Targeting conservation investments for on-site and off-site benefits using Data Envelopment Analysis

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Objectives

- Re-introduce challenge of cost-effective site selection for multiple benefits
- Describe Data Envelopment Analysis (DEA) approach to conservation targeting
- Describe and test novel approach to solving a high dimensional, spatially dynamic, site selection problem using DEA
- Compare dynamic DEA solutions with solutions derived from hypothetical expert weights

The familiar targeting problem

- Where to cost-effectively purchase conservation easements or place incentives for voluntary conservation practice adoption
- Dependent upon value judgments
- Computationally complex
- Difficult to administer programmatically

Familiar approaches

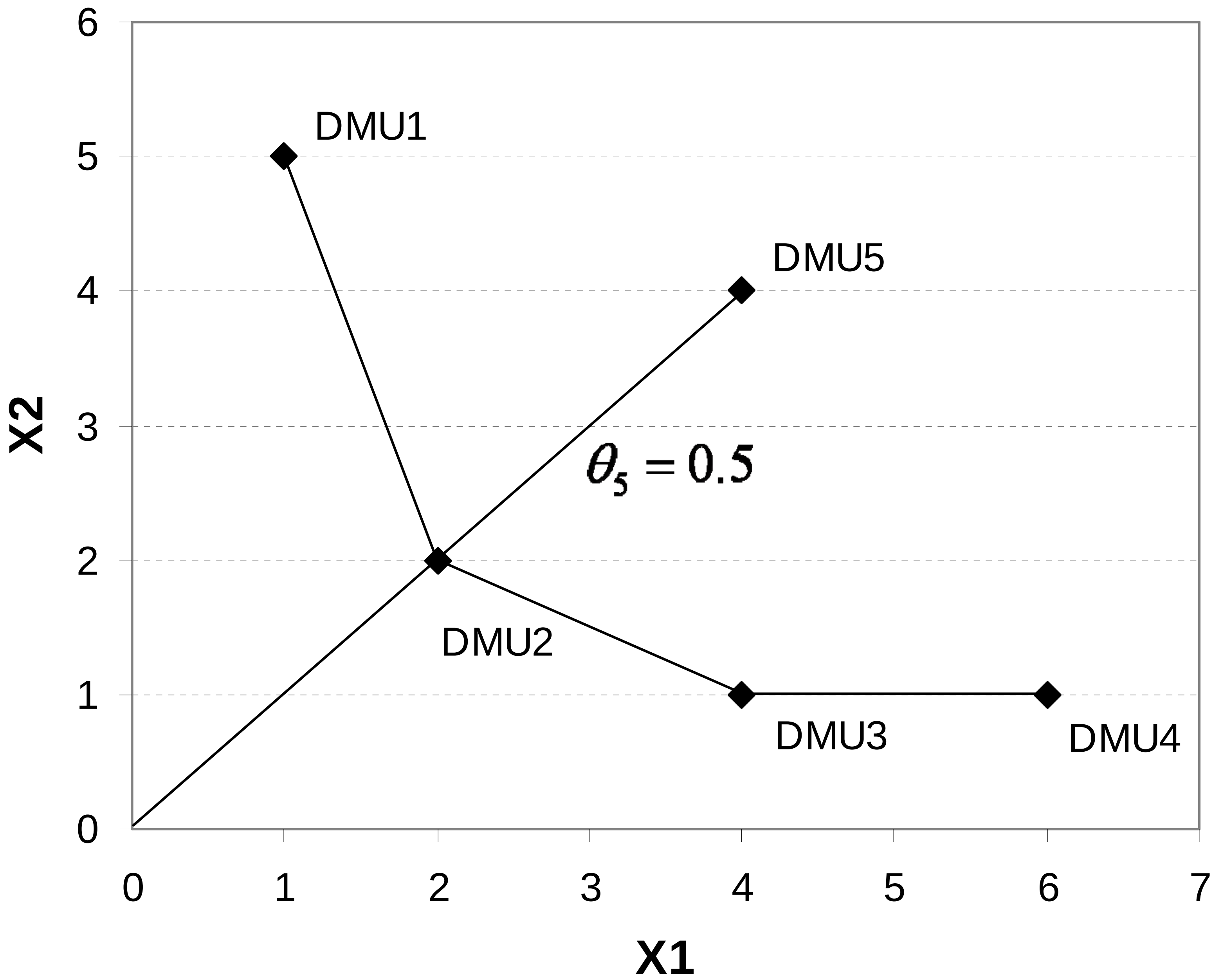
- Math programming approach to reserve site selection
- Weights

A DEA alternative (Ferraro 2004)

- Difficult to convert multiple, spatially heterogeneous biophysical attributes into a uni-dimensional measure
- How attributes combine to produce an amenity is generally unknown
- Uses a DEA-based non-parametric distance function to rank parcels for conservation in a NY watershed
- Compares distance function with a variety of parametric approaches that are commonly applied and finds robust performance

What is DEA?

