**Supporting Wildfire Mitigation Investment Prioritization**

Thelonious Funk, Alan T. Murray

*Department of Geography, University of California at Santa Barbara*

**Abstract**

Site prioritization for wildfire mitigation must consider a variety of spatial and non-spatial attributes, simultaneously considered and integrated. This paper explores challenges in attribute derivation, selection and integration. Further, support tools are proposed to facilitate this process. Mitigation efforts in a high wildfire danger region of Southern California illustrate the challenges and opportunities for spatial analytics in land prioritization.

**1. Introduction**

Given limited resources, hazard mitigation commonly requires prioritization and related decisions to be made. In such efforts, decision makers (DMs) are often required to consider variety of spatial and aspatial data, objectives, constraints, and uncertainty, integrating them into a problem that may be solved (Malczewski & Rinner, 2015). This process has come to be called GIS-MCDA: an integration between Geographic Information Science (GIS) and Multi-Criteria Decision Analysis (Malczewski, 1999). Numerous authors can be attributed for defining and advancing this field over the past three decades; Malczewski, Jankowski, Ligmann-Zielinksa, Siskos, Greco, Church, Murray, and Saaty to name a few.

Several of these authors, notably Malczewski and Jankowski, have emphasized the importance of criteria weighting as one of the core steps to the GIS-MCDA process (Malczewski, 1999, 2006; Jankowski, 1995; Malczewski & Rinner, 2015). Many methods for criterion weighting exist, and commonly fall under the categories of rating, ranking, pairwise comparison, and entropy (Malczewski & Rinner, 2015). These techniques, minus that of entropy, typically rely on the expert opinion of decision makers, and are commonly performed without spatial consideration.

In improving the robustness and accuracy of weight elicitation, recent literature has called for further applications of inverse and exploratory approaches to be made (Jankowski, 2020; Malczewski, NEED TO FIND). To answer these calls, we propose spatially explicit and exploratory methods to derive weights from a DMs’ set of preferred alternatives. Further, we present a web-based framework for further weight space and data exploration.

**2. Literature Review**

“An additive multiattribute utility method has a similar form to the weighted linear combination (see Sect. 4.2), except that the values are replaced by utilities. Although the method has a prominent place in classic decision analysis and theory, it has rarely been applied for tackling spatial decision problems using GIS (e.g., Keisler and Sundell 1997; Store and Kangas 2001; Vacik and Lexer 2001; Ligmann-Zielinska 2009). One of the barriers in applying the utility function method for solving spatial decision problems is a set of underlying assumptions such as preferential independence and utility independence (Keeney and Raiffa 1976). Usually, it is quite difficult, impractical, or even impossible to obtain a mathematical representation of the decision maker’s preferences in the form of utility functions (ReVelle et al. 1981; Lai and Hopkins 1989). The procedures for assessing utility functions with even a moderate number of attributes can be time consuming and tedious. Also, they place considerable information processing demands on the decision maker. It can be argued that decision makers are unable or reluctant to articulate their preferences without knowing the possible consequences associated with alternative decisions (ReVelle et al. 1981) (Malczewski & Rinner, 2015, p. 205).

**3. Data**

**4. Methods**

It has been noted previously that criteria weighting in MCDA is typically a forward process, where weights are elicited in advance by decision makers, using processes where criteria are rated, ranked, or measured by pairwise comparison to create some final composite score (Jankowski, 2006, Malczewski & Rinner, 2015). With these forward approaches such as WLC, AHP, or OWA, there are several problems:

1. They rely on the choices of experts or decision makers, entailing that resulting weights are not determined by observation.
2. Similarly, deriving weights prior to observing spatial results inherently makes the process a-spatial. There can be no consideration of how weighting may impact geographic outcomes (Malczewski, 1999).
3. Typically, they assume linearity among weight vectors, allowing for no consideration of discrete value changes, thresholds, or saturation.

In the below section, we address these concerns by introducing an exploratory method for inverse approaches. Using preference disaggregation ad a heuristic for exact rank minimization, we can infer additive value functions or linear weights from observed spatial preferences (Jacquet-Lagrèze & Siskos, 1982; 2001; Greco et al., 2008).

**4.1 Preference Disaggregation with Utility Functions**

Preference disaggregation, pioneered by authors including, XXX, is an inverse approach to weight elicitation that derives an *additive utility function* that conforms with the spatial preferences (i.e. ranking outcomes) of a decision maker().

**4.1.1**

Unlike the previous methods that rely on linear weight vectors preference disaggregation is dependent on utility functions, which, like weight vectors, range between 0 and 1 for each criterion. Uniquely, this *utility* of a given criterion may be non-linear, meaning that values of a criterion can provide benefit or diminishing returns within a certain threshold or past a certain limit. (Is an example needed? )

A piecewise linear utility function can be defined as:

s.t

It was noted that a utility function may be non-linear. This is true in theory, but in practicality this would make solving the function an NP-hard problem (SOURCE). To resolve this, it is common to use breakpoints, formulated as follows:

MATH HERE

Each

To phrase this more formally, our intent is to derive a weight vector from m criteria such that a decision makers preferred alternatives follow a defined preference ranking within a global or local dataset. Several schools of thought exist with GIS-MCDA literature to achieve this, each differing in what preference information is required and what objective(s) is being solved (). Regardless of which approach is used, general notation for the purpose of our application may be shared across methods. See below:

Let the set of all alternatives be defined as P = , our selection of preferred alternatives be s ⊆ P, our set of factors be F = {f₁, f₂, ..., fₖ}, and be the normalized risk factor score of alternative pᵢ for factor fⱼ. in this case is the raw value of factor fⱼ for alternative pᵢ min-maxed scaled between 0-1. Other methods such as quantile or gaussian transformations may also be applicable.

