the delivery coefficients with regard to different degrees of
330 pollution control implies that efficiency loss is likely to be small if an allocation involves
331 uneven percentage reductions across the subwatersheds and delivery coefficients were based on
332 the same percentage of reduction in all subwatersheds. As we show later, least-cost allocations
333 in general result in such uneven reductions. To examine whether the delivery coefficients are
334 sensitive to tillage practices, we derived delivery coefficients when no till was adopted on all
335 cropland. The distribution of the new delivery coefficients resembled that in Figure 3 and thus
336 is not presented here. The average of the new delivery coefficients was 0.26, which was only
337 slightly higher than the delivery coefficients presented in Figure 3. The result that the delivery
338 coefficients were also quite robust in relation to different tillage practices also indicates their
339 utility for supporting policy design and implementation.

340 341 **5.2. Assessing delivery coefficients as a tool to allocate nutrient reduction responsibilities**

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

349 For critical area targeting, we assume that subwatersheds that had delivery coefficients
 350 greater than the median should be managed with reduced nitrogen fertilizer application. There
 351 were 13 such subwatersheds, specifically, $\{critical\} = \{2,3,5,6,7,8,9,11,12,13,15,19,26\}$. For all
 352 three percentage scenarios, the average delivery coefficient for subwatersheds in $\{critical\}$ was
 353 0.28, while the average for all others was 0.18. For simplicity, the allocation among critical
 354 subwatersheds was set equal and no nitrogen reduction was required at other subwatersheds.⁵
 355 Specifically, let z be the rate of nutrient application reduction for subwatersheds in $\{critical\}$,
 356 which implies that the fertilizer application reduction is $N_j = z * N_j^0$. Then, z can be obtained
 357 from the following equation,

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

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

366 For downstream targeting, a similar procedure was used to make allocation and derive
 367 nitrate reduction impacts. First, about half of the subwatersheds were designated as downstream,
 368 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.

369 $\{downstream\} = \{8,9,10,11,12,13,14,15,19,20,23,24,25,26\}$ ⁶. Downstream subwatersheds did
 370 not necessarily have higher delivery coefficients than upstream subwatersheds. For all three
 371 percentage scenarios, the average delivery coefficients for downstream and upstream
 372 subwatersheds were about 0.21 and 0.24, respectively. As in the case of critical area targeting,
 373 the allocation among downstream subwatersheds was set equal and no nitrogen reduction was
 374 required at other subwatersheds. Specifically, the rate of nutrient application reduction (z) in
 375 this case is determined as follows,

$$376 \quad (8) \quad \frac{\sum_{j \in \{downstream\}} z * N_j^0 * A_j * d_j}{(\text{Baseline nitrate loading at watershed outlet})} = 0.1713,$$

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

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

388 These observations are also applicable to the allocations based on downstream targeting
 389 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.

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

397 398 **5.3. Comparing the four principles of allocation**

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

409 Even though the delivery coefficients were much higher for the critical subwatersheds
410 than for other subwatersheds, critical area targeting could still be more expensive than equal
411 allocation if cost increases fast. This is mainly because the impacts of the delivery coefficients
412 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: $(17.13-15.42)/17.13$.

413 slightly cheaper than the equal allocation. However, for $\theta = 1$, critical targeting was actually
414 34% more expensive. In our analysis of both downstream and critical area targeting, we
415 assumed that nitrogen fertilizer reduction was only required within the targeted subwatersheds.
416 One can also assume cases where nitrogen fertilizer reduction occurs both in the targeted and
417 untargeted subwatersheds, although the magnitudes of the reductions would be greater in the
418 targeted subwatersheds. In such cases, there may be more advantage for downstream or critical
419 area targeting.

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

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

436 the same sample mean but a standard deviation 75% larger. Table 3 shows that, when the
437 variance of the heterogeneity parameter increased by 75%, the cost savings more than doubled.
438 Nevertheless, such savings are quite modest compared to the SO₂ trading program which was
439 estimated to be about 40% cheaper than “command and control” regulations (Carlson et al.,
440 2000).

441 442 **6. CONCLUSIONS**

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

455 A markup (or markdown) in the policy goals can be used in the spirit of a margin of
456 safety if implementation based on delivery coefficients tends to systematically under-achieve
457 (or over-achieve) water quality goals. Moreover, for a specific watershed, the deviation from
458 water quality goals should also be put in perspective. For example, the deviation can be
459 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.