- Nonparametric mathematical programming technique introduced by Charnes, Cooper, and Rhodes (1978)
- Estimates and compare the relative efficiency of decisionmaking units (DMUs)
- No assumptions about technology
- Analyzes multiple outputs and inputs
- Is units invariant in certain circumstances



DMU1
DMU5
$\theta_5 = 0.5$
DMU2
DMU3
DMU4
X2
X1
0
1
2
3
4
5
6
7

$$\min \theta_0$$

subject to:

$$\theta_0 x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{i0}, \quad r = 1, \ldots, s$$

$$\lambda_j \geq 0 \quad j = 1, \ldots, n$$

$$\min \theta_5$$

subject to:

$$4\theta_5 - (1\lambda_1 + 2\lambda_2 + 4\lambda_3 + 6\lambda_4 + 4\lambda_5) \geq 0$$

$$4\theta_5 - (5\lambda_1 + 2\lambda_2 + 2\lambda_3 + 1\lambda_4 + 4\lambda_5) \geq 0$$

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 \geq 1$$

$$\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5 \geq 0$$

solution: $\theta_5 = 0.5, \lambda_2 = 1$

The curse of (spatial) dimensionality

- When spatial configuration matters in the production of environmental benefits, the problem space becomes **<u>very</u>** large
- In our 6x6 grid example to follow, where land is either conserved or not conserved, there are 2^{36} (68 billion) potential landscape configurations

Backwards elimination algorithm

1. Begin with initial program landscape and budget
2. Allocate all eligible fields (or bids) to conservation
3. Calculate landscape environmental benefits
4. Remove eligible field and calculate environmental benefits. Replace it, remove a different field, and calculate the environmental benefits again. Repeat for all fields. When compared to (3), this yields marginal benefits and costs for each eligible field
5. Use input-oriented constant returns to scale DEA model to estimate efficiency levels of fields in converting costs to environmental benefits
6. Remove least efficient field
7. If program costs > budget, return to step 3

   If program costs <= budget, the algorithm is finished

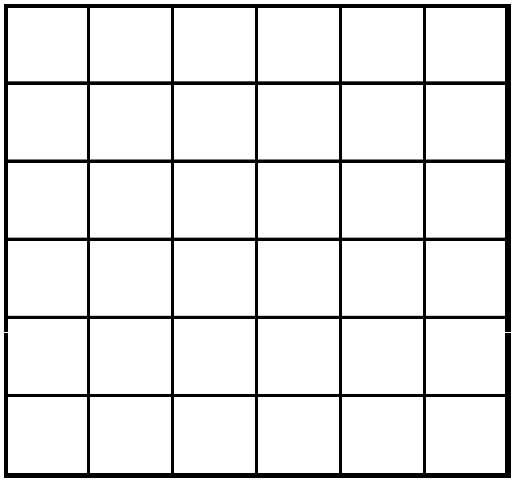
Computational benefits of algorithm

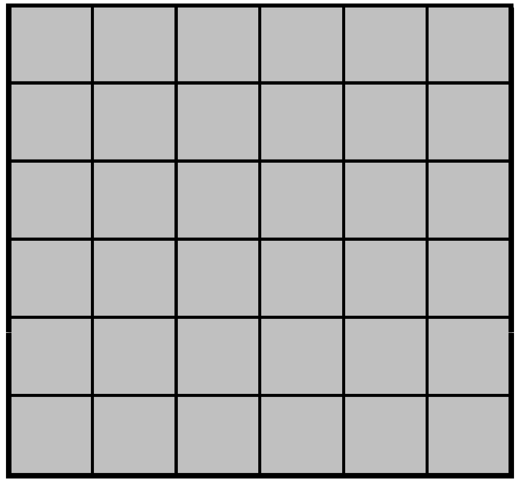
- Say you have a program area with *n* cells, in which cells are ether conserved or not conserved
- *m* cells are already in a conserved status
- You have a program budget to convert cells to conservation
- Examining all program area combinations requires $2^{(n-m)}$ iterations
- The backwards elimination algorithm requires at most *n*-*m* iterations

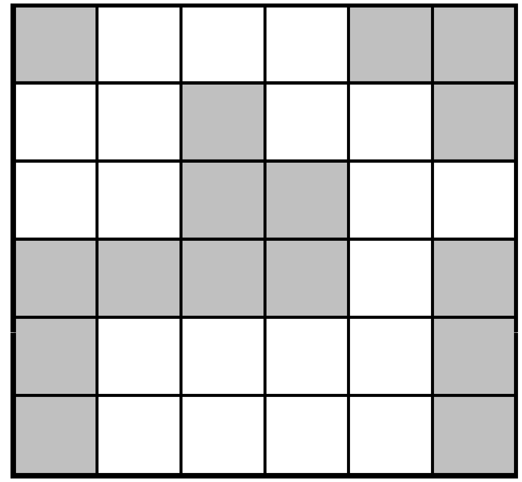
Stylized three-benefit bundle

- **Habitat** indicator depends upon queen’s case connectivity of conserved cells
- **Water quality** indicator depends on horizontal connectivity of conserved cells
- **Carbon** indicator is aspatial

