Supplemental Material to *Targeting Conservation Investments in Heterogeneous Landscapes: A distance-function approach and application to watershed management*

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To gain further insight into the effects of spatial correlation and heterogeneity on the performance of the DEA-based ranking approach, we conduct numerical analyses using artificial landscapes of two biophysical attributes. We assume that there are two biophysical attributes of interest, A and S. Let A denote the per-parcel acreage measure, $A_0 \leq A \leq A_1$, and S denote the per-parcel stream exposure measure, $S_0 \leq S \leq S_1$. Denote the joint density function of A and S that is available for contracting as *f*(A,S). This joint density function can be used to measure the share of land on a given landscape with certain attributes. For example, the share of land with $A_M \leq A \leq A_Z$ is given by $\int_{S_0}^{S_1} \int_{A_M}^{A_Z} f(A,S)\, dA\, dS$. The per-parcel cost is C, $C_0 \leq C \leq C_1$.

In the simulation, we focus on the characteristics of *f*(A,S); namely the spatial correlation and concentration of A and S across the landscape. To generate artificial landscapes of different characteristics, we specify marginal density functions for A and S and allow the variability of each to vary. We use a standard beta distribution with parameters *p* and *q* for the marginal distributions. The beta distribution allows one to vary the relative variability of the marginal distributions: high *p* and *q* correspond to lower spatial variability; $p > q$ skews the distribution and reduces the relative variability. Using a technique developed by Johnson and Tenenbein [1981] and applied by Babcock *et al.* [1997], we add correlation, ρ, to the marginal distributions and draw correlated A and S observations from the marginal distributions. We then define different combinations of p, q and ρ, where each combination represents a landscape with a given f(A,S). For each landscape, we generate 2,000 random correlated draws. The distribution of costs per parcel, which is held constant across all landscapes, has a low-variance density (p=q=50) and mild positive correlation with A and S in all landscapes.

We derive the DEA portfolio, which attempts to maximize the joint production of A and S for a given budget, under thirty-four budget levels ranging from $0 to enough money to purchase all 2000 parcels. For each attribute, the total amount of the attribute obtained at each budget level traces out a concave curve in cost-attribute space (see Figure 3 for a similar curve from the empirical analysis). A similar curve can be traced out for the portfolio that maximizes the acquisition of that attribute.[7] We then compare the amount of each attribute obtained by the two portfolios over the entire budget space. If *F(B)* is the fraction of the Total Amount of the Attribute Available that is acquired from the expenditure of B, one can contrast the performances of the two portfolios by comparing the areas under the curves and above the $45^{\text{ë}}$ line in each figure [Babcock *et al.* 1996]. This area is $Z = \int_0^1 F(B)dB - \frac{1}{2}$. For each portfolio in each artificial landscape, we estimate an area equal to 2Z by using trapezoids at each of the thirty-four budget intervals. The lower the ration of 2Z under the DEA portfolio to 2Z under the portfolio that maximizes the acquisition of the attribute, the less successful the DEA portfolio is at acquiring the attribute in that landscape.

The results of the numerical analysis are presented in Table 1. Consider, for example, the first row. On a landscape where A and S are positively correlated ($r = 0.3$) and the variability of A on the landscape is low (p=q=50) and the variability of S is high (p=q=0.50), the distance-function portfolio is 99.78% as efficient in obtaining the attribute A as the portfolio selected to maximize the acquisition of A. The results in Table 1 suggest that the DEA portfolio performs best when spatial correlations are positive and spatial heterogeneity is low, and that differences in spatial heterogeneity among the attributes have a greater effect on performance than do the spatial correlations among attributes (we only skew the distribution of one attribute because the results are symmetric). When one attribute has low variability and another has high variability, the effects on DEA portfolio performance are intensified: the DEA portfolio performs even better in obtaining the low variability attribute and even worse in obtaining the high variability attribute. In other words, the simulations indicate that negative correlations and differences in the relative variability among attributes reduce the performance of the distance-function-derived portfolio, with variability having a greater effect than correlation. Decision-makers can use this information when deciding whether a distance-function targeting approach would likely be robust to alternative attribute weightings, or whether additional constraints in the optimization model [5]-[8] should be added. In the next section, we describe the case study in which alternative targeting approaches are empirically evaluated.

Table 1 – Performance of DEA Portfolio as a Percentage of the Maximum Amount of A and S Obtainable Across All Budget Levels

Landscape					Percentage of Maximum Available	
	A		S		A	S
r	*p*	*q*	*p*	*q*		
+0.3	50	50	0.5	0.5	99.78%	78.90%
0	50	50	0.5	0.5	99.60%	77.58%
0	50	50	50	50	99.58%	99.20%
+0.3	50	50	50	50	99.57%	99.57%
+0.3	50	50	50	11.973	99.39%	99.86%
-0.3	50	50	11.973	50	99.34%	96.40%
-0.3	50	50	50	11.973	99.32%	99.64%
+0.3	50	50	11.973	50	99.03%	98.79%
-0.3	50	50	50	50	98.86%	99.67%
-0.3	50	50	0.5	0.5	98.52%	83.09%
+0.3	0.5	0.5	0.232	0.5	93.44%	81.77%
+0.3	0.5	0.5	0.5	0.5	88.76%	90.48%
0	0.5	0.5	0.5	0.5	87.09%	84.72%
+0.3	0.5	0.5	0.5	0.232	83.36%	94.92%
-0.3	0.5	0.5	0.5	0.5	82.73%	82.19%
-0.3	0.5	0.5	0.5	0.232	78.43%	89.81%
+0.3	0.5	0.5	50	50	77.61%	99.62%
0	0.5	0.5	50	50	76.77%	99.68%
-0.3	0.5	0.5	50	50	76.55%	99.46%

References

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