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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

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

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Table 3. Sensitivity analysis to alternative cost structures

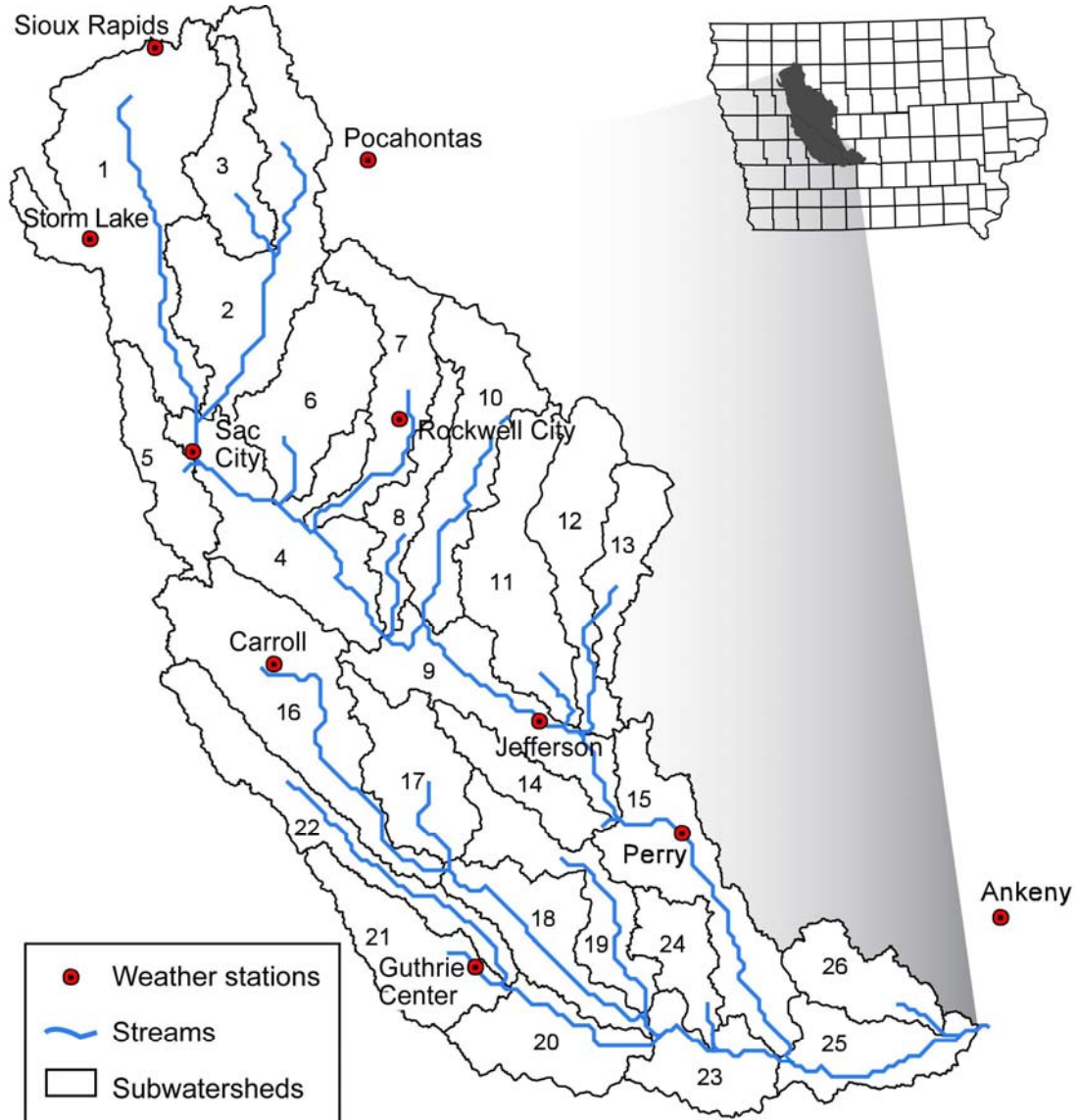
Sensitivity variables	Parameter values	Difference between the least cost allocation and the equal allocation (%)	
		Total costs	Total nitrate loading
Rate of N application reduction	10%	-5.00	0.00
	20%	-5.64	-0.82
	30%	-4.88	-0.77
Cost increasing rate ^{&}	$\theta = 1$	-5.00	0.00
	$\theta = 3$	-8.77	-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