Habitat







0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Score = 0

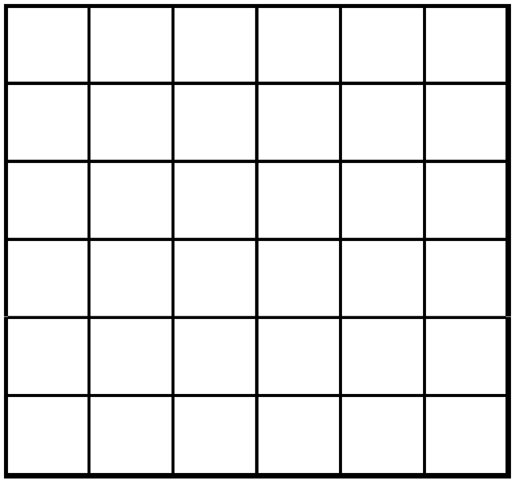
36	36	36	36	36	36
36	36	36	36	36	36
36	36	36	36	36	36
36	36	36	36	36	36
36	36	36	36	36	36
36	36	36	36	36	36

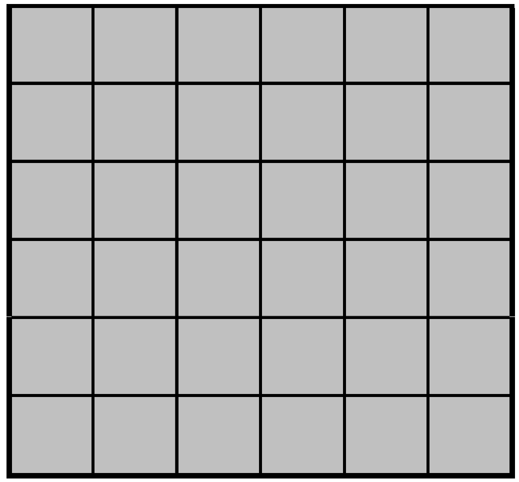
Score = 1296

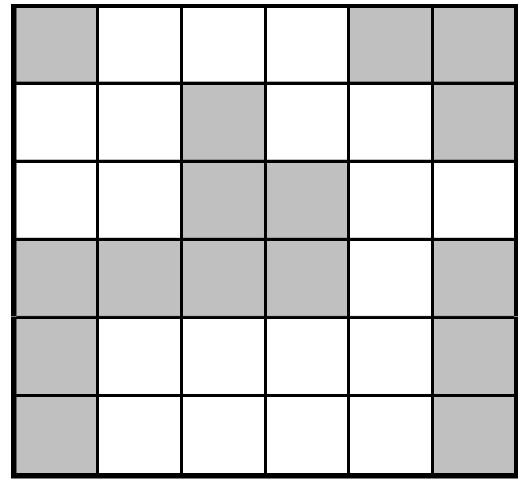
1	0	0	0	3	3
0	0	0	0	0	3
0	0	9	9	0	0
0	9	9	9	0	3
9	0	0	0	0	3
9	0	0	0	0	3

Score = 82

Water quality







0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Score = 0

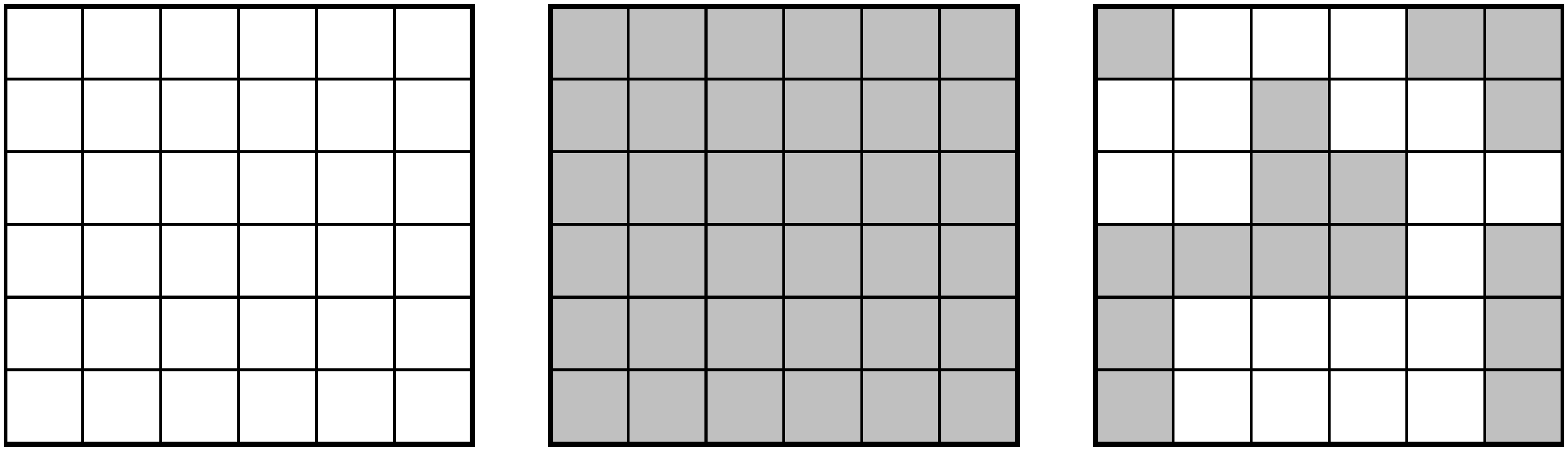
2	5	10	10	5	2
2	5	10	10	5	2
2	5	10	10	5	2
2	5	10	10	5	2
2	5	10	10	5	2
2	5	10	10	5	2

