Modeling Geographic Preferences for Policy Decisions

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Introduction

This webinar is based on work from…

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Decision Analysis with Geographically Varying Outcomes: Preference Models and Illustrative Applications

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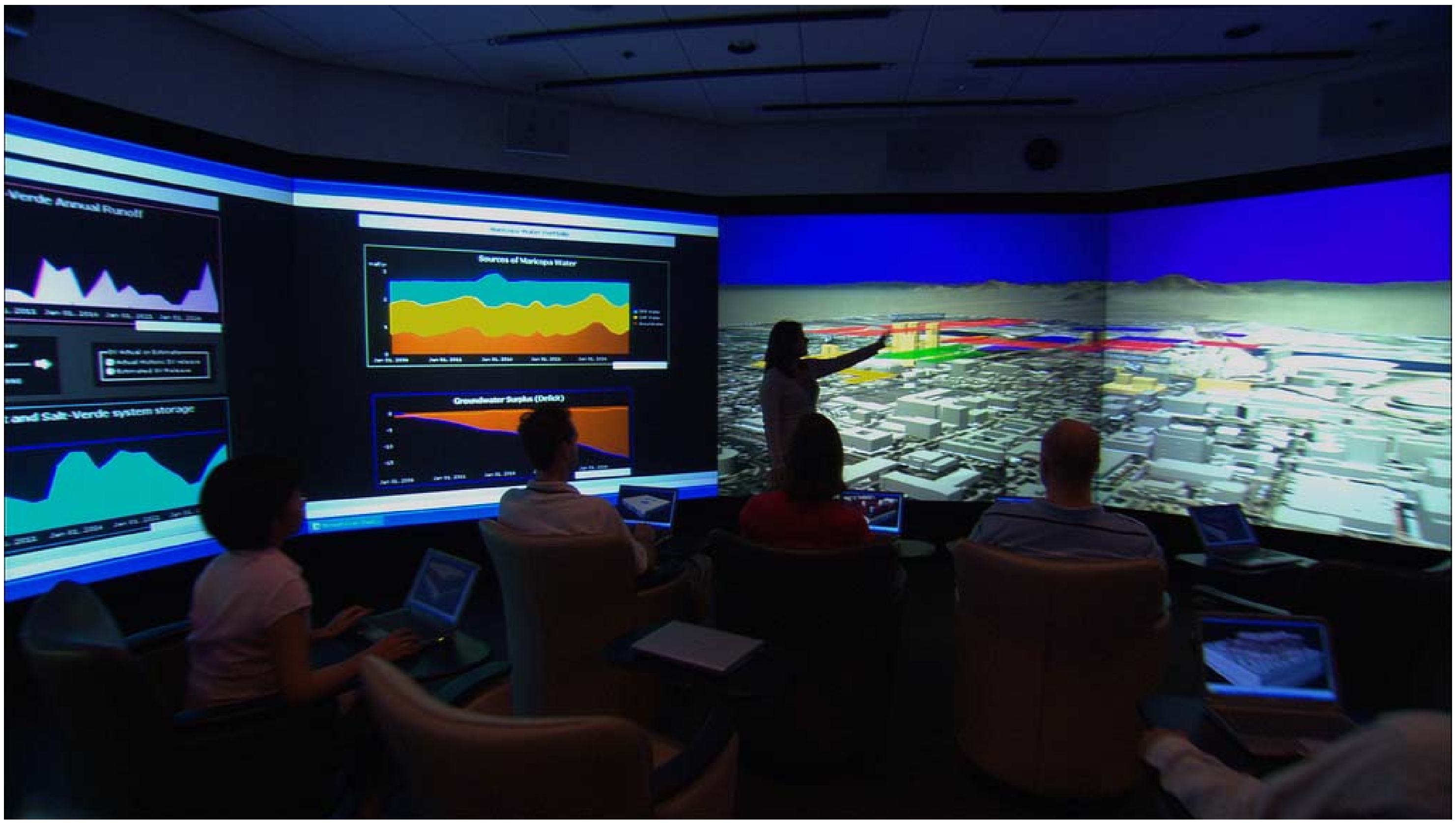
Preference Functions for Spatial Risk Analysis

L. Robin Keller[1] and Jay Simon[2,*]

When outcomes are defined over a geographic region, measures of spatial risk regarding these outcomes can be more complex than traditional measures of risk. One of the main challenges is the need for a cardinal preference function that incorporates the spatial nature of the outcomes. We explore preference conditions that will yield the existence of spatial measurable value and utility functions, and discuss their application to spatial risk analysis. We also present a simple example on household freshwater usage across regions to demonstrate how such functions can be assessed and applied.

Decision Center for a Desert City (https://sustainability.asu.edu/dcdc/)

Three decision analysts walk into a theater…

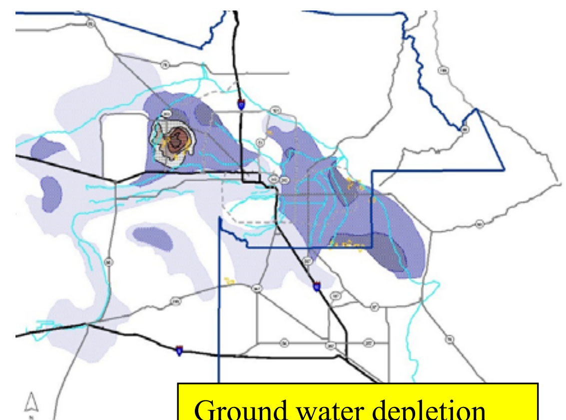


https://dt.asu.edu/

Why are decisions based on GIS data hard?

