**3. Study Region and Data (ROUGH)**

Santa Barbara, located on the coast of Southern California (Figure 3.1), is a known area of high fire risk (Calkin et al., YEAR; Moritz et al., 2014). Within this region, studies and experts have additionally noted the Wildland Urban Interface (WUI) of this region to be at particular risk of devastating wildfire (Moritz et al., 2014; Murray et al., 2023). This region, as shown in figure 3.2, represents the regions of Santa Barbara where wildfire risks created by standard factors (slope, vegetation, fuel moisture, etc.) intermix with urban development, posing increased risks of loss and conflagration (SOURCE).

**Figure 3.1: Map of Santa Barbara within CA**

**Figure 3.2: Map of Santa Barbara’s Wildland Urban Interface**

There are many different regions, neighborhoods, or parcels that could be identified for fire risk mitigation priority within Santa Barbara’s Wildland Urban Interface (Murray et al., 2023?) For a demonstration of preference disaggregation in inverse utility derivation, we propose three separate rook-contiguous sets of parcels stratified across Santa Barbara’s Wildland Urban Interface that may be deemed as high risk. Given that all three sets lie within the WUI, we can perform our analysis under local MCDA conditions, renormalizing data to use parcels within the WUI as the extent of our dataset. This localization of the process can support decision makers in better understanding what may distinguish these preferred sets from all others given our factors.

**Figure 3.3: Map of Selected Sets**

In terms of criteria, there are several factors in which we consider separate from what is commonly used in Wildland Fire risk modeling. The combination of these factors attempts to integrate multiple risk considerations for fire: Wildland fire spread (slope, Fire Behavior Fuel model), Conflagration and structure loss (areal structure density by count), and mitigation (Proximity and coverage by agriculture or other fuel breaks, travel time from the nearest fire station). Below is a table of our factors:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Factor** | **Contribution** | **Normalization** | **Data Type/Resolution** | **Source** |
| **Count of Structures within a ¼ mile window of parcel** | **Risk of conflagration and structure loss** |  | **vector** | Microsoft Building Footprints (YEAR) + Santa Barbara County (YEAR) + Digitization |
| **% Coverage of very high hazard zones within a ½ mile** | **Risk of fire ignition and spread** |  | **vector** |  |
| **Average Fire Behavior Fuel Model flame length within a ½ mile** | **Risk of fire ignition and spread** |  | **25Raster (30m)** | **LANDFIRE (2025)** |
| **% Coverage of Agriculture or other fuel breaks** | **Mitigation of fire spread** |  | **Santa Barbara Firewise** |  |
| **Slope (degrees)** | **Risk of fire spread** |  | **1 meter** |  |
| **Travel time from nearest fire station to parcel (minutes)** | **Mitigation of fire spread** |  | **Vector** | **CALFIRE + Open Route Services** |

**Table 3.1: Fire Risk Factors**

Our Fire Behavior Fuel Model (FBFM) layer was initially sourced from LANDFIRE, 2025. While it has not been common in the literature to transparently score and normalize FBFM data into a normalized single score as a proxy for fire risk, it has been done in conjunction with other data, such as slope and weather variables, to generate flame length and burn probability variables (Scott & Burgan, 2005; Statton, 2006). In the literature, risk values have been derived from output flame lengths: low risk for flame lengths < 4 feet, medium risk for flame lengths between 4-8 feet, high risk for flame lengths between 8-12 feet, and very high risk for lengths above 12. For the sake of quantifiable normalization and integration, these descriptive values have been translated to numeric form [0.25, 0.5, 0.75, 1] while assuming standard conditions.

**4. Methods**

**4.1.1 Formulation**

As noted in section 2, preference disaggregation is an umbrella term for deriving utility functions to conform or best fit a given set of preferences (SOURCE). While there have been several applications of these methods in GIS-MCDA (SOURCE SOURCE SOURCE), it is seldom, and applications are typically for small datasets. As far as we are aware, preference disaggregation in the manner we propose has not yet been applied to hazard mitigation.

In the application of fire risk assessment, we first must define our criteria, preferred alternatives, non-preferred alternatives, and normalized scores as follows:

For each criterion (*j)* of each parcel (*i)* we first derived a normalized risk score from raw values () to make criteria comparable via min-max scaling:

And along the normalized risk scores of each criterion, we may set *k* breakpoints between [0,1] to allow for changes in utility across this axis:

The utility can be set at each of these breakpoints, and interpolated between them:

Where Interpolation between :

And using interpolated utility values, we can derive a piecewise linear utility function for each criterion:

That is held under monotonicity constraints to avoid overfitting (SOURCE):

Which finally can be used to calculate the utility of a single parcel:

Now that the utility functions have been formulated for each parcels’ criteria (), we may define a decision makers preferred set of parcel alternatives as *U(p)* and a set of all other non-preferred parcels as *U(q).* Between these sets of preferred and non-preferred parcels, we formulate a constraint which may keep track of each parcel in *U(q)* that outscores *U(p)*, noting the magnitude in loss with an error constant ().

Cognitively, our objective in preference disaggregation is to have all preferred alternatives *U(p)* outrank all non-preferred alternatives *U(q)* in terms of their overall utility (*U(i)*). In practice, we solve a proxy of this by minimizing the total error found in the previous comparison constraint:

**4.1.2 Implementation**

As shown in figure 3.3, our selected preferred alternatives *U(p)* includes three separate locations across Santa Barbara’s WUI, counting a total of 271 parcels. In our non-preferred set *U(q)* there are 26,125 parcels, which account for all parcels within the WUI apart from our preferred selection. To solve the above preference disaggregation method with this data is computationally expensive. Given a preferred set of 271 and a non-preferred set of 26,125, there could be up to 7,079,875 constraints formulated per solve. In solving such as problem, we implemented Gurobi (12.0.3) through Python (3.13.7).

As mentioned in 4.1.1, the definition of breakpoints in this model are loose, and may be specified by a user. In preference disaggregation using a method such as this, it is possible and sometimes common for a decision maker to set specified breakpoints at across the value space of a given criterion (SOURCE). This typically requires an informed decision, where a decision maker may know that utility should or should not assigned at certain values (SOURCE).

In this paper, we do not define breakpoints on known utility / value relationships. Rather, as is standard practice (SOURCE), we can assign k breakpoints in even steps over a criterion’s values. While utility functions may not be non-linear or else they would be non-convex and NP-hard (SOURCE), they can be made increasingly less linear. As the number of breakpoints is increased, a utility function is given more flexibility to emulate that of a non-linear function.

To robustly consider different variations in weighting and utility linearity, we propose solutions under vary breakpoint conditions, where breakpoints are defined at equal intervals between [0,1] with iterative alpha values of (k-1).

When alpha is equal to one, two break points are set. One where = 0 and one where is equal to one. Given that we enforce piecewise linear monotonic constraints, the derived utility functions under this scenario are forced to be linear, matching that of typical global linear derived weights. Below we show the derived utility functions of our model using the above preferences under increasing alpha values of 1, 2, 3, and 4.

**5. Results**

In the figure’s to follow, it can be see that