Score = 204

0	0	0	0	0	0
0	0	10	0	0	0
0	0	10	10	0	0
2	5	10	10	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Score = 57

Carbon



0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Score = 0

5	5	5	5	5	5
5	5	5	5	5	5
5	5	5	5	5	5
5	5	5	5	5	5
5	5	5	5	5	5
5	5	5	5	5	5

Score = 204

5	0	0	0	5	5
0	0	5	0	0	5
0	0	5	5	0	0
5	5	5	5	0	5
5	0	0	0	0	5
5	0	0	0	0	5

Score = 57

Stylized conservation costs

20	30	40	40	30	20
25	35	45	45	35	25
30	40	50	50	40	30
30	40	50	50	40	30
25	35	45	45	35	25
20	30	40	40	30	20

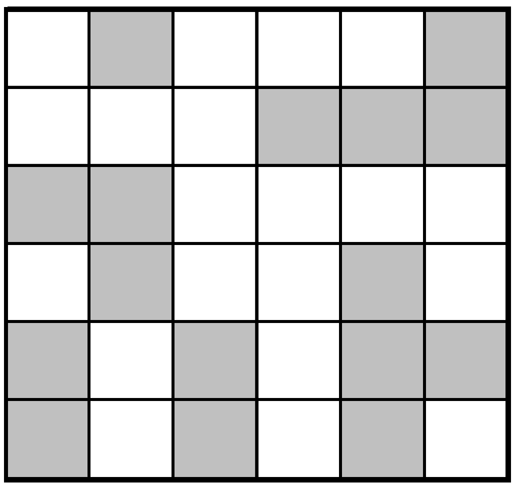
Testing the algorithm

- Generated landscapes with 16 cells initially assigned to conservation
- Solved using iterative backwards elimination algorithm to identify best cells to conserve given a $500 budget
- Also, iterated over all possible budget-feasible solutions to find any Pareto improvements over our algorithm

Preliminary test results

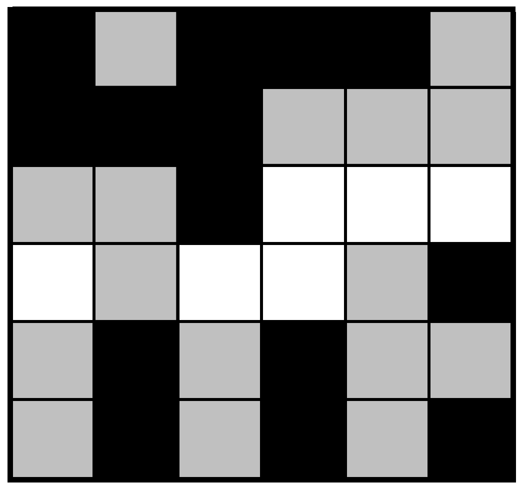
- Differences relate to how the algorithm sequences purchases and exhausts budget

Initial Condition



Habitat	6%
Water quality	18%
Carbon	44%
Budget avail.	$500

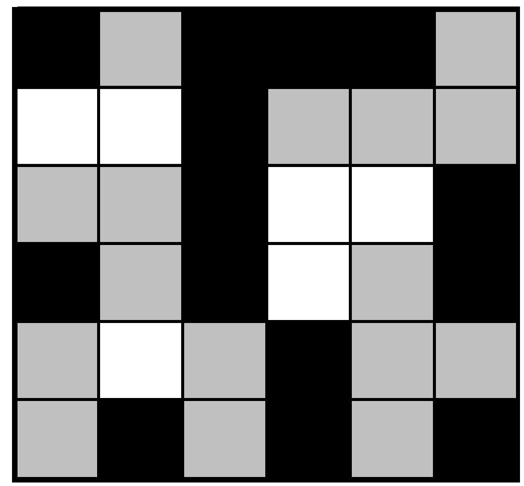
DEA By Backwards Elimination



Habitat	69%
Water quality	75%
Carbon	83%
Budget spent	$485

2.5 seconds run-time

A Pareto Optimal Solution



Habitat	69%
Water quality	76%
Carbon	83%
Budget spent	$500

13 minutes run-time

Test Run: DEA versus the Expert

Godzilla versus
Mechagodzilla
(Toho Films, 1974)