- Lots of information
- Multiple metrics & objectives
- Many locations
- Tradeoffs…
  - between attributes
  - between places
- Often many stakeholders
- Comparing alternatives is complicated!

Parks & open space in Maricopa County

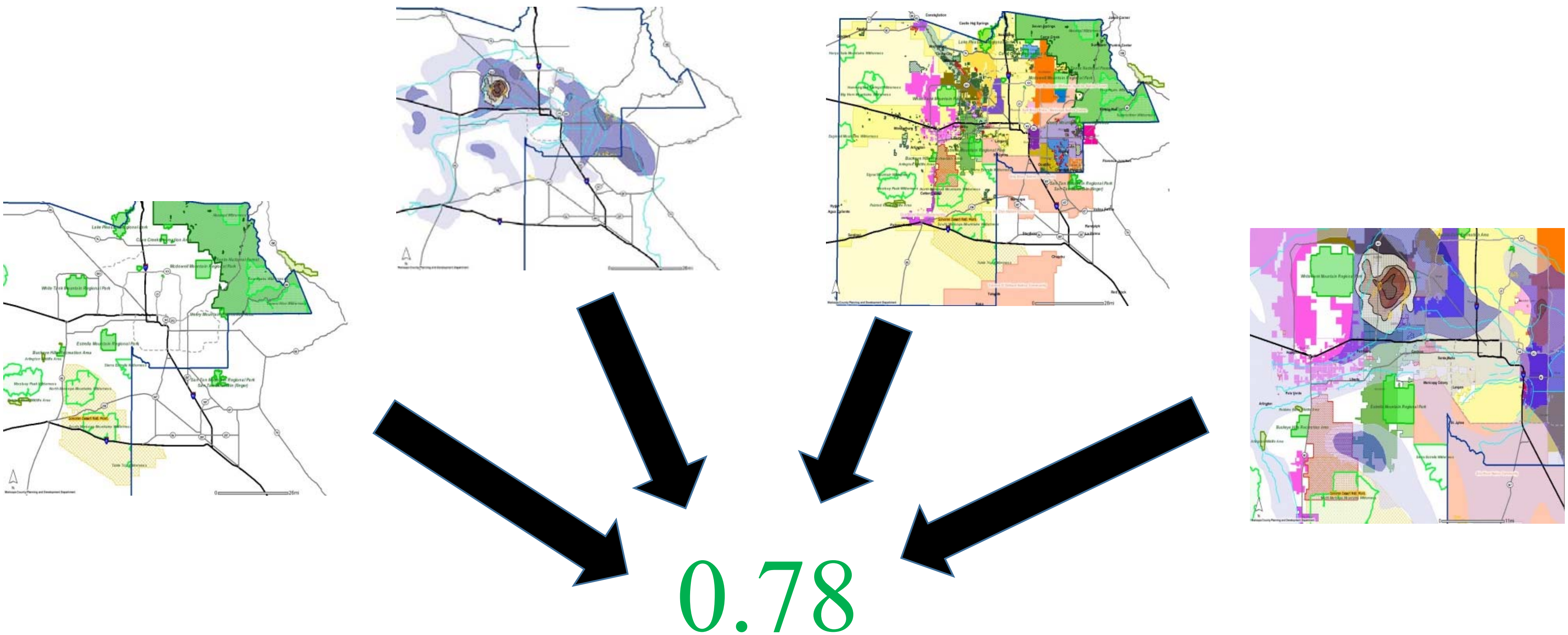


Ground water depletion In Maricopa County

Our goal: adapt established DA methods

- Framing: ask the right questions, use value-focused thinking
- Value/Utility function for geographic outcomes
  - Capture preferences
  - Reasonable to assess
- Requires stakeholders to evaluate simple tradeoffs, e.g.:
  - How much groundwater would you give up to lower average temperature by one degree in Region A?
  - How large of an average temperature increase would you accept in Region A to lower average temperature in Region B by one degree?
- Can then compute a score for each alternative consistent with what the stakeholders want

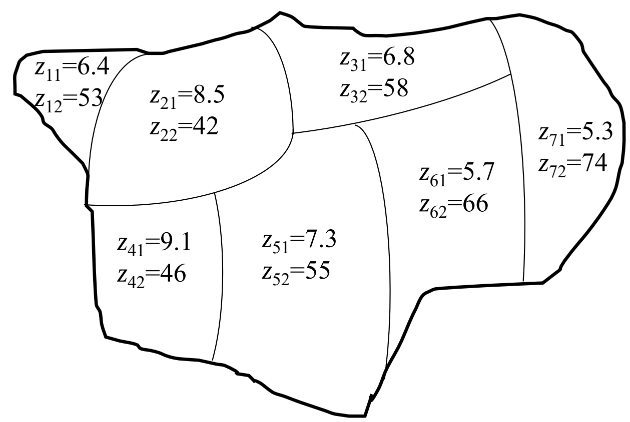
Evaluating alternatives



Geographic Outcomes and Preferences: The Mathematical Model

Geographic Outcomes

- m discrete regions (indexed by i)
- n attributes (indexed by j)
- z_{ij} denotes the level of attribute j in region i