As common in GIS-MCDA, a linear weight function may be defined for each alternative:

**s.t.**

Alternatives with a composite score from the above utility function may next be ordinally ranked:

As mentioned, there are several ways to derive utility value functions (interchangeable symbolically with weight vectors in this scenario), to conform with a decision makers ranking preferences. Each method’s applicability is dependent on the preference information provided, feasibility of a solution, noise and fundamental goals of a decision maker. Below is a table to illustrate the use cases and differences of the most common methods.

|  |  |  |  |
| --- | --- | --- | --- |
| **Method** | **Objective** | **Description** | **Author** |
| **UTilitiés Additives (UTA)** | Derive a single additive value function that exactly conforms to DM’s provided complete or partial preferences. | This is a preference disaggregation method that enforces pairwise constraints from the DM’s ranking preferences. If a DM’s preferences cannot be exactly replicated via an additive utility function than problem is infeasible. | Jacquet-Lagrèze & Siskos (1982) |
| **UTilitiés Additives (UTA-STAR)** | Derive a single additive value function that minimizes ranking violations between DM’s preferences and outcome ranking. | An augmentation of standard UTA with added double error variables for each preference, with the LP adjusted to minimize total error. This allows for exceptions to DM’s exact preferences. | Jacquet-Lagrèze & Siskos (2001) |
| **Robust Ordinal Regression (ROR)** | Derive a set of feasible value functions that are feasible in satisfying provided preference constraints. | This is intended to provide a set or range of feasible solutions that satisfy given preferences rather than a single solution. | Greco, Mousseau, & Slowiński (2008) |
| **RankSVM** | Derive a single value function that maximizes the difference between the scores of preferred alternatives and that of comparisons. |  | Joachims (2002) |
| **Exact/heuristic Mixed-Integer Programming** | Minimize average ranking of preferred alternatives via ranking comparison with binary pairwise variables. | Binary variables are introduced to track rank order. Rather than fitting preferences, rankings are forced. The problem is recognized as NP hard and requires heuristics for non-trivial problems. | Funk & Murray (2025) |

Most typically, models minimize a surrogate: average ranking, sum of ranks, or violations in pairwise comparison. Below is a generic formulation for minimizing these surrogates.

In the most exact way, the rank of each alternative () within (sP) can theoretically be minimized as such:

**Min f(w)**

Minimize surrogate of rank for

**Where f(w) could be:**

average rank of

This problem formulation is intended to be flexible, allowing for a decision maker to provide one or more contiguous or noncontiguous selections of parcels out of the defined population. Preferred alternatives in this problem are defined locations and may be compared to a global or local dataset, making any solution inherently spatially explicit (Source). Many related problems have already been solved, … example example, and similarly numerous methods could be applied to such a problem. Below is a table of existing suitable techniques.

QUESTIONS:  
1. Do we want to present methods as applied with our fire application? I.e. do we want to reference parcels, or our factors, or do we want to keep general?

2. What data are we most interested in including? LANDFIRE? The base variables we have had?

3. For results, are we more concerned by general methods and how they compare, or do we want to see actual fire application results?

References

* Jacquet-Lagrèze, E., & Siskos, J. (1982). “Assessing a set of additive utility functions for multicriteria decision-making: the UTA method.” *European Journal of Operational Research*, 10(2), 151–164.
* S. Greco, V. Mousseau, & R. Słowiński (2008). “Multiple criteria ranking using a set of additive value functions (UTAGMS).” *European Journal of Operational Research*, 191(2), 416–436.
  + See also robust/Group extensions: Greco et al. (2012, 2014).
* Joachims, T. (2002). “Optimizing Search Engines using Clickthrough Data.” *KDD 2002*. (Introduces a pairwise SVM ranking approach.)
  + RankSVM foundations and lineage: Herbrich, Graepel & Obermayer (1999/2000), *Advances in Large Margin Classifiers*; SVM-rank software page.
* Tamiz, M., Jones, D., & Romero, C. (1998). “Goal programming for decision making: An overview of the current state-of-the-art.” *European Journal of Operational Research*, 111(3), 569–581.
* Stewart, T. J., Janssen, R., & Van Herwijnen, M. (2004). “A genetic algorithm approach to multiobjective land-use planning.” *Computers & Operations Research*, 31(14), 2293–2313.
* Cao, K., Batty, M., Huang, B., Liu, Y., Yu, L., & Chen, J. (2011). “Spatial multi-objective land-use optimization: Extensions to the non-dominated sorting genetic algorithm-II.” *International Journal of Geographical Information Science*, 25(12), 1949–1969.