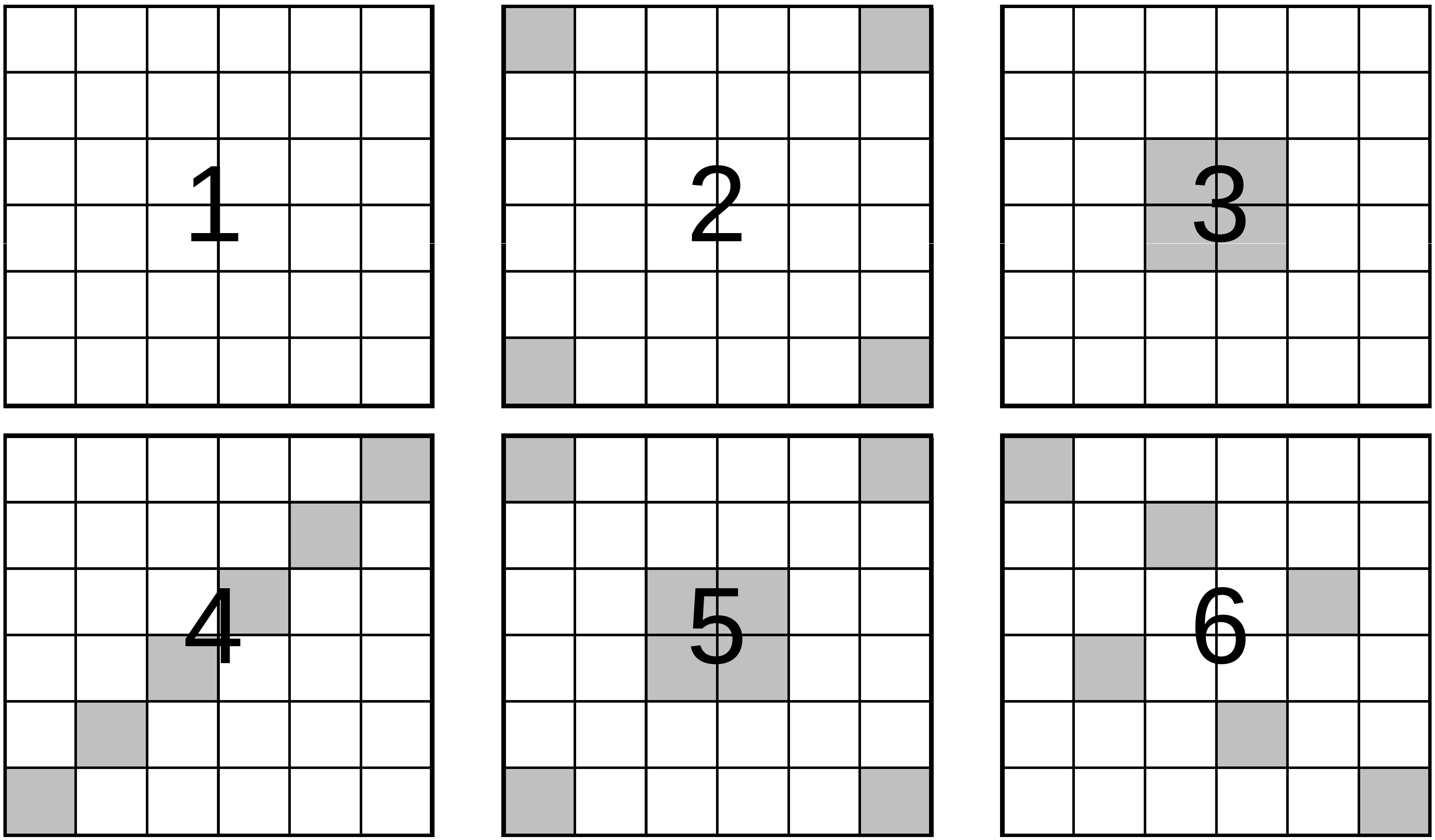
Test Run: DEA versus the Expert

- We compare results from dynamic DEA to results from applying a range of hypothetical expert weights that form a benefits index
- For comparison, the hypothetical expert solutions are found using the backwards elimination algorithm
- We also compare the dynamic DEA results to a static, one-shot DEA solution to show the importance of considering spatial dynamics

Important footnote

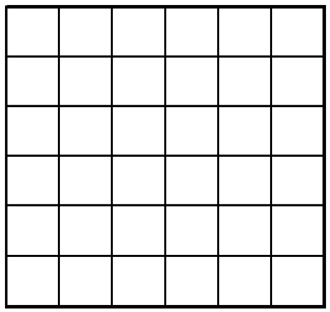
- Environmental benefits are normalized to percent of maximum attainable through complete conservation
- This is necessary for apples-apples comparison of DEA and expert weight approach
- In fact, because of units differences, a weighting approach requires normalizing
- The units invariance property of DEA eliminates this need