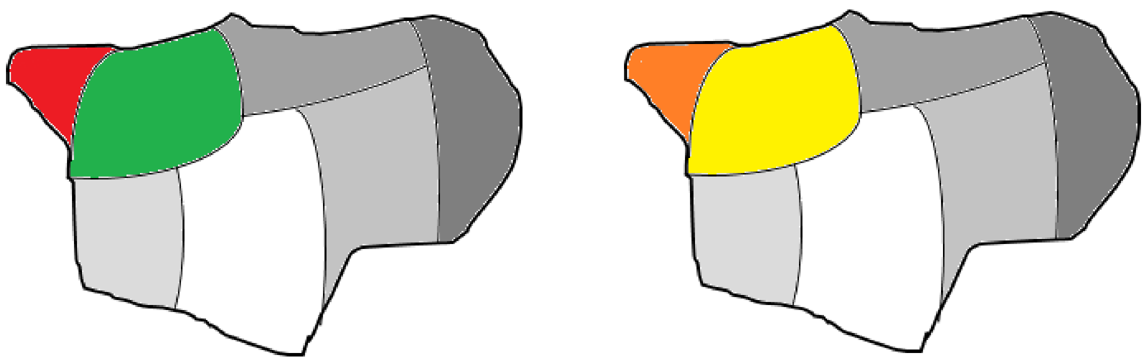
- Having **geographic preferences** means that summary metrics of attribute levels are not sufficient
  - In this case, we should use value functions

Conditions for Value Functions (the fine print)

- Preferences must satisfy several basic technical conditions for a geographic value function to exist at all
- Preferences must be:
  - Complete
  - Transitive
  - Continuous
  - Dependent on each region
- Not restrictive, but rules out some methods for comparing outcomes
  - Lexicographic ordering (not continuous)
  - Voting methods (not transitive)

Conditions for Practical Value Functions

- Preferential independence
  - Between attributes
  - Between regions



- Homogeneity
  - Tradeoffs between attributes within a single region don't vary by region
    - (90 degrees, 40 AQI) vs. (80 degrees, 60 AQI)

Geographic Value Functions (the math)

$$\boxed{V\left(z_{11}, z_{12}, \ldots z_{mn}\right) = \sum_{i=1}^{m} \sum_{j=1}^{n} a_i b_j v_j\left(z_{ij}\right)}$$

- a_i is a region weight, b_j is an attribute weight, and v_j is a single-region single-attribute value function
- These are the preference parameters that need to be assessed
- Can modify conditions to obtain other forms and capture additional preference information (magnitude of differences, gambles) if needed

Eliciting Geographic Preferences

- **Single attribute/region value functions**
- Similar methods as for traditional single-attribute value functions, e.g.:
  - Midvalue splitting
  - Fit to assumed functional form

- **Attribute weights**
- Similar methods as for traditional attribute weights, e.g.:
  - Value tradeoff method
  - Swing weights

Eliciting Geographic Preferences

- **Region weights**
  - Methods for attribute weights are valid
  - Number of regions might be very large
  - Approximation methods

Example: LUMPS Model for Phoenix

(Local-scale Urban Meteorological Parameterization Scheme)

LUMPS Model

- Urban heat flux model
- Evaluate development strategies to mitigate urban heat islands
- Impact depends on details of the neighborhood (2.5 meter resolution!)

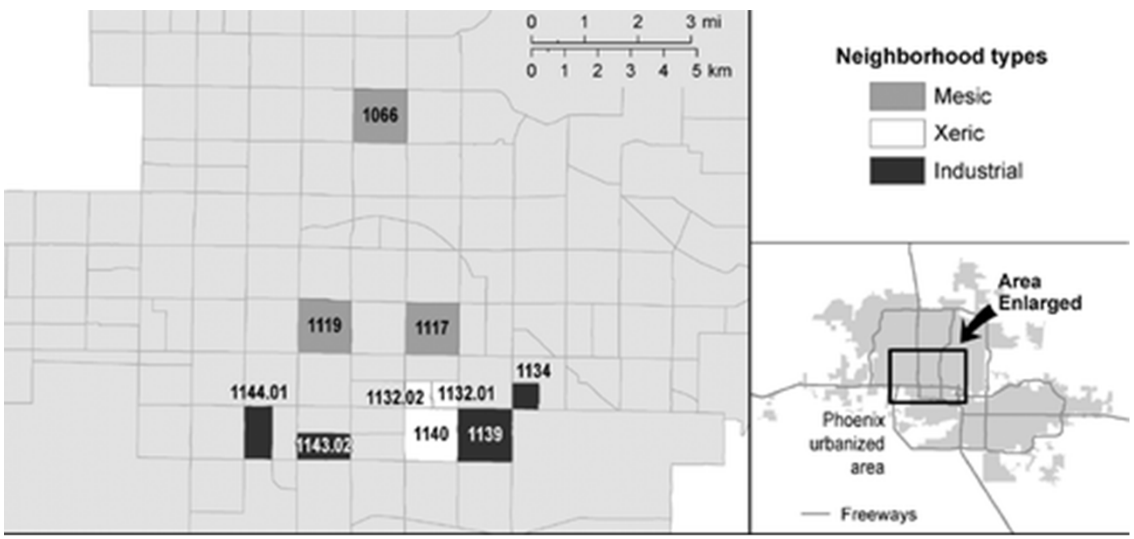


image source: Gober et al. (2009)

What are the objectives?

