DRAFT 0, August 19 2025

Supporting Wildfire Mitigation Investment Prioritization

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1. **Introduction**
   1. **Prioritization and Decision Making:** 
      1. Limited resources are a chronic issue of hazard mitigation, requiring prioritization and decision making (Moritz et al., 2014; Calkin et al., 2014).
      2. Multi Criteria Analysis, as the name states, integrates numerous attributes. In GIS, this is often spatial and aspatial data, all of which must be integrated together with extreme care. This requires weighting the significance of each variable. Derived weights of attributes (factors) decide the results of analysis. The decisions related to weighting must be made carefully and with a robust understanding of what each choice entails.
   2. **GIS and Multi Criteria Decision Analysis (MCDA):**
      1. Typically, methods in multi criteria decision analysis are forward facing, meaning that weights are derived prior to analysis (WLC, AHP, OWA) (Jankowski, 1995; Malczewski, 1999; Many more examples).
      2. Inverse MCDA and preference disaggregation (PD) do the opposite: They take observed selections or preferences and use them to derive parameters of a given model. They can, and often are, applied to rankings or rank preferences to derive weightings. These methods have existed for decades: UTA (Jacquet-Lagreze and Siskos, 1982), Robust Ordinal Regression (Greco, Mousseau, Slowinski, 2008), etc. Despite this, they are rarely if ever applied spatially.
   3. **Gaps**
      1. Numerous authors have denoted the need for more inverse methods along with sensitivity analysis and transparency within GIS-MCDA (Malczewski, 2006; Ligmann-Zielinska and Jankowski, 2008; Malczewski and Jankowski, 2020).
      2. Within Hazard and wildfire mitigation efforts, current literature relies on forward weighting or simulation methods that lack robustness, tractability, and flexibility to explore new risks (Finney, 2006; Syphard et al., 2017; more).
   4. **Contribution**
      1. *We support fire and hazard mitigation by formalizing and applying inverse MCDA techniques (rank minimization and preference disaggregation) spatially.*
      2. *Theoretical contribution: Inverse MCDA within GIS*
      3. *We demonstrate the value and feasibility of inverse MCDA applications on large scale real world problems, and propose it as an emerging tool in exploratory analysis.*
2. **Literature Review**
   1. **Background and Evolution of GIS Multi Criteria Decision Analysis**
      1. Suitability Analysis/Map Overlay (McHarg 1969;) 🡪 Common Forward Weighting (AHP, WLC< OWA, Goal Oriented Programming (Jankowski, Maciejewski) 🡪 Inverse methods (Jacquet-Lagreze and Siskos, 1982; Zopounidis, 1995; etc.).
      2. **Table 2.1: Most common methods found in forward MCDA weighting**
      3. Deriving weights in GIS-MCDA poses numerous challenges: spatial and aspatial data integration, hidden correlations, perturbation sensitivity.
      4. GIS-MCDA has had many applications within hazard and wildfire mitigation (Kanga et al., 2019, Murray et al., 2023, Calkin et al., 2014). What is found within GIS-MCDA for hazard mitigation is again forward focused, relying on methods for weight derivation not based in observation.
   2. **Findings of Inverse Methods in GIS** 
      1. Inverse and preference disaggregation methods have been common in decision science, particularly operations research, for quite some time but rarely have been applied to GIS.
      2. Inverse Analysis in spatial decision analysis has been mentioned (Jankowski, 2001), and calls for more of it have been made (Ligmann-Zielinska and Jankowski, 2008; Malczewski and Jankowski, 2020).
      3. Applications of inverse methods are sparce, and if they do exist, they are commonly limited to small datasets or to theory (Cirucci, 2014).
      4. There is little to no inverse weight derivation applied to GIS decision analysis within hazard or fire mitigation to support or derive weightings from selections or observed outcomes.
   3. **Difficulty of Inverse MCDA Methods**
      1. Inverse methods, particularly rank minimization, are known to be computationally challenging (NP hard). Constraints grow exponentially.
      2. Inverse Methods applied to spatial science requires additional spatial considerations: preprocessing, normalization, sampling, etc.
      3. Solutions require relaxations, sampling, preference disaggregation, or heuristics.
   4. **Multi-Criteria Decision Analysis within Hazard and Wildfire Mitigation?**
3. **Data**
   1. **Study Area: Wildland Urban Interface of Santa Barbara, CA**
      1. **Figure 3.1: Map of Santa Barbara’s Wildland Urban Interface and of Parcels within**
   2. **Variables**