Stylized landscapes

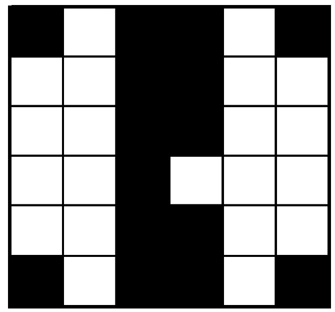


Results for Initial Landscape 1

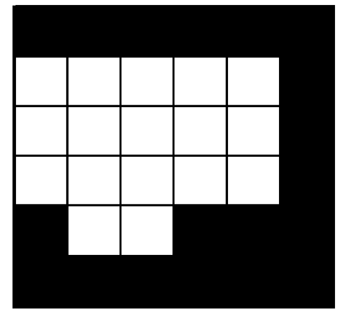
Initial Condition



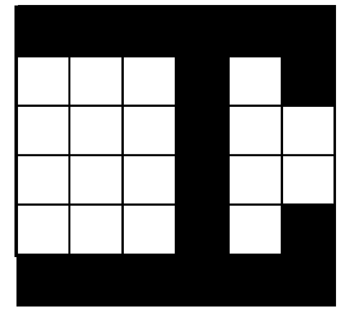
One-shot DEA



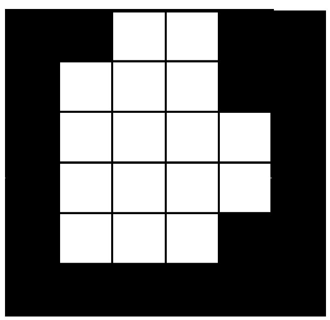
DEA By Backwards Elimination



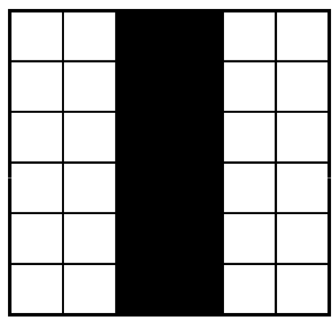
Expert Weight (0.33, 0.33, 0.33)



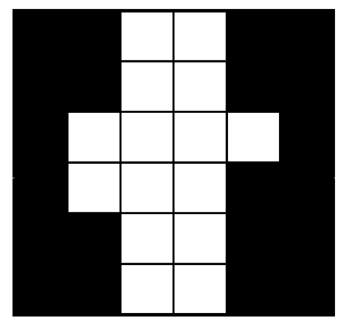
Expert Weight (1.00, 0.00, 0.00)



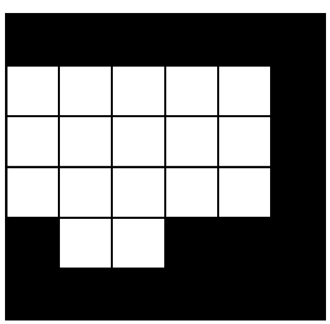
Expert Weight (0.00, 1.00, 0.00)



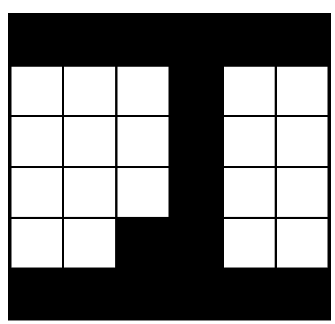
Expert Weight (0.00, 0.00, 1.00)



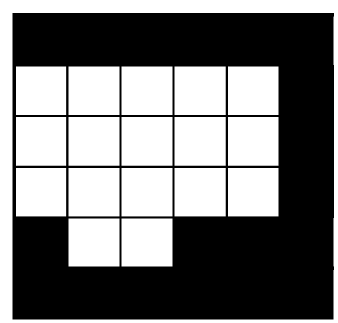
Expert Weight (0.50, 0.25, 0.25)



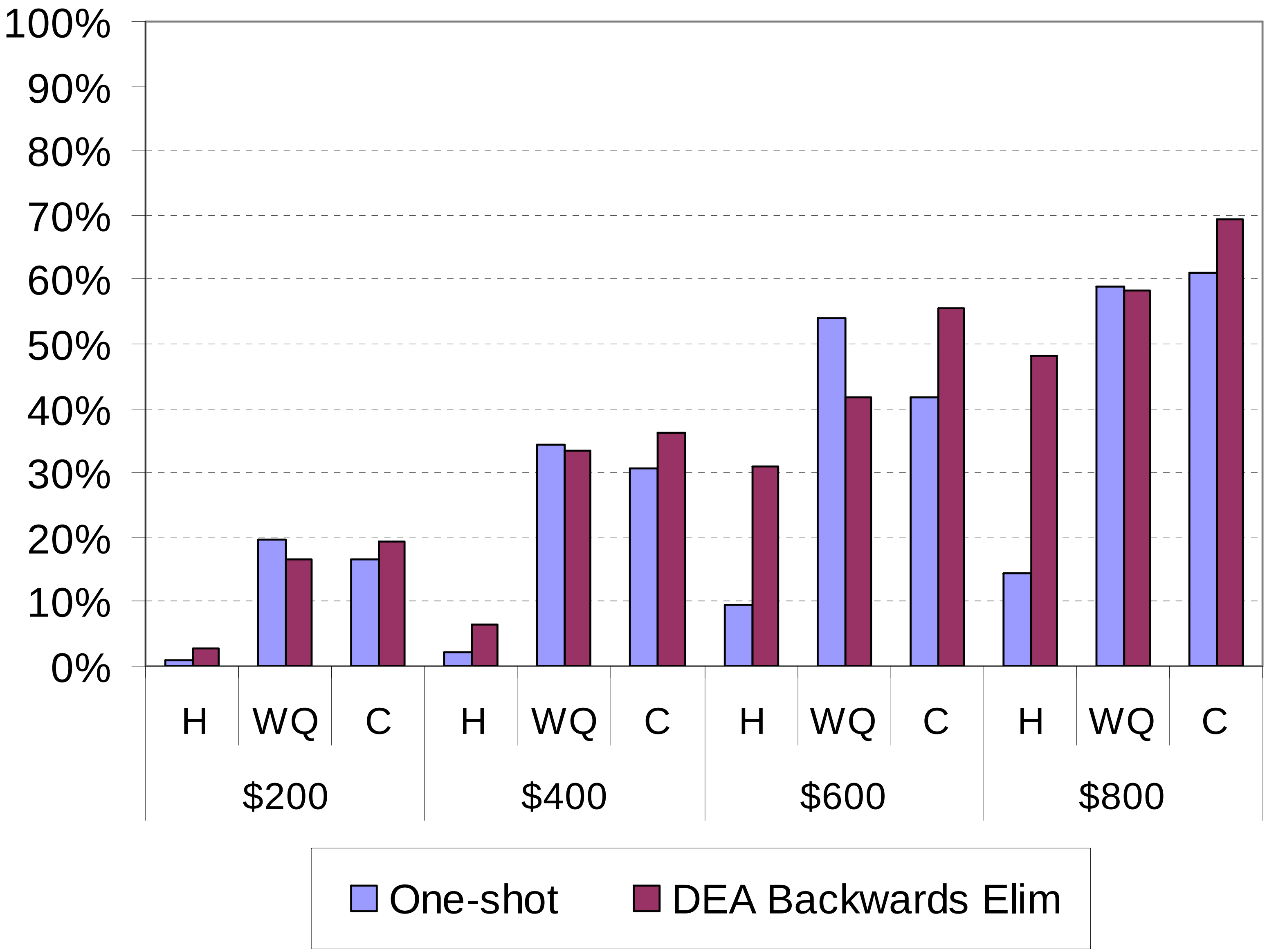
Expert Weight (0.25, 0.50, 0.25)