- Maximize *night cooling*
- Minimize *evaporation rate*

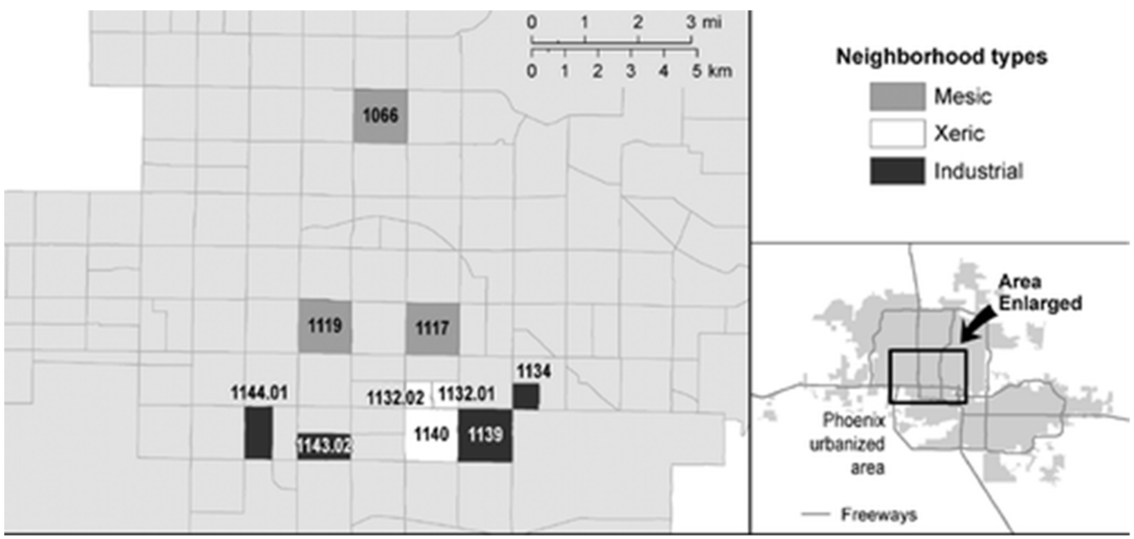


image source: Gober et al. (2009)

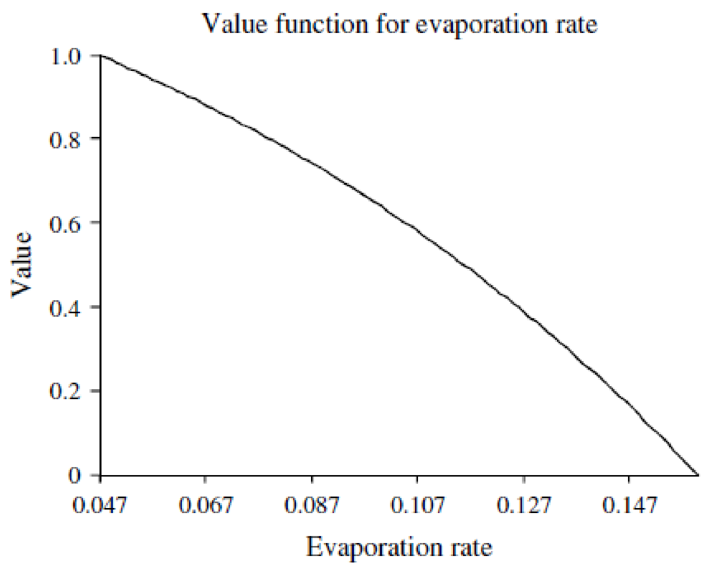
Development Strategies

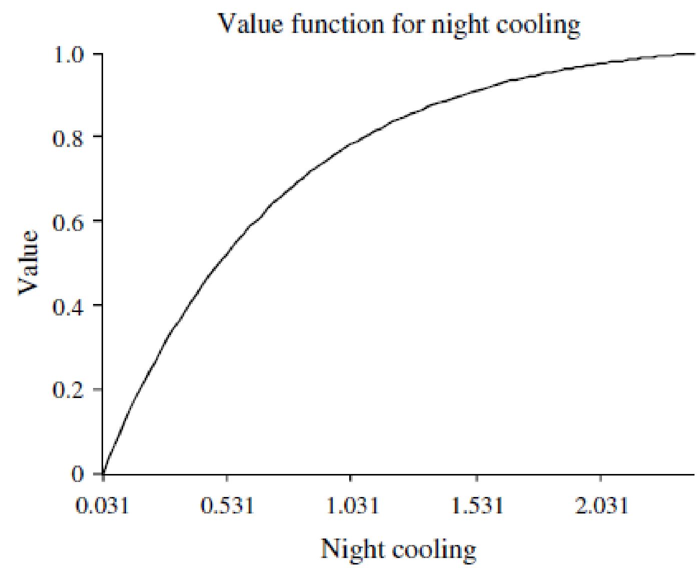
- Three representative strategies:
  - “Oasis” - Replace 20% of existing surfaces with vegetation requiring irrigation
  - “Desert” - Native soil instead of trees and grass
  - “Compact” - Increase total area covered with buildings by 10%

Gober et al. (2009)

Attribute Weights and Value Functions

- Exponential form
  - Intended to capture diminishing returns, but no additional detail