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[&]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.**

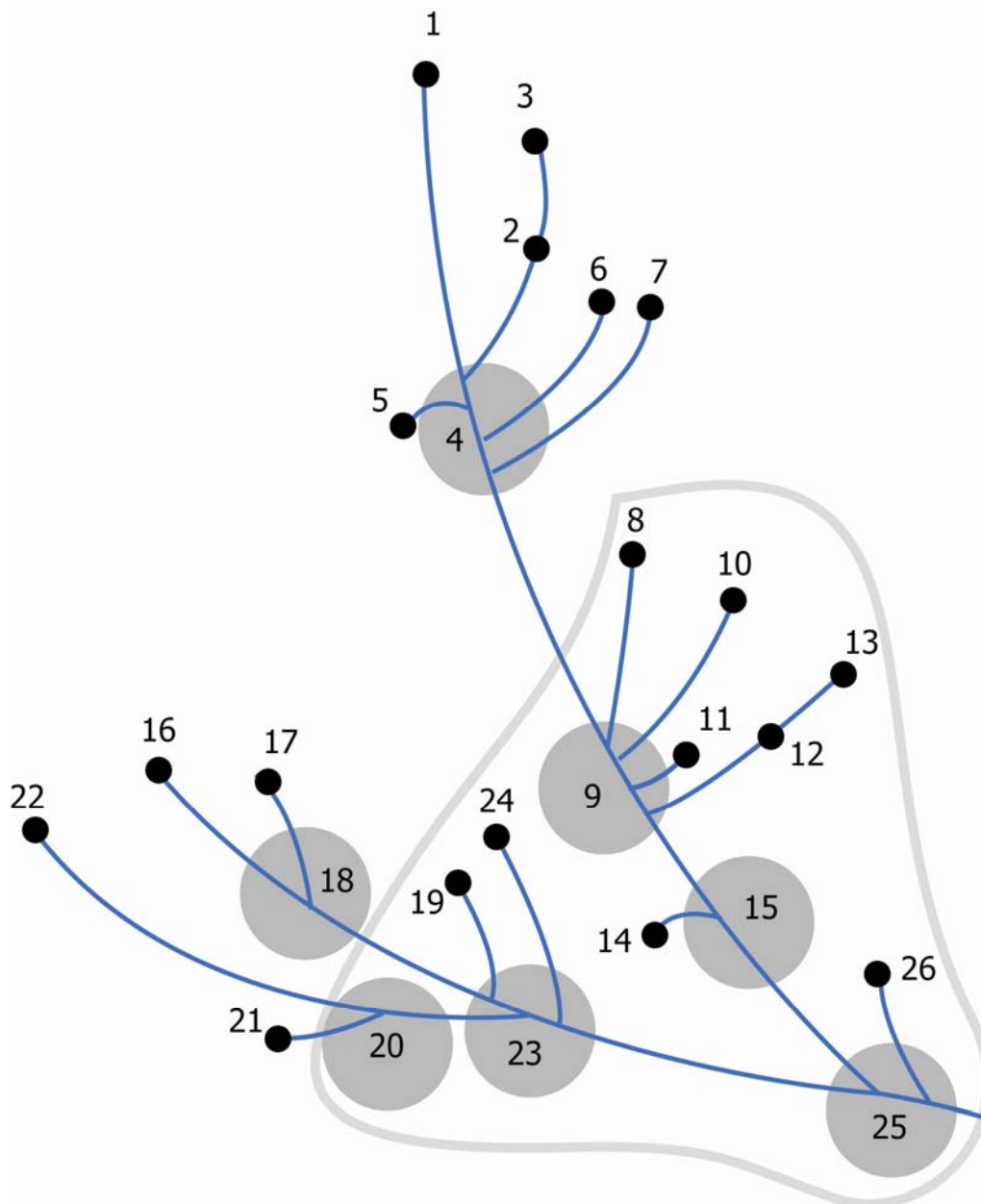
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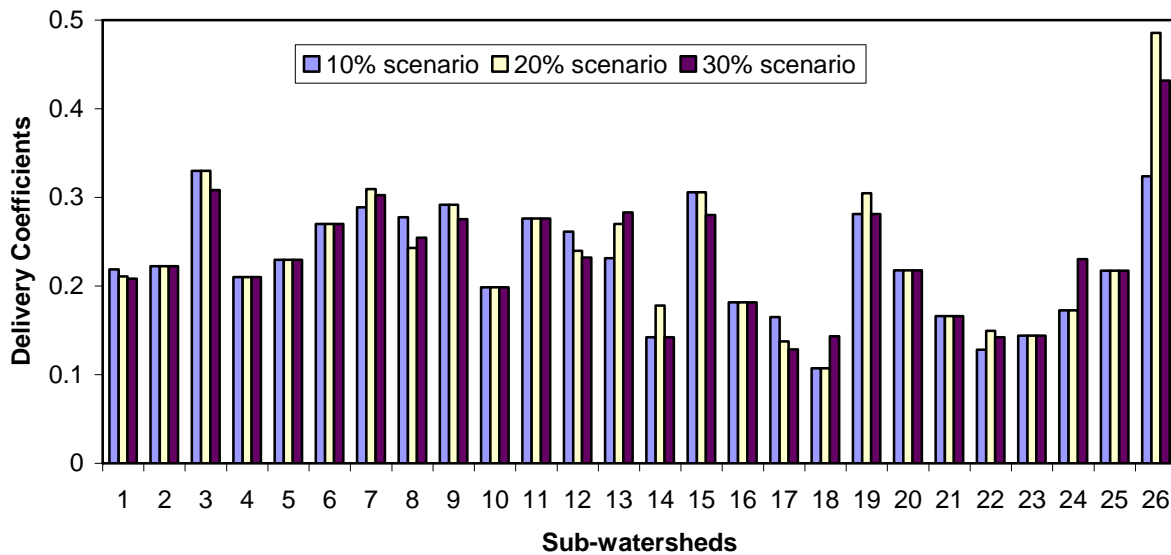
504 **Figure 2. A schematic diagram of the 26 subwatersheds (with designated downstream**
505 **subwatersheds inside the big gray loop)**