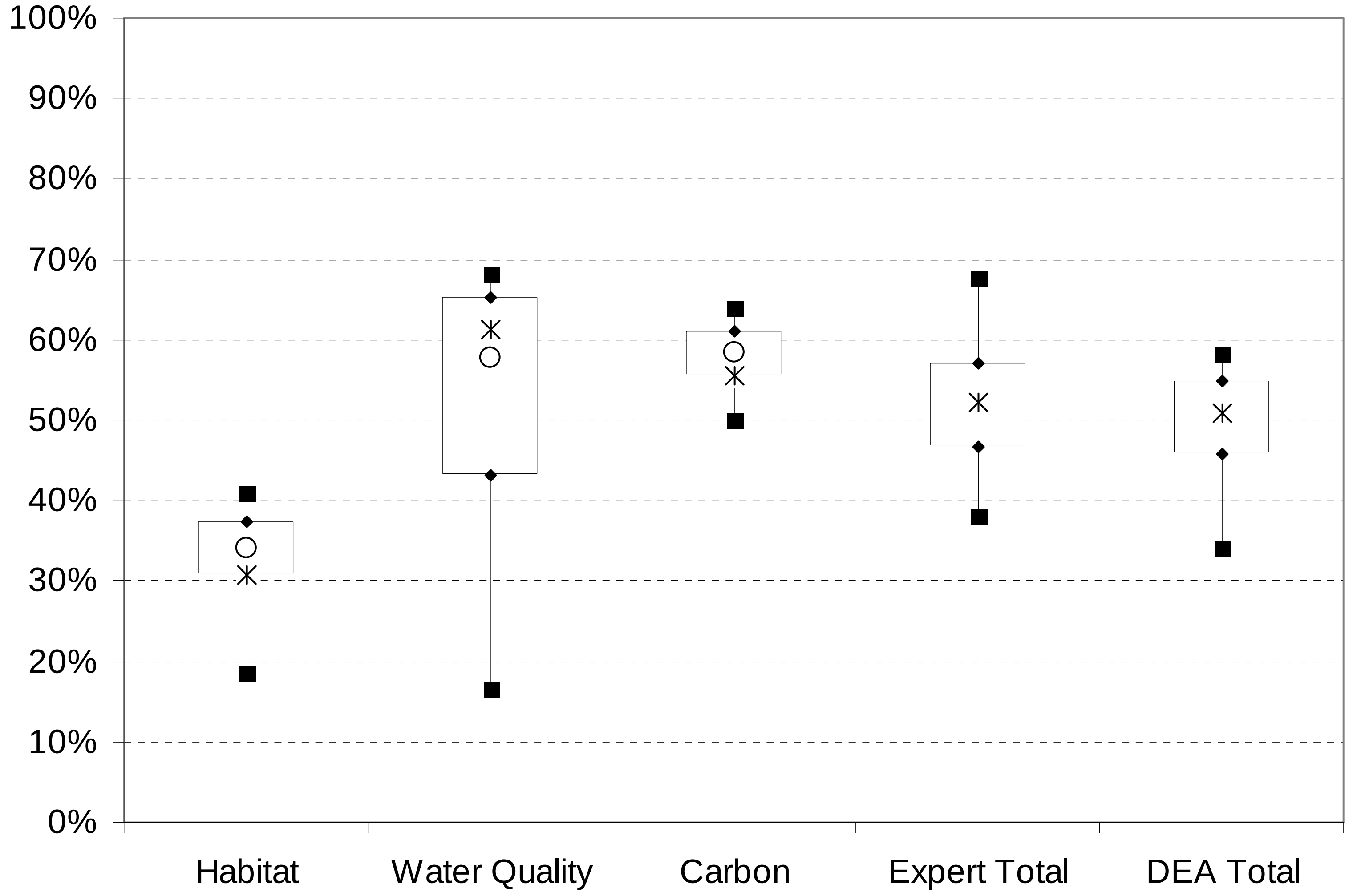
Expert Weight (0.25, 0.25, 0.50)