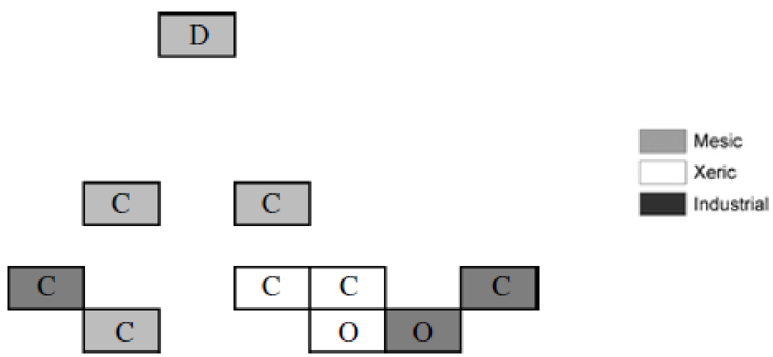




- 0.4 weight on evaporation rate, 0.6 weight on night cooling

Individually Optimal Strategies

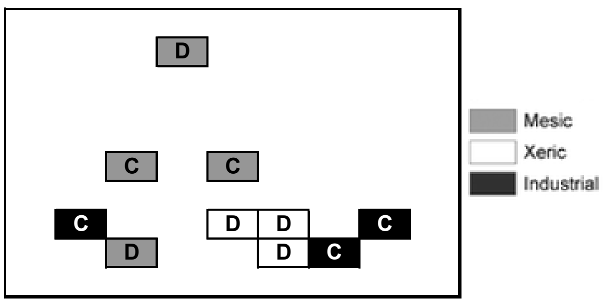
- Two oasis, one desert, seven compact:



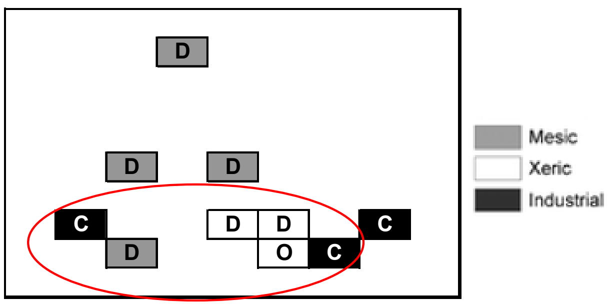
Optimal Strategies for a Specific Scenario

- Constraints:
  - Overall level of evaporation rate must decrease by at least 5%
  - Overall level of night cooling must increase by at least 5%

Equal region weights:

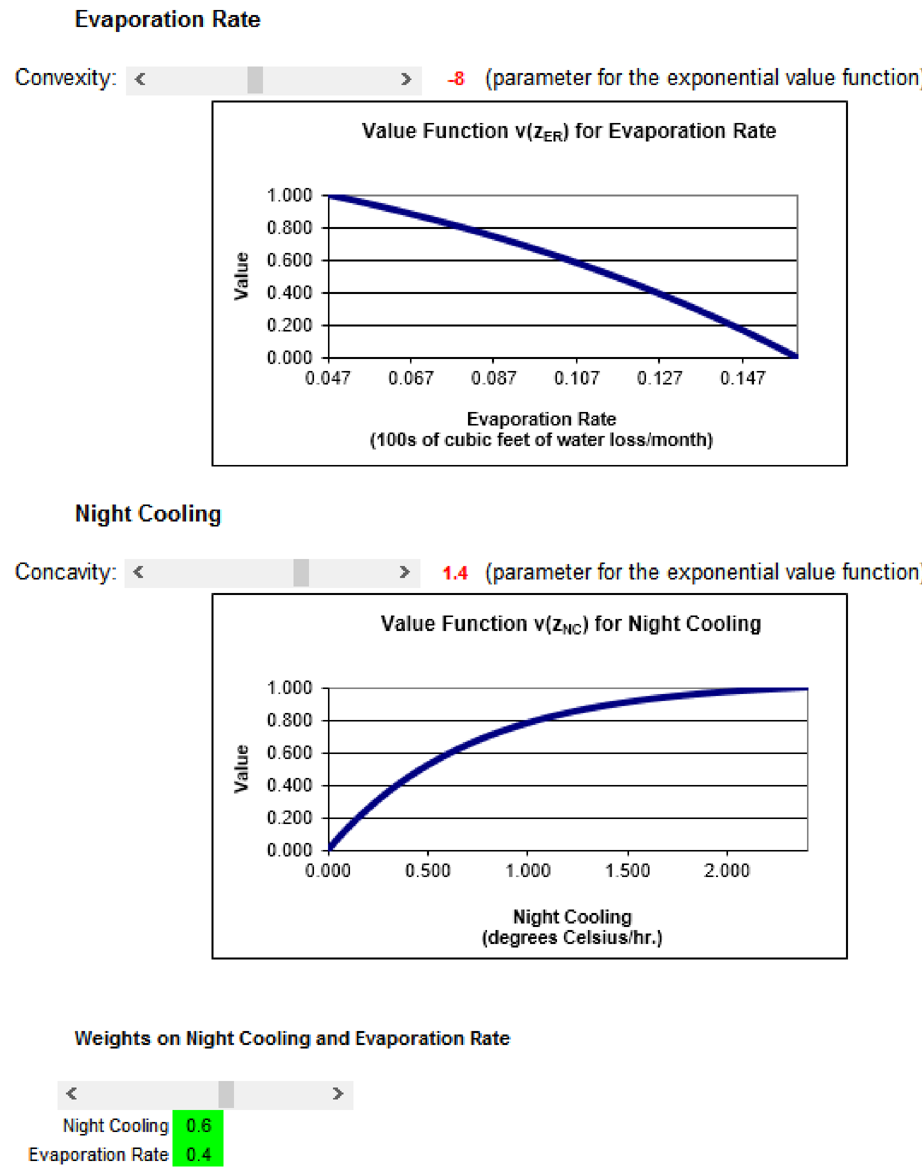


Central Phoenix weights 2x others:



Sensitivity Analysis

- Important to check how robust the results are to parameter changes
- Particular concern for geographic preferences, since outcomes may impact a variety of stakeholders



Two Recent Examples from Finland

Forest Management

Sironen and Minonen (2018)