**Table 3.1: Data**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Data** | **Source** | **Year** | **Data Type** | **Contribution Type** | **Summary** |
| DINS | CAL FIRE | 2022 | Point | Structure Damage Outcomes | Structure loss/damage by fire event. |
| Slope | USGS | 2013 | Raster (1m) | Environmental | Steeper slope = faster fire spread typically. |
| Elevation | USGS | 2013 | Raster (1m) | Environmental | Impacts weather fire interactions, moisture. |
| Vegetation Type | LANDFIRE | 2022 | Raster (30m) | Environmental | Categorical (forest, chapparal, grass, etc.) |
| Vegetation Cover | LANDFIRE | 2022 | Raster (30m) | Environmental | Percent of vegetation cover |
| Fuel Model | LANDFIRE | 2022 | Raster (30m) | Environmental |  |
| Canopy Cover | LANDFIRE | 2022 | Raster (30m) | Environmental | Percent Canopy cover for crown fire spread |
| Distance from Nearest Fire Station | CALFIRE | 2022 | Point | Mitigation | Response Times |
| Distance from Nearest Agriculture | Firewise + … | 2022 | Polygon | Mitigation | Acts as fuel breaks |
| Structres within ¼ mile | Microsoft Building Footprints + Santa Barbara County + Digitization | 2025 | Polygon | Conflagration |  |
| Distance to nearest neighboring structure | Microsoft Building Footprints + Santa Barbara County + Digitization | 2025 | Polygon | Conflagration |  |

* 1. **Preprocessing**
     1. As seen, there are many layers requiring spatial preprocessing: parcel aggregation/data assignment.
     2. Min-max normalization
  2. **Case Studies and Application of Methods:** Local MCDA can be applied to previous burn scars for weight derivation:
     1. Holiday Fire Burn Scar & DINS structure Loss
     2. Thomas Fire Burn Scar & DINS Structure Loss
     3. **Figure 3.2: Map of Holiday Fire Burn Scar, parcels, and structure loss**
     4. **Figure 3.2: Map of Thomas Fire Burn Scar, parcels, and structure loss**

1. **Methods**
   1. **Exploratory MCDA with interactive map**
      1. Shows volatility of weights
      2. **Figure 4.1: Suitability Map of each Variable Chosen for Analysis**
      3. **Figure 4.2: Subplots of Variable Distributions (maybe even for different normalization techniques?)**
      4. Sensitivity Analysis: Different Weightings can produce large shifts in rankings, exploratory analysis demonstrates how all analysis results are dependent on weighting. Weighting is of the utmost importance and must be robust.
   2. **Inverse MCDA: Rank Minimization**
      1. Given an expert provided selection of high f
      2. This problem can be solved exactly through mixed integer programming

**s.t.**

**- Pairwise Constraints:**

1.

2.

- (non-negativity)

- (binary constraints)

**where:**

* **y[i,j]** ∈ {0,1}: Binary, =1 if parcel j ranks above parcel i
* **M: Big M**
* ε: small positive constant (10^-6) for tie breaking
  + 1. But, this is not feasible. Several heuristics can be applied to rank minimization: Simulated annealing (Kirkpatrick et al., 1983), Discrete Weight Enumeration (Ligmann and Jankowski, 2008).

1. **Results**
   1. **Results of Applied Methods:** 
      1. Table 5.1: Comparison of Weighting Schemes
      2. Table 5.2: Rank Distributions
      3. Figure 5.3: Choropleth map of ranking (rank minimization)
      4. Figure 5.4: Choropleth map of ranking (UTA)
   2. **Sensitivity Analysis:**
2. **Discussion**
   1. **Contributions**
      1. Inverse MCDA in GIS
      2. Weight consideration, validation, and derivation framework for hazard factors, applied to Santa Barbara Wildfire
      3. Addressing limitations of computation for exact methods (call for improving direct rank minimization heuristics)
      4. Call for more weight validation and exploration in hazards