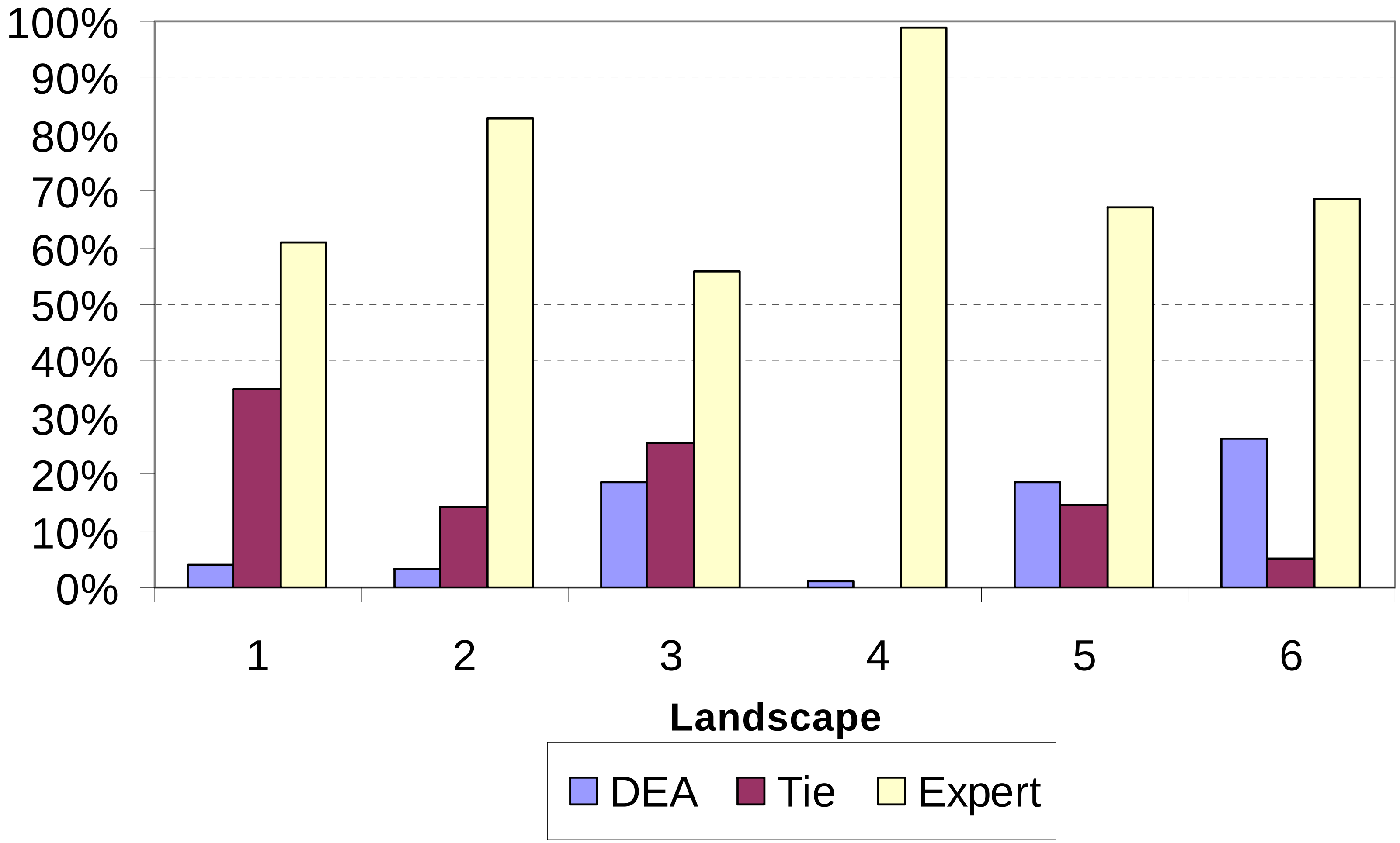
One-shot versus backwards elimination, Landscape 1



DEA versus the Expert, Landscape 1



DEA versus the Expert: the Score



Preliminary conclusions

- Algorithm has promise; need to iron out some kinks and scale up to real-world problem
- Modeling the conservation targeting problem as dynamic is highly appropriate
- Ambiguity about robustness of DEA over weights; depends upon uncertainty

Next steps, making it more real…

Perform at a watershed or county-scale and compare with MCDA-derived weights

- **Conservation costs:** rental rates
- **Habitat:** morphological spatial pattern analysis
- **Water quality:** AGNPS
- **Carbon:** simple LULC carbon coefficients

Discussion