- Projected 30-year impacts of various strategies
- Approximate region weights based on several metrics, including:
    - Proximity to main roads
    - Proximity to recreation routes
    - Proximity to lakes and rivers
    - Proximity to internationally valuable bird areas

Air Defense
Harju, Liesiö, and Virtanen (2019)

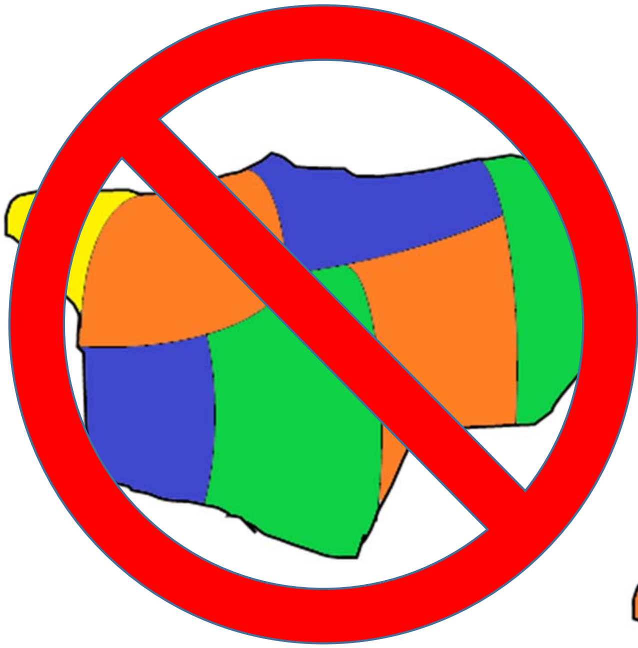
- Location of bases to provide air defense capability
- Four attributes related to defense objectives
- Approximate region weights via a preference ordering

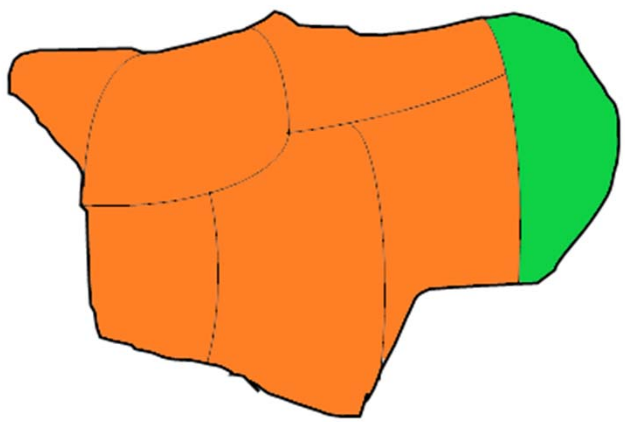
Eliciting Region Weights

Region Weight Elicitation Strategies

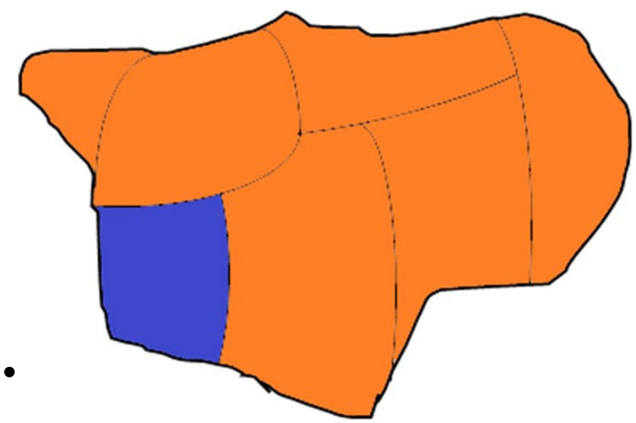
- Assessing a set of region weights is the task unique to geographic preferences
- Number of weights may be very large
- If using thorough quantitative methods: keep as simple as possible
- Otherwise, use appropriate approximation techniques

If assessing tradeoffs, using simple maps





vs.



Approximation Methods

- Tier-based approximation
  - E.g. classify each region as high/medium/low level of importance
  - Convert to a set of weights
  - Analogous to rank-based approximations
- Elicit incomplete preferences
  - A few tradeoff questions regarding the most crucial aspects of preferences
  - If # of alternatives is small, remaining questions may be moot
- Use natural measures as proxies (area, population, economic value, etc.)

Conclusion

- Modern issue, only becoming more relevant over time
- DA concepts are very helpful
  - Value-focused thinking
  - Main difference: attribute levels are vectors occurring over a map
  - Weights and value functions
  - Take advantage of preference conditions that simplify the process
  - Elicitation techniques
  - Sensitivity analysis
- Urban development example combines:
  - a sophisticated model to estimate outcomes resulting from alternatives
  - a (simple) preference model that allows us to compare those outcomes

References

- Our papers:
  - Simon, J., Kirkwood, C. W., & Keller, L. R. (2014). Decision Analysis with Geographically Varying Outcomes: Preference Models and Illustrative Applications. *Operations Research* **62**(1) 182-194.
  - Keller, L. R., & Simon, J. (2019). Preference Functions for Spatial Risk Analysis. *Risk Analysis* **39**(1) 244-256.
- LUMPS Model:
  - Gober, P., Brazel, A. J., Quay, R., Myint, S., Grossman-Clarke, S., Miller, A., & Rossi, S. (2009). Using watered landscapes to manipulate urban heat island effects: How much water will it take to cool Phoenix? *Journal of the American Planning Association* **76**(1) 109-121.
- Recent examples:
  - Sironen, S., & Mononen, L. (2018). Spatially Referenced Decision Analysis of Long-Term Forest Management Scenarios in Southwestern Finland. *Journal of Environmental Assessment Policy and Management* **20**(03) 1850009.
  - Harju, M., Liesiö, J., & Virtanen, K. (2019). Spatial multi-attribute decision analysis: Axiomatic foundations and incomplete preference information. *European Journal of Operational Research* **275**(1) 167-181.
- Previous literature:
  - Preference theory
    - Debreu (1960), Fishburn (1970), Krantz et al. (1971), Keeney and Raiffa (1976), Dyer and Sarin (1978, 1979)
  - Preferences in GIS-based decisions
    - Jankowski (1995, 2006); Keisler and Sundell (1997); Malczewski (1999); Chan (2005)