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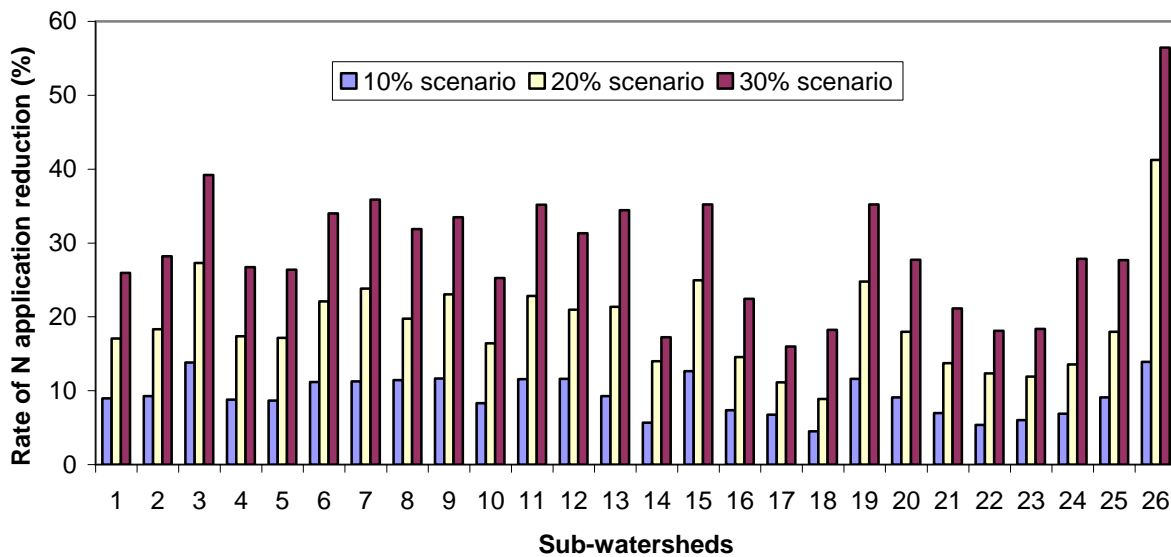
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508 **Figure 3. Delivery coefficients by the 26 subwatersheds.**



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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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