Q & A

Appendix

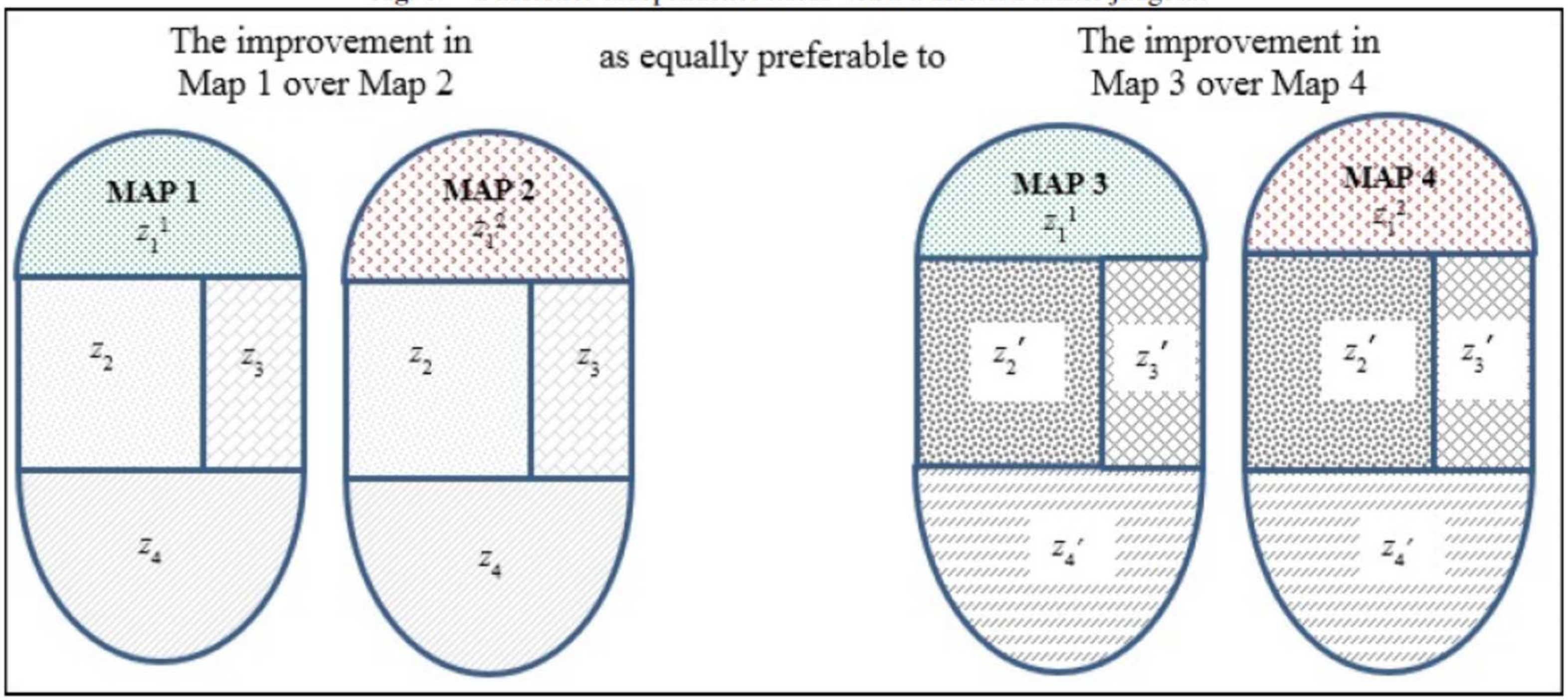
Measurable Value Functions

- These value functions are ordinal
- If preferences also satisfy *difference consistency* and *difference independence*, then they can be represented by measurable spatial value functions of the same forms

- **Difference consistency**: the preference differences between outcome pairs are consistent with the preference ordering of outcomes
- **Difference independence**: the preference differences between outcome pairs are not affected by the attribute levels in regions where they are equal

Difference Independence

Fig. 1. Difference independence holds when a decision maker judges...



- Figure 1 from Keller and Simon (2019)

What Do They Look Like: Utility Functions: n=1

- *Single spatial utility independence* → multilinear form:

$$\boxed{U\left(z_1,\ldots z_m\right)=\sum_{i=1}^{m} a_i u\left(z_i\right)+\sum_{i=1}^{m}\sum_{i'>i} a_{ii'} u\left(z_i\right) u\left(z_{i'}\right)+\cdots+a_{123\ldots m} u\left(z_1\right)\ldots u\left(z_m\right)}$$

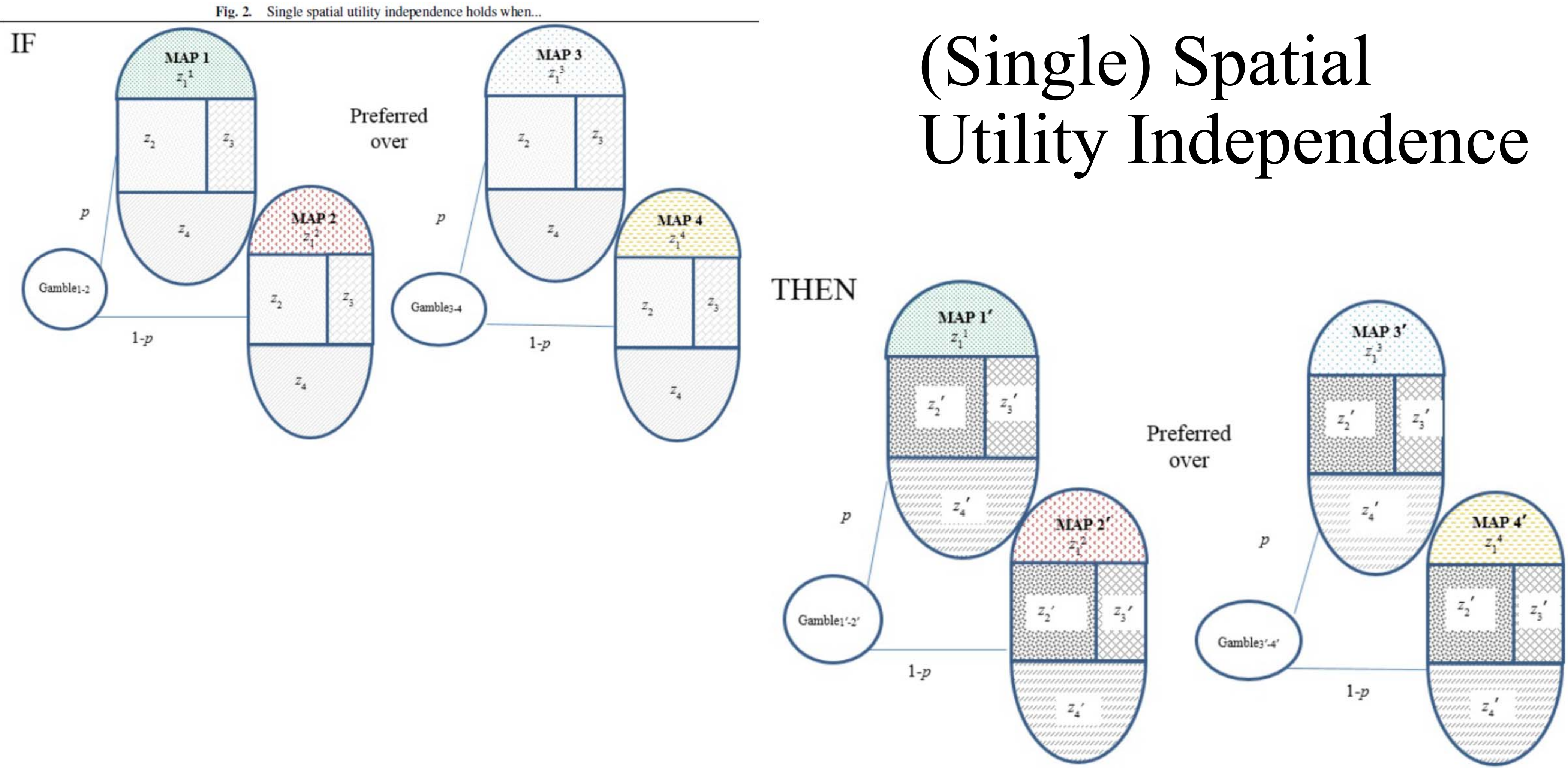
where the *a* terms with multiple subscripts are coefficients on interactions

- *Mutual spatial utility independence* → multiplicative form:

$$\boxed{U\left(z_1,\ldots z_m\right)=\sum_{i=1}^{m} a_i u\left(z_i\right)+a\sum_{i=1}^{m}\sum_{i'>i} a_i a_{i'} u\left(z_i\right) u\left(z_{i'}\right)+\cdots+a^{m-1} a_1\ldots a_m u\left(z_1\right)\ldots u\left(z_m\right)}$$

(does not require any additional assessment)

(Single) Spatial Utility Independence



- Figure 2 from Keller and Simon (2019)

What Do They Look Like: Utility Functions: *n*>1

- *Single utility independence* → multilinear form:

$$\boxed{U(\mathbf{z}) = \sum_{i=1}^{m} a_i \sum_{j=1}^{n} b_j u_j(z_{ij}) + \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{i',j' \in S_{ij}} k_{iji'j'} u_j(z_{ij}) u_{j'}(z_{i'j'}) + \cdots + k_{11,12,\ldots,mn} \prod_{i=1}^{m}\prod_{j=1}^{n} u_j(z_{ij})}$$

where the set S_{ij} consists of all *i'*,*j'* pairs where (*i'*, *j'*) is lexicographically greater than (*i*, *j*), and the *k* terms are weights on interactions

- *Spatial utility independence* and *Attribute utility independence* → multiplicative form:

$$\boxed{U(\mathbf{z}) = \sum_{i=1}^{m} a_i \sum_{j=1}^{n} b_j u_j(z_{ij}) + k\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{i',j' \in S_{ij}} a_i b_j u_j(z_{ij}) a_{i'} b_{j'} u_{j'}(z_{i'j'}) + \cdots + k^{mn-1} \prod_{i=1}^{m}\prod_{j=1}^{n} a_i b_j u_j(z_{ij})}$$

where *k* is a scaling constant (again, no additional assessment needed)